



Employment impacts of technological innovations in Sub-Saharan Africa: Firm-level evidence.

Draft paper submitted on the 14th of April 2016 for the 19th Annual Conference on Global Economic Analysis, The World Bank, Washington DC, USA.

Elvis Korku Avenyo (PhD Fellow)

Maastricht University/UNU-MERIT

Maastricht, The Netherlands.

e.avenyo@maastrichtuniversity.nl/avenyo@merit.unu.edu

Abstract

Innovation has become a key interest in recent years in Sub-Saharan Africa as it is evidenced to play eminent role in generating employment. There is however dearth of empirical evidence assessing the impact of innovations on firm-level employment growth in Sub-Saharan Africa. Extending and applying a novel dose response model under different intensities of innovation, this paper presents new evidence on the impact of firm-level Technological Process and Product (TPP) innovations on employment growth using the World Bank's Enterprise Survey (ES) merged with the newly available Innovation Follow-Up Surveys data covering the period 2010-2013 for 10 Sub-Saharan African countries. Our main findings are generally consistent with the stylized facts in the empirical literature with product and joint product and process (JPP) innovations having compensation impacts on employment growth while process innovations having displacement impacts. However, we found these conclusions to be invalid beyond sub-interval of firms' intensity of innovation. In extensions to decent employment, we found product and JPP innovations to be creating indecent jobs. In terms of policy, the paper recommends extension of social security to all types of workers in line with national and regional innovation policies and the ILO-WHO Social Protection Floor Initiative.

Key words: Decent Employment, Technological process and product (TPP) innovations, Dose response model and Sub-Saharan Africa.

JEL Classification: J23, J3, O31, O33, L1

1. Introduction

Innovation is recognized as a primary driver of economic growth and productivity as well as a major source of employment and competitiveness in the global market economy (Gault, 2010; OECD/Eurostat, 2005; Verspagen, 1992; Schumpeter, 1934). Innovation at the firm-level has been found to create new jobs, a primary source of economic growth and also found to trigger some positive indirect effects (see Crespi & Tacsir, 2013; Harrison, Jaumandreu, Mairesse, & Peters, 2014; Hall, Lotti, & Mairesse, 2008; Pianta, 2005). Empirical evidence available also indicates the critical role innovation played in leapfrogging productivity, industrial competitiveness and economic prosperity in the 'so called' newly developed countries of South Korea, Singapore, Malaysia and most recently China (Bokova, 2012). Advancing firm-level innovations and promoting firm-level innovative activities arguably offers strong prospects for sustainable growth, improvement in productivity and consequently avenues for quality employment creation in developing countries particularly Sub-Saharan Africa (SSA) (Gault, 2010; Lee & Kim, 2010).

The development discourse in SSA has been wrought with critical issues such as political instability, premature de-industrialization and persistent poverty with some of these issues been accentuated in recent years by the demographic pressure and increasing unemployment - particularly youth unemployment - glaring on the continent. ILO (2014) statistics show youth unemployment in SSA to be 12.58% in 2013 but estimates it to increase to 12.66% and 12.69% in 2014 and 2015 respectively. Innovation and the effects of innovative activities in SSA have been found to be key in resolving some of these issues and thus an important policy and research area (AU-

NEPAD, 2010). There is therefore a renewed and a growing focus on how to nurture new sources of employment through innovation.

With this new innovation-led ‘development thinking’, policy efforts¹ and strategies are being developed and implemented at the continental, regional and national levels in Africa to boost economic growth that translates into quality jobs through Science, Technology and Innovation (STI) (AU-NEPAD, 2014). With the implementation of the NEPAD African Science, Technology and Innovation Indicators (ASTII) Initiative, several African countries now have firm-level R&D and Innovation data, which provide useful innovation indicators in Africa. Evidence from these data sets indicates the pervasiveness of innovations in SSA (AU-NEPAD, 2010, 2014).²

The theoretical effect of innovation on employment however remains mixed (Harrison, et al., 2014; Crespi & Tacsir, 2013; Elejalde, Giuliodori, & Stucchi, 2013; Lachenmaier & Rottmann, 2010; Hall et al., 2008; Verspagen, 2004). As a result, empirical analyses of the links between innovation and employment still occupy a central stage in the development literature (Peters, 2005). According to AU-NEPAD (2014), one challenge facing African countries is how to “link” innovation to employment creation. It is in the spirit of closing this evidence gap and advancing the understanding of innovation impacts on employment growth in SSA that this study becomes vital.

The empirical literature mainly from developed countries focuses on innovations in manufacturing firms ignoring to a large extent innovation in service sector firms. With innovation in the service sector evidently exerting more beneficial effects on employment than in manufacturing (Gallouj & Djellal, 2010) and being the major contributor to GDP in most SSA economies, it is critical to consider and analyze the innovative activities of service sector firms. Understanding the context of innovations and the mechanisms between innovation and employment at the firm-level is considered as “central for the formulation and design of innovation policy” and for understanding the implications of labour market regulations on the intensity of innovation (Hall et al., 2008).

This paper aims to close these evidence gaps and shed light on the importance and relevance of innovation in the design of micro-policies for employment. This study however aims to examine the employment impacts of innovation from a counterfactual stance where innovative and non-innovative firms are assumed to have varying responses to the intensity of innovation.

This paper contributes to the literature in four major ways. Firstly, the paper provides, to our knowledge, the first rigorous empirical evidence assessing the impact of firm-level innovations on employment growth using a newly available firm-level data in SSA. Scholarly evidences available in the literature are mainly from the developed countries and Latin America. This may be partially due to the initial unavailability of innovation data in SSA. With the availability of innovation data in SSA, this paper contributes to the literature by providing empirical evidence that will redirect policy and provide a better

¹ Lagos Plan, Khartoum declaration, Addis Ababa declaration etc.

² Another dataset on innovation is the World Banks supplementary innovations survey that is employed in this paper. This dataset is particularly useful as it can be easily merged with the Enterprise Surveys available in almost all SSA countries.

understanding of innovative activities, the context of these innovative activities and the labour market implications in SSA.

Secondly, this paper contributes to the literature by applying a novel approach to analyze the employment impacts of innovation from a counterfactual stance where innovative and non-innovative firms have varying responses to the introduction of innovations and the intensity of innovations. In modern micro-econometrics, counterfactual causal analysis is becoming widespread in establishing causal relationships between economic variables. However, the application of counterfactual causal analysis remains missing in the innovation-employment literature. This paper tries to go further by employing a counterfactual perspective by going beyond the 'average effect' analysis popular in the literature. In addition, we model the firms' choice to introduce an innovation or otherwise, to rigorously examine the 'impact' of the various types of firm-level innovations on employment under heterogeneous responses with varying intensities of innovations.³

Thirdly, the paper assesses how innovations impact on employment growth varies along different innovation intensities. Innovative firms do not only innovate but also have different levels of innovativeness. What is relevant in most settings is not only whether a firm has introduced an innovation or otherwise, but also the intensity of the innovations. Analyzing the effect of process innovations, for example, by using a binary variable only determines whether process innovations and employment growth are positively or negatively correlated. We analyse the impact of innovations on employment growth across different innovation intensities thereby providing a deeper understanding of the causal relationship. This analysis helps to determine whether there is (are) innovation intensity (ies) where employment growth is maximized (or minimized).

Fourthly, the creation (compensation) and destruction (displacement) impacts of innovations may depend on the type and skill of workers (Harrison et al., 2014). This paper makes another important contribution to the literature by extending our analyses to understand the different impacts each innovation may have on the security and skill of workers.

In this paper, we adapt and apply the Dose Response Treatment Model under continuous treatment developed recently by Cerulli (2012) and used by Cerulli & Poti (2014). The Dose Response Treatment Model under continuous treatment is an econometric model for estimating continuous treatments under heterogeneous response where selection into treatment may be endogenous. This paper presents the first application of this perspective to analyze the employment impacts of innovation from a counterfactual stance where innovative and non-innovative firms have varying responses to the intensity of innovation. The data used in the paper comes from the World Bank Enterprise Survey (ES) and the Innovation Follow-Up Surveys for 10 Sub-Saharan African Countries. The study uses these comparable firm-level datasets for Congo Democratic Republic, Ghana, Malawi, Namibia, Nigeria, South Sudan, Sudan, Tanzania, Uganda and Zambia. Results reveal compensation impacts of product and

³ According to Cerulli & Poti (2014), the empirical application of counterfactual causal analysis remains a future development. This paper presents the first application of this perspective.

joint product and process (JPP) innovations on employment growth. Process innovation is found to have displacement impact on firm employment growth. These conclusions are however found to be valid only within a sub-interval of firms' intensity of innovation. In extensions to decent employment, we found product and JPP innovations to be creating unsecured jobs as compared to secured jobs.

The rest of the paper is organized into the following sections. Section 2 presents a brief literature review on the relationship between innovation and employment with special emphasis on empirical papers. In Section 3, the Dose Response Treatment Model and sources of data as well as appropriate robustness checks to validate our results are presented. Section 4 presents the results from the empirical estimation in line with the objectives of the paper. Section 5 presents the conclusion.

2. Related Literature

2.1. Theoretical relationship between innovation and employment⁴

Conceptually, the theoretical analyses of the effect of innovation on employment are done from either the micro or macro strand or both (see Pianta, 2005 and Vivarelli, 2014). This review however concentrates on the micro strand due to the fact that, innovations are introduced at the firm-level where their employment effects are manifested directly (Pianta, 2005).

The theoretical literature analyzing the employment effects of innovation essentially distinguishes between two main types of innovation as product and process innovations. This distinction is however not strict as complementarity is found to exist between the two types of innovation (Mohnen & Hall, 2013; Mairesse & Mohnen, 2010; Pianta & Antonucci, 2002). The overall effect (direct and indirect) of both types of innovation on employment at the firm-level is still theoretically contrasting and ambiguous (Lachenmaier & Rottmann, 2010; Hall et al., 2008; Pianta, 2002).

According to OECD/Eurostat (2005: paragraphs 163-164), process innovation is the...

"implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software. Process innovations can be intended to decrease unit costs of production or delivery, to increase quality, or to produce or deliver new or significantly improved products."

Process innovations in other words are anticipated to improve the efficiency of the production process with cost cutting effects leading to the employment of fewer workers. As a result, the direct effect of process innovation on employment is expected to be negative, referred to as the "displacement effect". There exists an indirect effect as well. A firm that introduces a process innovation is expected to be more efficient, become more cost competitive and thereby raise its productivity levels. The increase in productivity levels and output may be passed on by firms as lower prices in competitive markets thereby stimulating demand and thus employment of additional workers *ceteris paribus*. This is referred to as the "compensation effect." The size of the compensation effect however depends on the elasticity of demand for the firm's products, behavior of agents in the firm as well as competition from other firms

⁴ See Appendix B for the graphical representation of this relationship.

(Harrison et al., 2008). The total effect of process innovation on employment at the firm-level is therefore inconclusive as the compensation effect may outweigh the displacement effect and vice versa.

Product innovation on the other hand is defined as the...

“introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics”
(OECD/Eurostat, 2005: paragraph 156).

Product innovations are intended to make firms' more technologically competitive (Bogliacino & Pianta, 2010; Pianta & Antonucci, 2002). The improved competitiveness is expected to lead to the introduction of “new” products on the market through quality advantages thereby stimulating economic activity and market expansion and hence employment (Pianta & Antonucci, 2002). This enables a direct positive relationship between innovation and employment. However, the market expansion that enables the positive direct effect could be as a result of displacement (crowding out effect) of other less competitive firms in the industry.⁵ The effect of the product innovation is therefore theoretically unclear and inconclusive.

As noted earlier, complementarity is found to exist between process and product innovations (Mohnen & Hall, 2013; Mairesse & Mohnen, 2010; Pianta & Antonucci, 2002). The theoretical effect of introducing both types of innovations- referred to in this paper as joint Product and Process (JPP)- on employment depends on the size of the compensation and displacement effects emanating from both types of innovation. If product innovations is found to have larger compensation effects as compared with the displacement effects from process innovation, JPP innovations is expected to generally have compensation effects on employment growth and vice versa.

The effect of innovation on employment extends beyond the firm-level and may be found at the industry level and even beyond. These indirect effects may result from the competitive redistribution of output and demand due to changes in relative prices as well as input-output relations between firms in an industry. Firms may also adopt innovations generated in other industries leading to employment impacts (Pianta, 2005; Verspagen, 2004). This is however beyond the scope of this paper.

2.2. Empirical literature

Despite the theoretical ambiguity in the theoretical literature, there exist some level of general consensus in the empirical literature about the relationship between innovation and employment at the firm-level (see Vivarelli, 2014; Pianta, 2005 for recent survey of the literature). The total effect of innovation (TPP) on employment is found to be generally positive (see Lachenmaier & Rottmann, 2010; Hall et al., 2008). Copious empirical works in the literature find positive effects of product innovation on employment (see Harrison et al, 2014; Meriküll, 2010; Hall et al., 2008; Peters, 2008; Piva & Vivarelli, 2005, 2003; Smolny, 1998). However, the empirical literature on the

⁵ The crowding-out effect is however captured at firm level analyses if firms in the dataset are representative of the industry (see Harrison, Jaumandreu, Mairesse, & Peters, 2014).

effect of process innovation on employment is still inconclusive (see Doms, Dunne, & Roberts, 1995 for positive effects; Harrison et al., 2014; Crespi & Tacsir, 2013 for negative effect; Peters, 2008 for mixed effect; Hall et al., 2008; Smolny, 1998 for no significant effect).

The empirical studies similar to this paper include Harrison et al. (2008, 2014), Crespi & Tacsir (2013), Elejalde et al. (2013), Konte & Ndong (2012), Gebreeyesus (2011), Hall et al. (2008) and Antonucci & Pianta (2002). Antonucci & Pianta (2002) used the 1994-1996 Community Innovation Survey (CIS) drawn from manufacturing firms in Italy, Germany, France, Denmark, Netherlands, Finland, the UK, and Sweden. Modelling the determinants of employment change as a function of changes in demand (value added), innovative effort and change in labour costs per employee, the authors found a negative effect of technological change on employment. This was explained to be due to the price competitive strategies adopted by the firms. Harrison et al. (2008, 2014) analyzed the stimulating effects of innovation on employment using innovation survey data on both manufacturing and service sector firms in France, Germany, Spain and the United Kingdom. They developed a simple theoretical framework that disentangled the effect of innovation (product and process) on output growth and employment growth from existing products. The authors assumed both process and product innovating firms to be product innovators as both innovations “correspond to the introduction of new products”. The major finding emanating from the empirics is that, product innovation is a major source of employment and the compensation effects from it far outweigh the displacement effect from process innovation. Hall et al. (2008), Peters (2008), Crespi & Tacsir (2013) and Elejalde et al. (2013) using different adapted versions of the Harrison et al. (2008) model found similar results. Using a panel data from Italian manufacturing firms, Hall et al. (2008) found a crowding out effect associated with non-innovating firms resulting in a cancellation effect of the positive employment growth obtained from product innovation. Crespi & Tacsir (2013) and Elejalde et al. (2013) analyzed the effect of product and process innovations on employment in Latin America using innovation survey data focusing on the manufacturing industry. The authors found both product innovations to be skill-biased especially in high-tech manufacturing firms. Further analysis by Elejalde et al. (2013) indicates that, product innovation is skill biased but creates both skilled and unskilled jobs.

Empirical evidence analyzing the relationship between innovation and employment in SSA is scant. The idiosyncratic nature of innovation in SSA coupled with the structural features of innovation might lead to invalid extrapolation of results from other regions. The known empirical evidences available are Mahemba & Bruijn (2003), Gebreeyesus (2011) and Konte & Ndong (2013). Using a secondary survey data on informal micro-enterprises in Ethiopia, Gebreeyesus (2011) found innovative activities to be contributing to employment growth. The authors also found no bi-directional causality from employment growth to innovation. In a rare descriptive study that collected primary data on informal ICT firms in Senegal, Konte & Ndong (2013) found innovation as a contributor to job creation and economic growth.

3. Methodology

3.1. Data and descriptive analysis

3.1.1 Data

The empirical investigation in this paper employs data from the Enterprise Survey (ES) and the Innovation Follow-Up Surveys of the World Bank.⁶ The ES is a World Bank project, which collects enterprise data in 122 countries with a standard methodology allowing for cross-country comparisons. The ES methodology randomly stratifies firms by sector, size and location thus making the sample in each country representative. The Innovation Follow-Up Surveys are follow-up surveys to the ES and collect representative firm-level data on innovation and innovative activities of firms⁷ between last fiscal year and three fiscal years ago. The Innovation Follow-Up Surveys followed the Oslo Manual (OECD/Eurostat, 2005) and covered 19 countries between 2011-2014 out of which 15 of the countries covered are in Africa.

ES and the Innovation Follow-Up Surveys were merged at country level in this paper using a unique country identifier. It is important to point out that, we only considered countries that have ES in the same year as the Innovation survey.⁸ All merged country datasets were then appended using a global unique identifier for larger sample size as all individual countries have large missing values for almost all variables of interest. For instance, only few firms in each country recorded information for a variable such as “percentage sales from all product innovations”. Appending all the datasets across countries guarantees a larger sample size. In total, data from 10 SSA countries totaling 4,955 firms were attained. Table 1 presents the list of countries, the year of the surveys and the number of firms from each country under study. A look on Table 1 indicates varying national samples.

Table 1: Description of data by country and year of data collection

Country	Year of ES (For)	Year of Innovation Survey (For)	Number of firms
Congo, D.R. (DRC)	2013(2012)	2013(2012-2010)	385
Ghana (GH)	2013(2012)	2013(2012-2010)	549
Malawi (MLW)	2014(2013)	2014(2013-2011)	250
Namibia (NAM)	2014(2013)	2014(2013-2011)	379
Nigeria (NIGR)	2014(2013)	2014(2013-2011)	905
South Sudan (S. SU)	2014(2013)	2014(2013-2011)	543
Sudan (SUD)	2014(2013)	2014(2013-2011)	412
Tanzania (TZ)	2013(2013)	2013(2012-2010)	543
Uganda (UG)	2013(2013)	2013(2012-2010)	449
Zambia (ZAM)	2013(2012)	2013(2012-2010)	540
TOTAL			4,955

Source: Computed by author from ES and Innovation Follow-up surveys.

In order to standardize our dataset, we employed exchange rate data and implicit price deflators' data from the World Bank's World Development Indicators and the United Nations System of Accounts with base year 2005 respectively.

⁶ Both datasets cover manufacturing and service sector firms.

⁷ See the Oslo Manual (OECD & Eurostat, 2005) for measurement definition of these concepts.

⁸ Ethiopia, Rwanda, and Zimbabwe are also excluded as the sampling methodologies employed in the follow up survey differ from the ES global methodology.

3.1.2. Descriptive statistics

Due to the large number of cross missing values, there was a large drop in the total number of firms and in some cases all firms in some countries across regression specifications. As a result, the total number of countries and the total number of firms vary across innovation types and consequently across estimations. Despite the enormous drop in the number of firms, the representativeness of the population in terms of sector and size was relatively maintained.⁹ Table 2 shows the basic descriptive statistics for two main variables employed in this paper. For each variable, we subdivided the sample into innovators and non-innovators for each type of innovation in the period under consideration.¹⁰

Table 2: Descriptive statistics of innovation and employment growth variables.

	ALL	DRC	GH	MLW	NAM	NIGR	S. SU	SUD	TZ	UGA	ZAM
No. of firms in data	4,955	385	549	250	379	905	543	412	543	449	540
Product innovation											
No. of respondents	2456	383	544	-	-	-	-	-	541	448	540
Innovators	955	147	154	-	-	-	-	-	89	238	327
Non-innovators	1501	236	390	-	-	-	-	-	452	210	213
Product Intensity (Mean % sales)	34.97	44.95	36.65	-	-	-	-	-	43.5	37.64	25.97
Process innovation											
No. of respondents	4935	385	548	248	379	896	542	408	541	448	540
Innovators	2267	153	194	125	192	410	243	122	205	226	397
Non-innovators	2668	232	354	123	187	486	299	286	336	222	143
Process Intensity (Mean %)	67.87	62.25	56.7	75.8	75.4	72.8	63.17	77.1	57.39	61.06	73.7
Joint Process & Product Innovation (JPP)											
No. of respondents	2461	385	547	-	-	-	-	-	541	448	540
Innovators	682	110	94	-	-	-	-	-	50	142	286
Non-innovators	1779	275	453	-	-	-	-	-	491	306	254
JPP-Intensity (Mean %)	53.07	54.85	52.67	-	-	-	-	-	52.4	55.39	51.50
Total employment growth (Mean)											
Product	.098	.138	.112	-	-	-	-	-	.347	-.036	.118
Innovators											
Product Non-Innovators	.156	.112	.101	-	-	-	-	-	.409	.031	.068
Process Innovators	.434	.243	.248	.228	.012	.981	.412	.142	1.70	.072	.737
Process Non-Innovators	.413	.172	.261	.157	.074	.89	.569	.114	1.258	.066	.179
JPP Innovators	.114	.167	.169	-	-	-	-	-	.450	-.051	.117
JPP Non-Innovators	.140	.102	.091	-	-	-	-	-	.394	.024	.077

Source: Computed by author from ES and Innovation Follow-up surveys

From Table 2, a total number of 2456, 4935 and 2461 firms were attained from both datasets for product only, process only and JPP innovations respectively. 955 firms representing about 38.9% of firms introduced product innovations only with a mean

⁹ See appendix B.

¹⁰ See appendix C for definitions of variables.

percentage of sales from all product innovations (product intensity) of about 34.97% while 2267 firms representing about 45.9% of firms introduced at least one process innovation with an average intensity of about 67.87%. A total of 682 firms representing about 27.7% introduced both product and process innovations with an average JPP intensity of about 53.07%. In terms of total employment growth, JPP innovating firms grew by 11.40% compared to the 13.95% growth of non-JPP innovating firms. All process innovating firms experienced 43.39% growth in total employment as compared to the 41.33% of non-process only innovators. Product innovators on the other hand experienced a 9.77% growth in total employment while non-product innovators grew by 15.55%. The above descriptive indicate that, in our sample, total employment growth tends to be lower for both product only and JPP innovators as compared to non-product and non-JPP innovators. Contrary, process innovators experienced a higher growth in employment as compared to non-process innovators. A closer look across each country descriptive statistics however indicates a much-mixed employment growth across innovation types. For example, both product only and JPP innovators in Uganda experienced negative growth in employment with only process only innovators experiencing a positive growth during the period under consideration. Product innovators in Tanzania experienced a lower employment growth as compared to non-product innovators while Ghana and South Sudan experienced the same situation for process only and non-process only innovators.

3.2. Model

The Dose Response Model employed in this study is an econometric model for estimating continuous treatments under heterogeneous responses where selection into treatment may be endogenous (see Cerulli, 2012). A firm's decision to innovate as well as engage in innovative activities may not be random and may be influenced by confounders and vice versa. Cerulli & Poti (2014) applied (the only known application) the methodology to analyze the impact of public support intensity and firm R&D performance. A variant model was also developed and used by Imbens & Hirano (2004) with Fryges & Wagner (2008) applying the Imbens & Hirano (2004) model to investigate the relationship between exports and productivity growth. The choice of the Dose Response Treatment Model under continuous treatment model is based on its non-requirement of full normality and its applicability to data where lots of the firms have not introduced any type of innovation and vice versa (see Cerulli & Poti, 2014).

3.2.1. Description of model

Assume there are two exclusive groups of firms: innovative firms (treated) and non-innovative firms (untreated). Let the innovation indicator, $W_i = \{0,1\}$ show whether a firm has introduced an innovation ($W_i = 1$) or non-innovative, $W_i = 0$. Firms are assumed to have different innovation intensities (t_i) with non-innovative firms having $t_i = 0$. Innovative firms are assumed to take values greater than zero ($t_i > 0$) as these firms have within the period under consideration, introduced at least one innovation with different intensities from a vector of innovations $I_i = \{PC, PR, TPP\}$ where I_i refers to the vector of innovations introduced by firm i , PC , PR and TPP refer to process only, product only and joint technological process and product innovations respectively. t_i is therefore assumed to take values strictly within the continuous range of $[0:100]$.

Let employment growth (outcome) from innovative firms (treated) be defined as Y_{1i} and employment outcomes of non-innovative firms (untreated) be Y_{0i} .¹¹ Employment outcomes are assumed to be exclusive to a firm. Assume further a vector of M confounders as $X_i = \{x_{1i} \dots x_{Mi}\}$ for all firms. Let N refer to the total number of firms, N_1 refer to the total number of innovative firms and N_0 be the total number of non-innovative firms with $N = N_1 + N_0$.

Following Cerulli (2012) and Cerulli & Poti (2014), let the population outcomes (suppressing subscripts for simplification) be written as:

$$\begin{aligned} w = 1: y_1 &= a_1 + f_1(x) + g(t) + e_1 \\ w = 0: y_0 &= a_0 + f_0(x) + e_0 \end{aligned} \quad (1i)$$

where y_1 and y_0 are the employment outcomes of innovative and non-innovative firms, a_1 and a_0 are two scalars, $f_1(x)$ and $f_0(x)$ are firm's responses to the vector of confounding variables (x) to innovating and not-innovating, $g(t)$ is the response function to the intensity or the level of innovation (treatment) taking value 0 if $w = 0$ and $\neq 0$ if $w = 1$. Following Cerulli & Poti (2014), assume $f_1(x)$ and $f_0(x)$ have a linear parametric form as $f_1(x) = x\delta_1$ and $f_0(x) = x\delta_0$. The causal parameters conditional on x, t are defined as:

$$\begin{aligned} ATET(x, t > 0) &= E(y_1 - y_0 | x, t > 0) \\ ATENT(x, t = 0) &= E(y_1 - y_0 | x, t = 0) \\ ATE(x, t) &= E(y_1 - y_0 | x, t) = \begin{cases} (a_1 - a_0) + x(\delta_1 - \delta_0) + g(t) & \text{if } t > 0 \\ (a_1 - a_0) + x(\delta_1 - \delta_0) & \text{if } t = 0 \end{cases} = \begin{cases} a + x\delta + g(t) & \text{if } t > 0 \\ a + x\delta & \text{if } t = 0 \end{cases} \end{aligned} \quad (1ii)$$

where ATET and ATENT refer to Average Treatment Effect on the Treated (innovative firms) and Average Treatment Effect on Non-Treated (non-innovative firms) respectively. ATE is the Average Treatment Effect.

Cerulli (2012) and Cerulli & Poti (2014) derived the Average Treatment Effect (ATE) conditional on x, t, w as:

$$ATE(x, t, w) = \begin{cases} ATE(x, t > 0) & \text{if } w = 1 \\ ATE(x, t = 0) & \text{if } w = 0 \end{cases} = w[a + x\delta + g(t)] + (1 - w)[a + x\delta] \quad (2)$$

By averaging Equation (2) on x, t, w , the unconditional ATE is obtained as:

$$\begin{aligned} ATE &= E_{(x,t,w)} [ATE(x, t, w)] = E_{(x,t,w)} \{w[a + x\delta + g(t)] + (1 - w)[a + x\delta]\} \\ &= E_{(x)} \left\{ E_{(t)} \left\{ E_{(w)} \{w[a + x\delta + g(t)] + (1 - w)[a + x\delta] | x, t\} | x \right\} \right\} \\ &= p(w = 1)E_{(x)} \{E_{(t>0)} [a + x\delta + g(t)] | x\} + p(w = 0)E_{(x)} \{E_{(t=0)} [a + x\delta] | x\} \\ ATE &= p(w = 1)(a + \bar{x}_{t>0}\delta + \bar{g}) + p(w = 0)(a + \bar{x}_{t=0}\delta) \end{aligned} \quad (3i)$$

where $\bar{g}$ is the average response function taken over $t > 0$.

¹¹Temporary and permanent employment growth, ratio of male to female employment, growth of skilled and unskilled employments were used as outcome proxies for decent employment in the extended model.

Applying the Law of Iterated Expectations (LIE) where $ATE = p(w = 1)(ATE_T) + p(w = 0)(ATE_N)$ and following Cerulli (2012) and Cerulli & Poti (2014), the remaining causal parameters can be rewritten from Equation 3i as:

$$ATE_T = (a + \bar{x}_{t>0}\delta + \bar{g}) \quad (3ii)$$

$$ATE_N = (a + \bar{x}_{t=0}\delta) \quad (3iii)$$

Combining Equations (2), (3ii) and (3iii) by adding and subtracting (3ii) and (3iii) from (2) gives:

$$ATE(x, t, w) = w[a + x\delta + g(t) + (a + \bar{x}_{t>0}\delta + \bar{g}) - (a + \bar{x}_{t>0}\delta + \bar{g})] + (1 - w)[a + x\delta + (a + \bar{x}_{t=0}\delta) - (a + \bar{x}_{t=0}\delta)] \quad (4i)$$

$$ATE(x, t, w) = w[(a + \bar{x}_{t>0}\delta + \bar{g}) + (x_{t>0} - \bar{x}_{t>0})\delta + (g(t) - \bar{g})] + (1 - w)[(a + \bar{x}_{t=0}\delta) + (x_{t=0} - \bar{x}_{t=0})\delta] \quad (4ii)$$

Rewriting in terms of (3ii) and (3iii), Equation (4ii) becomes:

$$ATE(x, t, w) = w[ATE_T + (x_{t>0} - \bar{x}_{t>0})\delta + (g(t) - \bar{g})] + (1 - w)[ATE_N + (x_{t=0} - \bar{x}_{t=0})\delta] \quad (5i)$$

and

$$ATE_T(x, t) = ATE(x, t, w = 1) = ATE_T + (x_{t>0} - \bar{x}_{t>0})\delta + (g(t) - \bar{g}) \quad (5ii)$$

$$ATE_N(x, t) = ATE(x, t, w = 0) = ATE_N + (x_{t=0} - \bar{x}_{t=0})\delta \quad (5iii)$$

Following Cerulli (2012) and Cerulli & Poti (2014), the Dose Response Function is derived by simply averaging Equation (5i) over x as:

$$ATE(t, w) = E_x\{ATE(x, t, w)\} = w[ATE_T + (g(t) - \bar{g})] + (1 - w)ATE_N \quad (6)$$

Equation (6) can be re-written as:

$$ATE(t) = \begin{cases} ATE_T + (g(t) - \bar{g}) & \text{if } t > 0 \\ ATE_N & \text{if } t = 0 \end{cases} \quad (7)$$

where $ATE(t)$ is the main causal parameter of interest and defined as the Average Treatment Effect dependent on the intensity or the level of innovation.

Using the Potential Outcome Model (POM) and assuming Conditional Mean Independence (CMI), Cerulli (2012) derived the estimation equation for the causal parameters by substituting equation (1i) into the observable outcome $y = y_0 + w(y_1 - y_0)$ as:

$$E(y|x, w, t) = a_0 + x\delta_0 + wATE + w[x - \bar{x}]\delta + w[g(t) - \bar{g}] \quad (8)^{12}$$

Following Cerulli (2012) and Cerulli & Poti (2014), assume $g(t)$ is a three degree polynomial as $g(t) = bt + ct^2 + dt^3$, equation (8) can be rewritten as:¹³

¹² See Cerulli (2012, pages 8 and 9) for proof.

$$y = a_0 + x\delta_0 + wATE + w[x - \bar{x}]\delta + b[t - E(t)]w + c[t^2 - E(t^2)]w + d[t^3 - E(t^3)]w + \varepsilon \quad (9)$$

Under Conditional Mean Independence (CMI), OLS estimation of equation (9) is argued to provide consistent estimates of the causal parameters of interest (Cerulli, 2012; Cerulli & Poti, 2014).

The Dose Response Function is estimated as:

$$\widehat{ATE}(t_i) = w \left[\widehat{ATE} + \hat{b} \left(t_i - \frac{1}{N} \sum_{i=1}^N t_i \right) + \hat{c} \left(t_i^2 - \frac{1}{N} \sum_{i=1}^N t_i^2 \right) + \hat{d} \left(t_i^3 - \frac{1}{N} \sum_{i=1}^N t_i^3 \right) \right] + (1 - w) \widehat{ATE} \quad (10)$$

where $\widehat{ATE}(t_i)$ is a consistent Dose Response Function with $\widehat{ATE}(t_i) = ATE(t_i)_{t_i > 0}$.

Empirical evidence from the innovation literature indicates that, the decision to innovate or not (w) and the intensity or the level of innovation (t) are likely to be endogenous.¹⁴ The assumption of Conditional Mean Independence (CMI) therefore breaks down and estimation of equation (9) with OLS gives biased estimates (Cerulli, 2012). Following Cerulli (2012), equation (9) is re-written as:

$$y = a_0 + x\delta_0 + wATE + w[x - \bar{x}]\delta + b[t - E(t)]w + c[t^2 - E(t^2)]w + d[t^3 - E(t^3)]w + \varepsilon \quad (11.1)$$

$$w = \begin{cases} 1 & \text{if } w^* = \eta_1 x_1 + \varepsilon_w > 0 \\ 0 & \text{if } w^* = 0 \end{cases} \quad (11.2)$$

$$t = \begin{cases} t' = \eta_2 x_2 + \varepsilon_t & \text{if } w^* > 0 \\ t^* = 0 & \text{if } w^* = 0 \end{cases} \quad (11.3)$$

where w^* is the latent unobservable counterfactual of innovative and non-innovative firms. The intensity of an innovation is only observed ($t = t'$) when a firm introduces an innovation ($w = 1$), otherwise it is assumed to be unobserved (see Amemiya, 1985, pages 384-385). Equation 11.2 and 11.3 are specified as a Type II Tobit model (see Amemiya, 1985) where 11.2 regresses a vector of covariates x_1 that influences the decision of a firm to innovate or not to innovate and Equation 11.3 defines the vector of covariates, x_2 that determines the intensity of innovation.

The outcome estimation equation can be rewritten from equation 11.1 simply as:

$$y = a_0 + x\delta_0 + wATE + w[x - \bar{x}]\delta + bwT_1 + cwT_2 + dwT_3 + \varepsilon_y \quad (12)$$

where $T_1 = [t - E(t)]$, $T_2 = [t^2 - E(t^2)]$ and $T_3 = [t^3 - E(t^3)]$ are considered to be endogenous together with w . ε_y is an error term with zero mean and constant variance.

3.2.2 Estimation/Identification procedure

¹³ According to Cerulli (2012) and Cerulli & Poti (2014), $g(t)$ can be assumed to have linear, partial linear or polynomial regression forms. We assume a polynomial regression form here to control for possible non-linearity of the intensity of innovations.

¹⁴ See Harrison et al., 2014)

The estimation in this paper is performed at two stages. The first stage involves a probit Maximum Likelihood Estimation (MLE) of the Type II Tobit models of Equation 12.2 and 12.3. The choice of the probit MLE is based on its “strong consistency and asymptotic normality properties” (see Amemiya, 1973). Given data on our variables, we obtain the fitted values from the probit MLE in Equations 12.2 and 12.3. The fitted values obtained from the first stage probit MLE are then used as instruments in Equation 12.1 for the second stage where we performed a two stage least squares (2SLS) estimation (see Wooldridge, 2013, page 529; Cerulli, 2012).

The second stage estimation poses issues of parameter identification as Equation 12 is assumed to have the same covariates in the Type II Tobit models. To resolve the parameter identification problem, we extended the identification assumption by Cerulli (2012) to specify the vector of covariates in Equations 11.2 and 11.3 as:

$$\begin{aligned} x_1 &= (x, q_1) \\ x_2 &= (x, q_2) \end{aligned} \tag{13}$$

where q_1, q_2 are a vector of instrumental variables that appear and explain the probability of a firm to innovate (Equation 11.2) and the intensity of innovation (Equation 11.2) respectively thereby satisfying the exclusion restriction (Wooldridge, 2013).

The two stages of estimation are performed using the *ctreatreg* econometric package in *Stata SE/13.1* (see Cerulli, 2012) which performs both the probit MLE and the 2SLS estimations automatically rather than the estimation of the two stages explicitly as both procedures have been found to give similar results (Wooldridge, 2013). However, econometric packages have been found to be particularly useful in obtaining valid standard errors and test statistics as compared to the invalid standard errors and test statistics obtained from the “manual” estimation of both stages (Wooldridge, 2013).

3.2.3 Testing for endogeneity

In this section, we provide statistical evidence to test the robustness and consistency of our results. The problem of endogeneity is present as noted above, biases and yields inconsistent estimates if equation 9 is estimated. As a result, estimation of the system of equations in equation 12 provides consistent coefficients using instrumental variables (IV). One difficulty in using IV, as well established in econometric literature, is the identification of valid instruments. The theoretical and empirical literatures on employment and innovation have however, suggested several instruments that have been found to provide solution to the problem of endogeneity (see among others Harrison et al., 2014; Crespi & Tacsir 2013; Elejalde et al., 2013; Hall et al., 2008 and Peters, 2008). Some of the identified instruments include increased range, clients as source of information, continuous external R&D engagement (see Harrison et al., 2014; Hall et al., 2008); R&D intensity, share of market, internal R&D, patent, science (see Peters, 2008); public support for innovation activities (see Crespi & Tacsir 2013).

We proceed in this paper by testing the validity of these instruments identified in the literature. Using the C statistic χ^2 (difference-in-Sargan) under the null hypothesis of exogeneity, we test for the exogeneity of our innovation variables. Under the null hypothesis of valid instruments, test of overidentifying restrictions were conducted

using the Hansen's J statistic chi-squared test for joint validity of the instruments. Test results using different combinations of instruments for which data is available for are presented in Table 3.

Table 3: Testing for endogeneity

Dependent variable: Employment growth	A ^b Product innovation	B ^c Process innovation	C ^d JPP
Constant	0.101 (0.0503)	-0.0476 (0.380)	0.356 (0.398)
Innovation type	-0.437 (0.253)	-1.334 (0.841)	-5.246 (6.359)
Intensity of innovation	0.0140 (0.00546)	1.585 (0.894)	0.0839 (0.093)
Number of firms	1815	2114	1941
C statistic χ^2 (difference in Sargan)	13.6646	13.6112	11.3897
Prob. value	0.0011	0.0011	0.0034
Hansen's J χ^2	2.49109	2.80158	1.2654
Prob. Value	0.1145	0.2464	0.2606
Hansen's J χ^2	16.9193 ^e	20.4174 ^f	16.261 ^g
Prob. value	0.0047 ^e	0.0010 ^f	0.0027 ^g

Standard errors in parentheses. Coefficients and standard errors are robust to heteroskedasticity

^b Instruments used are license, patent, continuous external RD.

^c Instruments used are license, patent, continuous external RD.

^d Instruments used are license, patent.

^e Instruments used are license, patent, continuous external RD, clients as source of information, competitors product, demand product, cost product.

^f Instruments used are license, patent, continuous external RD, continuous internal RD, competitors product, demand product, cost product.

^g Instruments used are license, patent, competitors product, demand product, cost product.

Panels A, B and C in Table 3 presents IV test estimates from artificial regressions for product, process and JPP innovations respectively. The C statistic χ^2 (difference-in-Sargan) tests across all innovation types rejected the null hypothesis, with a strong significance, the exogeneity of our innovation variables. We therefore proceeded to test the validity of various combinations of instruments identified in the literature. The Hansen's J χ^2 test failed to reject different combinations of license, patent and continuous external RD as valid instruments for both product and process innovation; license and patent as valid instruments for JPP innovation.¹⁵ The first-stage regressions of our innovation variables on the set of instruments are strongly significant supporting the validity of our instruments.¹⁶

¹⁵We also tested the exogeneity of our innovation variables and the validity of our instruments using the Durbin and Wu-Hausman statistics and the Sargan's and Basmann's chi-squared tests respectively. Test results confirm the problem of endogeneity and the validity of our instruments.

¹⁶ See appendix D and E.

Following Harrison et al. (2014), we conducted further, a test of the ‘discriminatory power’ of the Hansen’s $J\chi^2$ tests by introducing ‘questionable’ instruments. We introduced in addition to the valid instruments identified above, product-quality improvement variables such as the importance of innovation to- offer products already offered by competitors; deal with decrease in demand; decrease cost of production and ;open or increase market share- as instruments. Since these product-quality variables are directly related to price, we expect these sets of additional instruments to be rejected as valid instruments (see Harrison et al., 2014). Results from the Hansen’s $J\chi^2$ tests shown in the bottom two columns of Panel A, B, C as e, f, g respectively show the rejection of the validity of these additional instruments at 1% significance level across all types of innovation. This is additional evidence that, our estimates are unbiased and consistent.

4.1 Empirical results and discussion

The empirical results showing the impact of each type of innovation on employment growth is reported in Tables 3, 4 and 5 for product, process and JPP innovations respectively. Panels A and B in each table show the OLS and IV estimates respectively. We estimated different model specifications where we sequentially add different sets of control variables to extend both the basic OLS and IV specifications for robustness check. We included in all extended regressions size, sector, year and location dummies. It is useful to mention that, the estimated coefficient of each type of innovation is an estimate of the Average Treatment Effect as indicated in estimation equation. In other words, the estimated coefficient of product innovation for example indicates, ceteris paribus the average effect of the firm’s innovative products on employment growth.

Table 4: Employment growth impacts of firm-level product innovation

	A-OLS				B-IV ^e
	(1)	(2)	(3)	(4)	(5)
	Growth of total employment				
Product innovation	0.173*** (0.028)	0.065** (0.032)	0.088*** (0.027)	0.096*** (0.027)	0.955** (0.394)
Log of experience			0.005 (0.015)	0.006 (0.016)	0.013 (0.024)
Log of total employment (-3)			-0.087*** (0.023)	-0.083*** (0.023)	-0.067** (0.031)
Real growth of sales per worker			-0.172*** (0.017)	-0.177*** (0.018)	-0.180*** (0.014)
R&D			0.040* (0.022)	0.039* (0.021)	0.021 (0.042)
Log of labour cost per worker (USD)			0.007** (0.003)	0.006 (0.005)	0.001 (0.008)
Age			-0.004*** (0.001)	-0.004** (0.002)	-0.007** (0.003)
Age Square			0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
Tw	-0.009* (0.005)	-0.006 (0.005)	-0.010** (0.004)	-0.010** (0.004)	-0.146* (0.086)
T2w	0.000* (0.000)	0.000 (0.000)	0.000** (0.000)	0.000** (0.000)	0.004* (0.002)
T3w	-0.000* (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000 (0.000)

Size of firm^{&}					
Medium		0.120***	0.126***	0.122***	
		(0.032)	(0.031)	(0.037)	
Large		0.255***	0.265***	0.258***	
		(0.076)	(0.072)	(0.091)	
Countries^{\$}					
Ghana	0.092***		-0.017	-0.042	
	(0.018)		(0.024)	(0.045)	
Tanzania	0.381***		-0.196***	-0.256***	
	(0.050)		(0.043)	(0.076)	
Uganda	-0.009		-0.165***	-0.185***	
	(0.022)		(0.036)	(0.069)	
Zambia	0.092***		-0.059	-0.101	
	(0.017)		(0.043)	(0.090)	
N	1970	1970	1111	1111	1089
R²	0.031	0.132	0.522	0.543	.
adj. R²	0.023	0.123	0.507	0.526	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include country, size, year, sector and location fixed effects.

All coefficients and standard errors are robust to heteroskedasticity.

^{\$} Congo, Democratic Republic as the base country.

[&] Firms with small employees, ≥ 5 and ≤ 19 , were used as the baseline.

[£] All IV estimations used license as instrument for intensity of product innovation; Patent and external RD as instruments for introduction of product innovation.

Table 5: Employment growth impacts of firm-level process innovation

	A - OLS			B-IV[£]
	(1)	(2)	(3)	(4)
Growth of total employment ^a				
Process innovation	0.540***	-0.190	-0.190	-5.951*
	(0.155)	(0.162)	(0.162)	(3.389)
Support		0.591	0.675	0.463*
		(0.497)	(0.521)	(0.281)
Log of total employment (-3)		-0.816***	-0.790***	-0.816***
		(0.183)	(0.184)	(0.093)
Real growth of sales per worker		-0.638***	-0.655***	-0.699***
		(0.163)	(0.167)	(0.047)
R&D		0.347**	0.298*	0.359**
		(0.166)	(0.164)	(0.178)
Log of labour cost per worker (USD)		-0.031***	-0.041**	-0.009
		(0.012)	(0.020)	(0.023)
Log of age		0.895***	0.738***	0.589
		(0.253)	(0.279)	(0.358)
Log of age squared		-0.155***	-0.132**	-0.093
		(0.051)	(0.054)	(0.074)
Tw	-0.374	1.016	0.866	32.68*
	(0.704)	(0.802)	(0.787)	(17.17)
T2w	-0.000***	0.000	0.000	0.011*
	(0.000)	(0.000)	(0.000)	(0.006)
T3w	0.130	-0.595	-0.564	-21.58*
	(0.468)	(0.591)	(0.580)	(11.88)
Size of firm^{&}				
Micro<5		0.833***	1.158***	1.270***

	(0.311)	(0.326)	(0.384)
Small >=5: <=19	2.119***	2.474***	2.593***
	(0.496)	(0.534)	(0.434)
Medium >=20: <=99	3.613***	4.009***	4.267***
	(0.994)	(1.032)	(0.548)
Country^{\$}			
Ghana		0.0379	-0.072
		(0.072)	(0.243)
Malawi		-0.571***	-0.954**
		(0.155)	(0.378)
Namibia		0.099	-0.241
		(0.172)	(0.408)
Nigeria		0.817***	0.392
		(0.199)	(0.355)
South Sudan		-0.0516	-0.311
		(0.138)	(0.332)
Sudan		0.005	-0.217
		(0.156)	(0.379)
Tanzania		-0.051	-0.286
		(0.239)	(0.366)
Uganda		-0.318**	-0.524
		(0.126)	(0.337)
Zambia		0.243	-0.204
		(0.196)	(0.333)
N	3947	2118	2118
R²	0.018	0.325	0.338
adj. R²	0.017	0.317	0.327

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include sector, year and location fixed effects.

All coefficients and standard errors are robust to heteroskedasticity.

^{\$} Congo, Democratic Republic as the base country.

[&] Firms with employees greater than 100 were used as the baseline (Large >=100).

[£] All IV estimations used external RD as instruments for process intensity while license and patents were used as instruments for the introduction of process innovation.

^a Growth of total employment calculated as (Total Employment₁ -Total Employment₃)/ Total Employment₃.

Table 6: Employment impacts of joint process and product innovations (JPP)

	A-OLS			B-IV	
	(1)	(2)	(3)	(4)	(5)
Growth of total employment					
JPP innovation	0.122*** (0.019)	0.071*** (0.019)	0.084*** (0.020)	0.189** (0.085)	0.275*** (0.076)
Real growth of sales per worker (RGSPW)		-0.174*** (0.016)	-0.193*** (0.021)	-0.159*** (0.007)	-0.184*** (0.008)
JPP*RGSPW			0.048 (0.031)		0.067*** (0.014)
Log of labour cost per worker (USD)		-0.002 (0.003)	-0.0022 (0.003)	-0.002 (0.003)	-0.002 (0.003)
R&D		-0.005 (0.020)	-0.007 (0.020)	-0.014 (0.027)	-0.030 (0.024)
Ownership		0.076*** (0.024)	0.072*** (0.023)	0.073*** (0.026)	0.075*** (0.024)
Log of total employment (-3)		-0.055***	-0.049***	-0.114***	-0.116***

		(0.014)	(0.014)	(0.016)	(0.014)
Log of age		0.187***	0.182***	0.090*	0.091*
		(0.033)	(0.033)	(0.054)	(0.049)
Log of age squared		-0.040***	-0.038***	-0.023**	-0.022**
		(0.008)	(0.008)	(0.011)	(0.010)
Tw	1.512	-8.081	-7.820	48.944	15.20
	(5.401)	(5.735)	(5.845)	(35.540)	(32.36)
T2w	-47.97	203.376	201.5	-2159.745	-581.2
	(93.63)	(140.864)	(141.8)	(1402.533)	(1269.0)
T3w	176.4	-1225.832	-1237.5	13225.223	3297.0
	(376.1)	(767.958)	(767.2)	(8729.582)	(7840.7)
Size of firm ^{&}					
Medium		0.069*	0.0634*	0.151***	0.139***
		(0.037)	(0.037)	(0.026)	(0.024)
Large		0.277***	0.267***	0.404***	0.387***
		(0.070)	(0.071)	(0.053)	(0.048)
Country ^{\$}					
Ghana		-0.035	-0.036	-0.024	-0.017
		(0.024)	(0.024)	(0.035)	(0.031)
Tanzania		-0.047	-0.0667*	-0.206***	-0.188***
		(0.041)	(0.039)	(0.065)	(0.057)
Uganda		-0.136***	-0.140***	-0.189***	-0.179***
		(0.032)	(0.031)	(0.040)	(0.036)
Zambia		-0.039	-0.039	-0.016	-0.042
		(0.027)	(0.027)	(0.059)	(0.052)
N	1548	1262	1262	1242	1242
R²	0.022	0.534	0.540	.	.
adj. R²	0.019	0.513	0.520	.	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include sector, year, location and 26 industry dummies.

All coefficients and standard errors are robust to heteroskedasticity.

^{\$} Congo, Democratic Republic as the base country.

[&] Firms with small employees, ≥ 5 and ≤ 19 , were used as the baseline.

[£] All IV estimations used license and patents as instruments.

Table 4 presents the standardized results of our basic and extended specifications analyzing the impact of product innovations on employment growth in five countries namely Democratic Republic of Congo, Ghana, Tanzania, Uganda and Zambia. Panel A of Table 4 presents the OLS estimates. The coefficient of product innovation which is an estimate of the Average Treatment Effect (ATE) of product innovations on employment growth in all the countries under consideration have a significantly positive impact on employment growth across all OLS specifications. In panel B, we report IV estimates where we considered the percentage of sales from all innovative products (intensity of product innovation) and the introduction of product innovation as endogenous. Employing license, patent and external RD as instruments, results indicate a significantly positive impact of product innovations on employment growth with a noticeable increase in the coefficient of product innovation from the OLS estimate indicating the downward biasedness of the OLS results. This result implies that, product innovations stimulate economic activity and market expansion leading to compensation impacts on employment growth. This result is in line with existing empirical findings by Harrison et al. (2014, 2010), Meriküll (2010), Hall et al. (2008), Peters (2008), Smolny (1998), Piva & Vivarelli (2005, 2003). These studies find product innovations to generally have positive job creation effects.

In Table 5, we present standardized results for process innovation impacts on employment growth for Democratic Republic of Congo, Ghana, Malawi, Namibia, Nigeria, South Sudan, Sudan, Tanzania, Uganda and Zambia. OLS estimates in column 3 of Panel A indicate a negative but insignificant impact of process innovation on employment growth. IV estimates shown in column 4 of Panel B however show negative and significant impact of process innovations on employment growth. This result indicates displacement impacts from the direct adoption of new processes with cost reduction and efficiency gains leading to negative employment growth. This may be partially explained by the imperfect market structures characterizing most SSA economies where firms' may be considered to have some level of 'local' monopoly power. Due to this likely agent behaviour, process innovating firms may have failed to transfer the productivity gains during the observed period through price reductions to stimulate demand and employment growth to compensate for the direct displacement impacts. This result enlarges the relatively scarce existing findings by scholars such as Crespi & Tacsir (2013).

The theory of economies of scope indicates that, the joint introduction of both process and product innovations (JPP) by firms' is expected to imply a strictly higher positive impact on a firm's employment growth than the introduction, separately, of each type of innovation impacts on employment growth (Harrison et al., 2014). In other words, the causal parameter, ATE, of JPP innovation is expected to be strictly higher than the ATE of the separate introduction of process and product innovations on employment growth. We sort to test this hypothesis by combining firms that have introduced jointly, product and process (JPP) innovations to analyze whether firms that have introduced both innovations have a higher total employment growth or otherwise for Democratic Republic of Congo, Ghana, Tanzania, Uganda and Zambia. The main result from the JPP regression, which is quite robust across all specifications is that, the joint introduction of both process and product innovations by firms' have a significantly positive employment growth impacts. The ATE of JPP is however smaller than the ATE of product only innovations but bigger than the ATE from process only innovations. This result indicates that, the compensation impact from product innovation outweighs the displacement effects from process innovation thereby reinforcing the positive employment growth impacts of JPP innovations. We do not find evidence of economies of scope in JPP innovations as a result of the crowding out effect from process innovations resulting in the partial cancellation of the positive impact obtained from product innovation. The stability of this result indicates SSA firms' during the period under consideration favored and adopted technological competitive strategies with product quality advantages leading to market expansion than cost competitive strategies in SSA than found by Pianta & Antonucci (2002) in European firms'. This may be due to the increasing middle class with incessant demand for new products coupled with relatively cheaper labour in SSA.

Other significant predictors from the extended specifications across all innovation types are: log of total employment three (3) years ago, real growth of total sales per worker, age, age squared and size of firm. The study also found foreign owned businesses have significantly positive impact on employment growth and tends to grow more than locally owned firms' for JPP innovations. Firms' that spent on formal R&D activities as well those that received government support during the last three years were found to have significant positive impacts on employment growth for process innovation only.

Log of age (age in the product innovation specifications) of the firm has an inverted U-shaped relationship with the employment growth of the firm with a significantly positive sign, however at decreasing rate (negative sign of significant squared value of log age). This implies that, the employment growth of firms fall, as firms' grow older. The total employment of the firm at the beginning of the period (3 years ago) has also been found to have a negative impact on the employment growth of firms across all specifications and innovation types. Firms' with larger total employment at the beginning of the period are found to grow much less than smaller firms in terms of employment. In addition, real growth of total sales per worker shows a negative impact on employment growth across all innovation specifications indicating a consistent inverse relationship suggesting that gains from sales (the evolution of demand for firms' products) occur through labour saving. Analyses of the possible indirect mechanisms through which innovation may impact employment growth however show that, firms' that have jointly introduced product and process innovations tend to significantly create new jobs (positive employment growth) with gains in real growth of sales per worker as compared to non-JPP innovators. We however failed to find any evidence of similar indirect impacts of innovation in other specifications.

4.1.2 Dose response functions

As noted earlier, innovative firms have different intensities of innovations that may have different impacts on employment growth. We therefore aim to estimate the dose response functions in this section to analyse the impact of different levels of innovation intensities on employment growth of the firm. Based on the regression results in Tables 4, 5 and 6, we determine the average expected conditional employment growth rates between periods t and $t - 3$ given the innovation intensity in period t and the other covariates. The kernel density estimate distributions of $ATE(x)$, $ATET(x)$ and $ATENT(x)$ and Dose Response Functions plotted at 5% significance level for all types of innovations derived from our IV estimation are shown in Figure 1.¹⁷

The kernel density estimate is a non-parametric estimation that enables vivid visualization of the distributions of the $ATE(x)$, $ATET(x)$ and $ATENT(x)$. A look at the distributions of the kernel density estimates in Panels *A.i*, *B.i*, and *C.i* of Figure 1 reveal less dispersion of our causal parameters across all innovations. The dispersion is more pronounced in process innovations with $ATE(x)$ and $ATET(x)$ concentrating at higher values of employment growth than $ATENT(x)$ indicating a higher average employment growth due to process innovations as compared to non-process innovations. The kernel density estimates of JPP innovations reveal differences in the employment growth of JPP innovators and non-innovators with non-JPP innovation generating much employment growth. The difference is less pronounced between product innovators and non-product innovators but the distribution indicates a lower employment growth due to product innovations. In summary, the kernel density estimations reveal less employment growth impact of both product and JPP innovations compared to non-innovators. However, process innovations are found to have higher employment growth impacts as compared to non-process innovations.

¹⁷ See Appendix F for the kernel density estimate and Dose Response Functions from the OLS estimations.

Figures 1.A.ii, 1.B.ii, 1.C.ii show the dose response functions where we assess the impact of different innovation intensities on employment growth. Figure 1.Aii shows an inverted U relationship between the employment growth of firms' and process innovation intensities. The inverted U relationship implies that, employment in process innovating firms' grow at lower process intensities and falls thereof as firms' introduce more process innovations. In other words, process innovation positively impacts employment growth at lower levels of process intensity, reaches maximum and falls with process innovation deepening thereby exhibiting displacement effects. Pairwise treatment effects comparing these extreme values to non-process innovators indicate strong significance of the inverted U relationship. At about 67% of process intensity, firms attain the highest employment growth of about 35% and a displacement impact in total employment of about 16% at 100% process intensity. This means that, all other things being equal, the introduction of process innovation with an intensity of about 67% by a non-process innovating firm leads to growth in employment by 35%. However, the firm exhibits negative employment growth once the 67% process intensity is exceeded with 100% process intensity exhibiting negative employment growth outcomes. This result shows that, firms that introduce process innovations but with low process intensities are less cost efficient and therefore employ more labour to boost output. However, as the production process becomes more cost efficient due to process innovation deepening, productivity per worker increases resulting in the employment of fewer workers. This result provides us with an additional insight on the impact of process innovations on employment. Despite our regression results indicating a negative impact of process innovations, the dose response reveals that, the negative impact only occurs at higher sub-interval of process intensities with lower process intensities having positive employment growth impacts.

The dose response function showing the impact of a firm's percentage sales from all product innovations on employment growth plotted at 5% significance level is shown in Figure 1.Bii. The relationship is found to have a cubic hyperbola shape with firm employment growth falling from a positive point, reaching a minimum, rising to a maximum and declining thereof as percentage sales from all innovative products increase. The implication of this shape is that, within specific intervals of percentage sales from all product innovations, employment is decreasing whiles we experience increasing growth only within a specific interval of a firms' percentage sales from all product innovations. Pairwise treatment effects indicate strong significance with the maximum employment growth rate of 17.6% attained by firms with sales from all innovative product of about 4.6% while the minimum employment growth rate of about -17.3% is attained if the total sales of the firm come from the new innovative products, that is 100% sales from all product innovations. In other words, if a non-innovating firm suddenly introduces product innovation with the sales from this product innovation making up about 4.6% of total sales, employment grows by about 17.6%. However, if non-innovating firms' introduce product innovations with the sales from all product innovations making up 100% of total sales, employment growth falls by 17.3%. This result implies that, within certain intervals of percentage sales from product innovations, product innovations have compensation effects on employment growth whiles other intervals have displacement effects on employment growth. An explanation to this result may be, relatively younger innovating firms or less established innovating firms in product markets have only one or few products in the market and sales from these products mostly make -up their total sales. As a result, these firms may

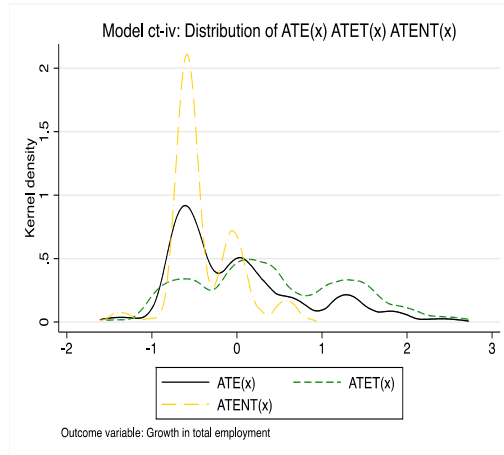
not be growing as much due to competitive pressure from already established firms in the product market. A major finding by Harrison et al. (2014), Peters (2008) etc. is that, firm level employment grows the higher the sales growth due to new innovative product. Our evidence indicates contrary conclusion with product innovations contributing to employment growth only within a sub-interval of percentage sales from all new product innovations.

Figure 1.Ciii shows the dose response function for JPP innovation plotted at 5% significance level. JPP innovations generally tend to exhibit positive employment growth response across all JPP intensities except the 30%-50% JPP intensity interval where employment growth tends to be negative. Pairwise treatment effect confirms a significant employment growth rate with the implication that, if a JPP non- innovator introduces JPP innovation, the firm generally grows positively except the intensity is within the sub interval of 30%-50% where employment growth is negative. This evidence is in sharp contrast with the finding of Harrison et al. (2014), Lachenmaier & Rottmann (2010), Hall et al. (2008) where innovations were found to have general compensation effects on employment growth at the firm-level.

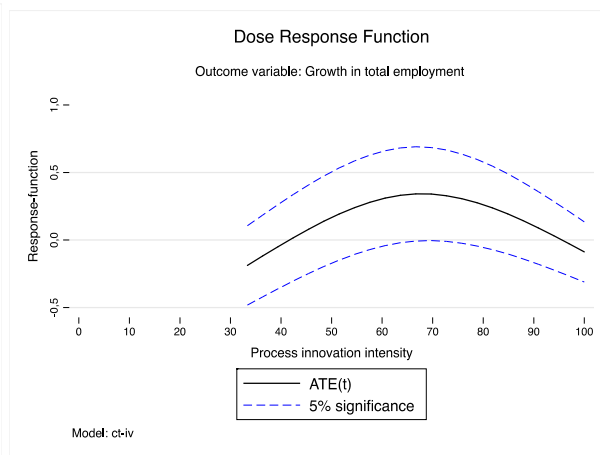
Figure 1: IV Kernel density estimations and Dose Response Functions

A: Process innovation

i.

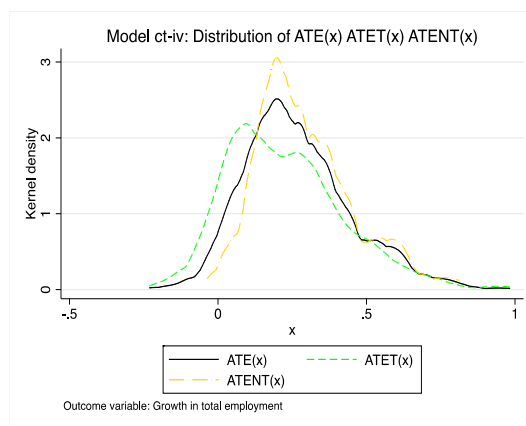


ii.

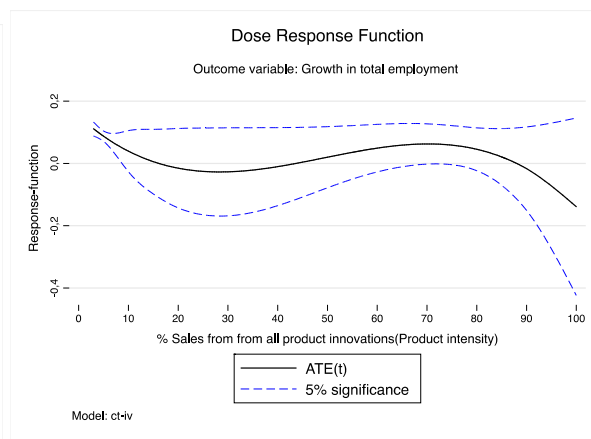


B: Product innovation

i.

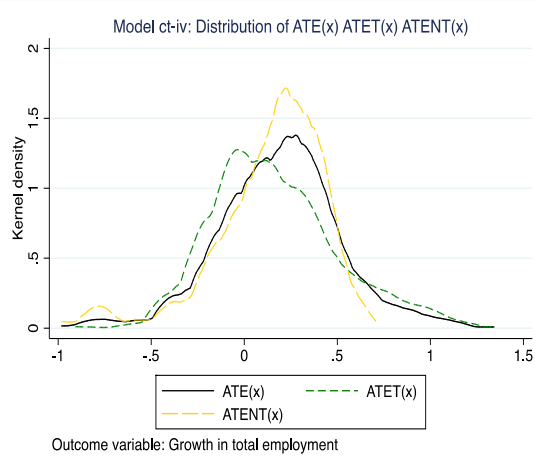


ii.

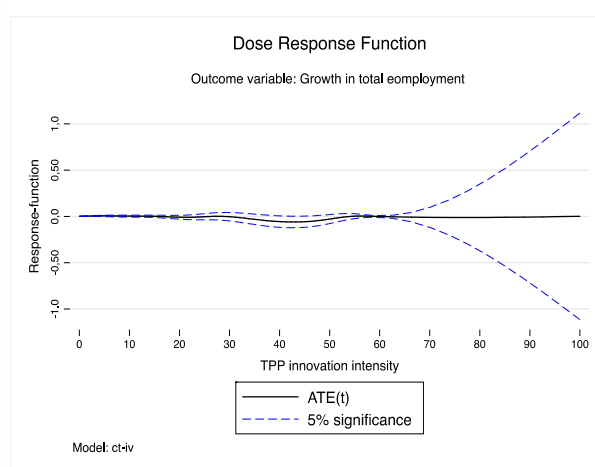


C: JPP innovation

i.



ii.



4.2 Extensions to decent employment

The role of productive and decent employment¹⁸ as a critical mechanism through which the benefits of growth are distributed is widely recognized in the growth-poverty nexus (See Islam, 2004; Osmani, 2005; Islam, 2013; Martins & Takeuchi, 2013; ILO, 1972, 2008, 2011, 2012a, 2013; Holmes et al., 2013; Crespi & Tacsir, 2013). Decent jobs and productive employment have also been found to be important in achieving the newly adopted Sustainable Development Goals (SDG's) such as hunger, universal primary education, reducing child and maternal mortality mainly through the provision of income both at the wage sector or in self-employed activities. As a result, a renewed focus in international development policy currently is how to nurture and generate new sources of productive and decent employment. Using growth of permanent versus temporary employment as proxy for security of job; growth of skilled versus unskilled employment as proxy for quality of employment growth; and the ratio of male to female workers in last fiscal year as proxy for equity of job, we sort to extend our analyses in this section to examine the innovation impacts of employment differentiated by quality, security and labour skills in SSA. According to Harrison et al. (2014), these separate analyses are major contributions to the literature.

The empirical results showing the impact of product and JPP innovations on each proxy of decent employment are reported in Tables 7, 8, 9 and 10.

Table 7: Permanent vs. temporary employment impacts of product innovation

	A-OLS		A-IV ^E	B-OLS		B-IV ^E
	(1)	(2)	(3)	(5)	(6)	(7)
Growth of permanent employment				Growth of temporary employment		
Product innovation	-0.162*** (0.028)	-0.087*** (0.027)	-0.930** (0.382)	0.067*** (0.018)	0.036* (0.021)	0.531* (0.289)
Log of experience		-0.004 (0.015)	-0.013 (0.023)		-0.014 (0.013)	-0.014 (0.017)
Log of total employment (-3)		0.082*** (0.019)	0.062** (0.030)		-0.037* (0.020)	-0.031 (0.023)
Real growth of sales per worker		0.174*** (0.017)	0.178*** (0.013)		-0.048*** (0.010)	-0.047*** (0.010)
R&D		-0.037* (0.021)	-0.023 (0.041)		0.025 (0.016)	0.007 (0.031)
Log of labour cost per worker (USD)		-0.005 (0.005)	-0.001 (0.008)		0.009** (0.004)	0.005 (0.006)
Age		0.004*** (0.001)	0.007** (0.003)		-0.001 (0.001)	-0.003 (0.002)
Age Square		-0.000** (0.000)	-0.000** (0.000)		0.000 (0.000)	0.000 (0.000)
Tw	0.008* (0.004)	0.008** (0.004)	0.143* (0.083)	-0.005* (0.003)	-0.004 (0.004)	-0.081 (0.063)
T2w	-0.000* (0.000)	-0.000** (0.000)	-0.004* (0.002)	0.000 (0.000)	0.000 (0.000)	0.002 (0.002)
T3w	0.000* (0.000)	0.000** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)

¹⁸ The ILO (2012a) defines productive employment as employment yielding sufficient returns to labour to permit the worker and her/his dependents a level of consumption above the poverty line. Decent employment/work refers to work that is productive and secured.

Size of firm						
Medium	-0.126***	-0.119***		0.069**	0.059**	
	(0.029)	(0.036)		(0.028)	(0.027)	
Large	-0.265***	-0.243***		0.092	0.108	
	(0.067)	(0.088)		(0.066)	(0.067)	
Countries^{\$}						
Ghana	0.018	0.043		0.003	-0.01	
	(0.023)	(0.043)		(0.021)	(0.033)	
Tanzania	0.185***	0.249***		-0.103**	-0.157***	
	(0.040)	(0.073)		(0.042)	(0.055)	
Uganda	0.148***	0.176***		-0.086**	-0.103**	
	(0.032)	(0.067)		(0.036)	(0.051)	
Zambia	0.048	0.095		-0.074**	-0.096	
	(0.044)	(0.088)		(0.033)	(0.066)	
N	2113	1111	1089	2065	1111	1089
R²	0.035	0.566	.	0.018	0.163	.
adj. R²	0.016	0.540	.	-0.001	0.132	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include country, size, year, sector and location.

All coefficients and standard errors are robust to heteroskedasticity.

^{\$} Congo, Democratic Republic as the base country.

[£] All IV estimations used license as instrument for intensity of product innovation; patent and external RD as instruments for introduction of product innovation.

Table 8: Impact of product innovation on the ratio of male to female employment in last year

	A-OLS			B-IV	
	(1)	(2)	(3)	(4)	(5)
	Ratio of male to female employment in last year (R_M_F)			Log(R_M_F)^R	
Product innovation	6.406***	3.913*	3.419**	3.051	2.175
	(2.056)	(2.044)	(1.613)	(22.50)	(1.883)
Log of total employment (-3)			4.638***	8.146***	0.490*
			(1.096)	(2.309)	(0.193)
Real growth of sales per worker			-1.089***	-2.365	-0.183
			(0.350)	(1.707)	(0.143)
R&D			-0.507	-0.794	0.0491
			(1.368)	(5.285)	(0.442)
Log of labour cost per worker (USD)			-0.152	1.177	0.090
			(0.325)	(1.404)	(0.117)
Age			-0.073	-0.216	-0.035
			(0.086)	(0.358)	(0.030)
Age Square			0.000	0.001	0.000
			(0.001)	(0.002)	(0.000)
Tw	0.070	0.084	-0.224	-4.423	-0.257
	(0.300)	(0.298)	(0.246)	(3.494)	(0.316)
T2w	-0.004	-0.004	0.005	0.111	0.005
	(0.008)	(0.008)	(0.007)	(0.090)	(0.008)
T3w	0.000	0.000	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size of firm					
Medium			-1.751	-7.656	-0.348
			(1.691)	(5.206)	(0.436)
Large			-8.583**	-7.295	-0.929
			(3.892)	(12.18)	(1.019)
Countries^{\$}					
Ghana		5.412***	0.967	13.33	0.573

		(0.731)	(1.853)	(9.599)	(0.803)
Tanzania		2.697***	-0.991	-9.293	-0.512
		(0.553)	(2.413)	(14.38)	(1.203)
Uganda		1.711**	-3.600*	-1.461	-0.629
		(0.725)	(1.838)	(6.779)	(0.567)
Zambia		2.160***	-1.838	-12.40	-1.923
		(0.732)	(3.141)	(15.90)	(1.330)
N	815	815	411	176	176
R²	0.122	0.178	0.486	.	.
adj. R²	0.118	0.170	0.440	.	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include country, size, year, sector and location.

All coefficients and standard errors are robust to heteroskedasticity.

\$ Congo, Democratic Republic as the base country.

^EAll IV estimations used increased range as instrument for intensity of product innovation; patent and external RD as instruments for introduction of product innovation.

^R Employs the log of the ratio of male to female employment in last year as the dependent variable.

Table 9: Growth of permanent vs. temporary employment impacts of JPP innovations

	A-OLS			A-IV^E	B-OLS			B-IV^E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Growth of permanent employment				Growth of temporary employment			
JPP	-0.119***	-0.061***	-0.07***	-0.175**	0.033***	0.0152	0.0274**	0.128*
	(0.018)	(0.022)	(0.019)	(0.084)	(0.012)	(0.013)	(0.013)	(0.068)
Log of labour cost per worker (USD)			0.002	0.002			-0.004*	-0.004
			(0.003)	(0.003)			(0.002)	(0.002)
R&D			0.009	0.011			-0.01	-0.025
			(0.019)	(0.026)			(0.017)	(0.021)
Ownership			-0.08***	-0.07***			0.052***	0.058***
			(0.023)	(0.026)			(0.02)	(0.021)
Log of total emp'ment (-3)			0.048***	0.107***			-0.026**	-0.065***
			(0.013)	(0.015)			(0.012)	(0.012)
Real growth of sales per worker			0.171***	0.157***			-0.042***	-0.033***
			(0.015)	(0.007)			(0.012)	(0.0057)
Log of age			-0.18***	-0.088*			0.100***	0.064
			(0.032)	(0.053)			(0.026)	(0.043)
Log of age squared			0.039***	0.023**			-0.022***	-0.015*
			(0.007)	(0.011)			(0.006)	(0.009)
Tw	-0.552	-2.657	7.180	-54.06	-0.733	0.188	-6.381	-34.77
	(4.188)	(4.357)	(5.227)	(35.12)	(3.409)	(3.308)	(4.885)	(28.27)
T2w	39.24	57.98	-182.4	2353.9*	13.37	-4.046	119.9	1289.1
	(67.16)	(68.15)	(126.7)	(1386.2)	(59.71)	(58.09)	(122.5)	(1115.5)
T3w	-167.0	-188.0	1123.9	-14386.6*	-63.76	14.01	-504.7	-7643.4
	(242.9)	(245.7)	(693.9)	(8627.7)	(238.5)	(233.7)	(659.1)	(6942.9)
Size of firm^{&}								
Medium			-0.071**	-0.15***			0.013	0.061***
			(0.035)	(0.026)			(0.032)	(0.021)
Large			-0.27***	-0.39***			0.127***	0.198***
			(0.069)	(0.053)			(0.048)	(0.042)
Country^{\$}								

Ghana		-0.070*** (0.017)	0.034 (0.023)	0.024 (0.034)		0.032*** (0.010)	-0.014 (0.02)	0.002 (0.028)
Tanzania		-0.323*** (0.045)	0.049 (0.039)	0.201*** (0.064)		0.139*** (0.036)	-0.004 (0.034)	-0.107** (0.052)
Uganda		0.031 (0.023)	0.129*** (0.030)	0.183*** (0.040)		-0.019 (0.019)	-0.061** (0.028)	-0.062* (0.032)
Zambia		-0.071*** (0.018)	0.038 (0.027)	0.011 (0.059)		0.019* (0.01)	-0.010 (0.021)	-0.035 (0.047)
<i>N</i>	1648	1648	1262	1242	1613	1613	1262	1242
<i>R</i> ²	0.021	0.116	0.544	.	0.004	0.042	0.146	.
adj. <i>R</i> ²	0.018	0.112	0.524	.	0.002	0.037	0.108	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include sector, year, location and 26 industry dummies.

All coefficients and standard errors are robust to heteroskedasticity.

\$ Congo, Democratic Republic as the base country.

& Firms with small employees, ≥ 5 and ≤ 19 , were used as the baseline.

£ All IV estimations used license and patents as instruments.

Table 10: Growth of skilled vs. unskilled employment impacts of JPP innovations

	A-OLS			A-IV [£]	B-OLS			B-IV [£]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth of skilled employment				Growth of unskilled employment				
JPP	0.112*** (0.028)	0.063* (0.033)	0.058* (0.03)	0.718 (0.679)	0.081*** (0.018)	0.058** (0.024)	0.050* (0.026)	0.574 (0.542)
Log of labour cost per worker (USD)			0.002 (0.005)	0.003 (0.013)			-0.002 (0.004)	-0.002 (0.010)
R&D			-0.010 (0.029)	-0.065 (0.120)			-0.016 (0.024)	-0.051 (0.095)
Ownership			0.094*** (0.033)	0.0743 (0.112)			0.090*** (0.030)	0.077 (0.09)
Log of total emp'ment (-3)			-0.067*** (0.024)	-0.259** (0.103)			-0.014 (0.012)	-0.125 (0.081)
Real growth of sales per worker			-0.202*** (0.046)	-0.150*** (0.044)			-0.096*** (0.026)	-0.0705** (0.035)
Log of age			0.214*** (0.042)	0.465 (0.343)			0.085*** (0.030)	0.283 (0.278)
Log of age squared			-0.042*** (0.009)	-0.091 (0.067)			-0.021*** (0.007)	-0.0594 (0.0544)
Tw	-3.365 (7.807)	-2.689 (7.609)	-22.46* (12.05)	226.1 (287.9)	-6.535* (3.390)	-6.061 (3.831)	-10.46* (5.921)	224.1 (250.3)
T2w	5.358 (174.4)	5.050 (167.2)	663.6* (380.6)	-15555.4 (16445.8)	121.2* (73.05)	117.4 (78.15)	284.3* (168.9)	-13659.3 (13742.5)
T3w	31.98 (792.0)	27.14 (759.8)	-3751.5* (2155.0)	102651.0 (106618.4)	-515.9 (337.6)	-508.1 (355.4)	-1519.9 (947.1)	88875.7 (88499.2)
Size of firm^{&}								
Medium			0.053 (0.054)	0.279** (0.137)			0.019 (0.038)	0.178 (0.112)
Large			0.298*** (0.091)	0.864** (0.375)			0.210*** (0.076)	0.524* (0.310)
Country^{\$}								
Ghana		0.060** (0.028)	-0.066* (0.038)	-0.319 (0.311)		0.036** (0.018)	-0.004 (0.028)	-0.199 (0.242)
Tanzania		0.359*** (0.085)	-0.041 (0.070)	-0.595 (0.427)		0.075** (0.036)	-0.018 (0.051)	-0.401 (0.343)

Uganda	-0.029 (0.038)	-0.154*** (0.054)	-0.546 (0.412)	0.012 (0.023)	-0.033 (0.033)	-0.356 (0.335)		
Zambia	0.063** (0.028)	-0.087** (0.044)	-0.233 (0.319)	0.026 (0.022)	-0.021 (0.038)	-0.100 (0.242)		
<i>N</i>	751	751	615	606	751	751	615	606
<i>R</i> ²	0.019	0.101	0.466	.	0.032	0.048	0.303	.
adj. <i>R</i> ²	0.014	0.092	0.425	.	0.027	0.038	0.250	.

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include sector, year, location and 26 industry dummies.

All coefficients and standard errors are robust to heteroskedasticity.

\$ Congo, Democratic Republic as the base country.

& Firms with small employees, ≥ 5 and ≤ 19 , were used as the baseline.

£ All IV estimations used license and patents as instruments.

The standardized results of our basic and extended specifications presented in Tables 7 and 8 show the impact of product innovations on the security of job and equity of employment proxies of decent employment in Democratic Republic of Congo, Ghana, Tanzania, Uganda and Zambia. Table 7 presents both the OLS and IV estimates for permanent and temporary employment used as proxies for employment security. Results indicate displacement impact of product innovation on permanent employment growth whiles we find product innovation to have compensation impacts on temporary employment. This result is robust across all specifications. This result implies that, product innovators prefer to hire on temporary basis rather than on permanent basis. One explanation for this result maybe the labour cost differences as firms that employ temporary workers are not required by law to pay social securities and income tax for their temporary employees. Another explanation may be firms' preference to hire workers on temporary basis due to the uncertainty about the performance of product innovations. The results do not change after controlling for the skill differences. Using the ratio of male to female employees in a firm as a proxy for employment equity, our OLS results indicate that product innovations are gender biased towards male employment at 5% significance. However, after controlling for possible endogeneity, the significance vanishes but the sign of the coefficient remains the same (see Table 8).

Table 9 and 10 present the empirical results for JPP innovations on employment security and employment quality respectively. From Table 9, results are similar to that of product innovations where we find robust evidence of displacement impact of JPP innovations on permanent employment growth whiles we find JPP innovations to have compensation impacts on temporary employment. In Table 10, we present the impact of JPP innovations on quality of employment using the growth of skilled versus unskilled employment as proxies. Results indicate significantly positive impact of JPP innovations on both skilled and unskilled employment growth in the OLS specification. This result adds to the scarce literature on skill-biasedness of innovation by Crespi & Tacsir (2013) and Elejalde et al. (2013) where the authors find product innovation are skill biased but creates both skilled and unskilled jobs. After controlling for possible endogeneity, we find JPP innovations to have no significant impact on the growth of both skilled and unskilled employment.

5. Conclusion

The relationship between innovation and employment remains central especially in Sub-Saharan African economies where 'innovation-led' development thinking is emerging. In this paper, we sought to contribute to the deeper understanding of the

causal relationship between technological innovations and employment by investigating the employment impacts of innovation in Sub-Saharan Africa by employing a counterfactual perspective where we considered varying innovation intensities.

This paper adapted the Dose Response model under continuous treatment and used the World Bank's Enterprise Survey (ES) merged with the newly available Innovation Follow-Up Surveys data for 10 Sub-Saharan African countries namely Congo Democratic Republic, Ghana, Malawi, Namibia, Nigeria, South Sudan, Sudan, Tanzania, Uganda and Zambia. Our results highlight the critical importance of innovation activities in stimulating employment growth in Sub-Saharan Africa within sub-intervals of innovation intensity. Specifically, results from the paper reveal the relevance of product and JPP innovations as important sources of firm-level employment growth while process innovation is found to have displacement impacts on firm employment growth. We have shown that these conclusions only hold within specific sub-intervals of firms' intensity of innovation. In other words, the impact of firms' innovation activities on employment growth varies and depends on the firms' innovation intensity.

In extensions to decent employment, we employed proxies for security of job, quality of employment and equity of job, we found product and JPP innovations to be creating unsecured jobs as compared to secured jobs. We also found product and joint product and process (JPP) innovations to be male and skill biased respectively but with significance vanishing after controlling for endogeneity.

The policy implications of these results cannot be overemphasized. In a continent where policy is being directed towards enhancing innovations at the firm-level, our results reveal policy makers need to be wary if the primary motive of the innovation policies are to generate employment and decent employment avenues in the short term. This is because, the intensity of innovations are not homogeneous but heterogeneous across firms with different compensating and displacement impacts on employment growth. We see a trade-off between unsecured jobs and unemployment. The paper therefore recommends policy efforts that will extend social security to all type of workers, be it temporary or permanent, in line with national, regional and continental innovation policies and the ILO-WHO Social Protection Floor Initiative by ensuring minimum income security to all workers. We also recommend labour market regulations and restructuring to promote innovations that create secured and equitable employments in SSA in the long term.

REFERENCES

- African Union-New Partnership for Africa's Development (2010). *African innovation outlook*. AU-NEPAD, Pretoria, South Africa.
- African Union-New Partnership for Africa's Development (2014). *African innovation outlook II*. NEPAD Planning and Coordinating Agency (NPCA), Pretoria, South Africa.
- Antonucci, T., & Pianta M. (2002). The employment effects of product and process innovations in Europe. *International Review of Applied Economics* 16(3): 295–308.
- Amemiya, T. (1973). Regression Analysis when the Dependent Variable Is Truncated Normal. *Econometrica*, 41(6), 997–1016. <http://doi.org/10.2307/1914031>
- Amemiya, T. (1985). *Advanced Econometrics* (1 edition). Harvard University Press.
- Bogliacino, F., & Pianta, M. (2010). Innovation and Employment: a Reinvestigation using Revised Pavitt classes. *Research Policy*, 39(6), 799–809. <http://doi.org/10.1016/j.respol.2010.02.017>
- Bokova, I. (2012). *The Global Innovation Index: An integrated policy approach in science, technology, and innovation for sustainable development*. A UNESCO idea in Action
- Cerulli, G. (2012). *A continuous treatment model for estimating a Dose Response Function under endogeneity and heterogeneous response to observable confounders: Description and implementation via the Stata module "ctreatreg"* (CERIS Working Paper No. 201218). Institute for Economic Research on Firms and Growth - Moncalieri (TO). Retrieved from <https://ideas.repec.org/p/csc/cerisp/201218.html>
- Cerulli, G., & Poti, B. (2014). *The Impact of Public Support Intensity on Business R&D: Evidence from a Dose-Response Approach* (ERSA conference paper No. ersa14p625). European Regional Science Association. Retrieved from <https://ideas.repec.org/p/wiw/wiwsa/ersa14p625.html>
- Crespi, G., & Tacsir, E. (2013). *Effects of innovation on employment in Latin America*. United Nations University - Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT) Working Paper No. 001. Retrieved from <https://ideas.repec.org/p/unm/unumer/2013001.html>
- Doms, M., Dunne, T., & Roberts, M. J. (1995). The role of technology use in the survival and growth of manufacturing plants. *International Journal of Industrial Organization*, 13(4), 523–542. [http://doi.org/10.1016/0167-7187\(95\)00503-X](http://doi.org/10.1016/0167-7187(95)00503-X)
- Elejalde, R. D., Giuliadori, D., & Stucchi, R. (2013). *Employment and innovation: Firm level evidence from Argentina* (ILADES-Georgetown University Working Paper No. inv291). Ilades-Georgetown University, Universidad Alberto Hurtado/School of Economics and Bussines. Retrieved from <https://ideas.repec.org/p/ila/ilades/inv291.html>
- Fryges, H., & Wagner, J. (2008). Exports and Productivity Growth: First Evidence from a Continuous Treatment Approach. *Review of World Economics*, 144(4), 695–722. <http://doi.org/10.1007/s10290-008-0166-8>
- Gault, F. (2010). *Innovation strategies for a global economy: Development, implementation measurement and management*. Cheltenham, UK and Northampton, MA, USA: Edward Elgar and Ottawa International Development Research Centre.
- Gallouj, F. & Djellal, F. (2010). *The handbook of innovation and services: A multi-disciplinary perspective*. Edward Elgar Publishing, Cheltenham, UK.

- Gebreeyesus, M. (2011). *Innovation and micro-enterprise growth in Ethiopia*. In Szirmai, A., Naudé, W., & Goedhuys, M. (eds.) (2011): Entrepreneurship, Innovation and Development, Oxford, Oxford University Press.
- Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. *Industrial and Corporate Change*, 17(4), 813–839. <http://doi.org/10.1093/icc/dtn022>
- Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35, 29–43. <http://doi.org/10.1016/j.ijindorg.2014.06.001>
- Holmes, R., McCord, A., Hagen-Zanker, J., Bergh, G., Zanker, F. (2013). *What is the evidence on the impact of employment creation on stability and poverty reduction in fragile states: A systematic review*. Overseas Development Institute.
- ILO. (1972). *Employment, incomes and equality: a strategy for increasing productive employment in Kenya*. Report Of An Inter-Agency Team Financed By The United Nations Development Programme and organized by the International Labour Office
- ILO. (2008). *Policy coherence for generating employment and decent work in Mozambique*. Background paper for the High –Level Forum on “Working Out of Poverty: A Decent Work Approach to Development and Growth in Africa”, September 8-9, 2008, Monrovia, Liberia.
- ILO. (2011). *Growth, employment and decent work in the Least Developed Countries*. Report of the ILO for the Fourth UN Conference on the Least Developed Countries, 9-13 May 2011, Turkey.
- ILO. (2012a). *Understanding deficits of productive employment and setting targets: A methodological guide of the employment sector*. Geneva: International Labour Office.
- ILO. (2013). *Youth unemployment rate estimates and projections by region, 2007-2017*. Retrieved from http://www.ilo.org/global/about-the-ilo/multimedia/maps-and-charts/WCMS_212431/lang--en/index.htm.
- ILO. (2014). *Global employment trends 2014: Risk of a jobless recovery?* International Labour Office, Geneva.
- Imbens, G. W. & Hirano, K. (2004). The propensity score with continuous treatments. *Applied Bayesian modeling and causal inference from incomplete-data perspectives*, 226164, 73-84.
- Islam, R. (2004). *The nexus of economic growth, employment and poverty reduction: An empirical analysis*. International Labour Office, Issues in Employment and Poverty Discussion Paper 14.
- Islam, R. (2013). *Integrating productive employment into the post-2015 development agenda*. Southern Voice on Post MDG International Development Goals, Occasional Working Paper 3.
- Konte, A., & Ndong, M. (2012). *The informal ICT sector and innovation processes in Senegal*. UNU-MERIT Working Paper Series Number 2012-009
- Lachenmaier, S., & Rottmann, H. (2010). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization* 29, 210-220.
- Lee, K., & Kim, B.Y. (2010). Both institutions and policies matter but differently at different income groups of countries: Determinants of long run economic growth revisited. *World Development*, 37(3), 533-49.

- Mahemba, C. M. & Bruijn, E. J. (2003). Innovation Activities by Small and Medium-sized Manufacturing Enterprises in Tanzania. *Creativity and Innovation Management*, 12 (3), 162-173.
- Mairesse, J., & Mohnen, P. (2003). *R&D and productivity: A reexamination in light of the innovation surveys*. Paper to be presented at the DRUID Summer conference on creating, sharing and transferring knowledge: The role of geography, institutions and organizations.
- Mairesse, J., & Mohnen, P. (2010). *Using innovation surveys for econometric analysis*. UNU-MERIT Working Paper Series Number 2010- 023
- Martins, P., & Takeuchi, L.R. (2013). *Employment in a post-2015 framework: Proposals for monitoring indicators*. Overseas Development Institute Working Paper Series.
- Mohnen, P., & Hall, B. (2013). Innovation and productivity: An update. *Eurasian Business Review*, 3(1), 47-65.
- Meriküll, J. (2010). The Impact of Innovation on Employment. *Eastern European Economics*, 48(2), 25–38. <http://doi.org/10.2753/EEE0012-8775480202>
- OECD/Eurostat (2005). *Oslo Manual. Guidelines for collecting and interpreting innovation survey*. OECD publications, Paris (3rd Edition).
- Osmani, S.R. (2005). *The role of employment in promoting the Millennium Development Goals*. Paper prepared under the joint ILO-UNDP Programme on ‘Promoting Employment for Poverty Reduction’: UNDP/ILO
- Peters, B. (2005). *Employment Effects of Different Innovation Activities: Microeconomic Evidence* (ZEW Discussion Paper No. 04-73 [rev.]). ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research. Retrieved from <https://ideas.repec.org/p/zbw/zewdip/7183.html>
- Peters, B. (2008). *Innovation and Firm Performance: An Empirical Investigation for German Firms*. Springer Science & Business Media.
- Pianta, M. (2005). *Innovation and Employment*. In Fagerberg, J., Mowery, D. and Nelson, R. (eds.) (2005): *The Oxford Handbook of Innovation*. Oxford, United Kingdom: Oxford University Press
- Pianta, M., & Antonucci, T. (2002). Employment effects of product and process innovations in Europe. *International Review of Applied Economics*, 16(3). Retrieved from http://works.bepress.com/mario_pianta/34/
- Pianta, M. (2001). Innovation, demand and employment. In Petit and Soate 2001a: 142-165
- Piva, M. & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian micro-data. *Journal of Economics* 86 (1), 65-83
- Piva, M., & Vivarelli, M. (2003). *Innovation and employment: Evidence from Italian micro-data*. Institute for the Study of Labor (IZA) Discussion Paper Series No. 730
- Schumpeter, J. A. (1934). *Theory of economic development*. Cambridge, Mass.: Harvard University Press.
- Smolny, W. (1998). Innovation, prices and employment: A theoretical model and an application for West German Manufacturing Firms. *Journal of Industrial Economics* 46: 359–81.
- Verspagen, B. (1992). Endogenous innovation in Neo-Classical growth models: A survey. *Journal of Macroeconomics*, 14 (4), 631-662.
- Verspagen, B. (2004). *Innovation and jobs: A micro-and-macro perspective*. Eindhoven Centre for Innovation Studies Working Paper Number (04)15.

- Vivarelli, M. (2014). Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. *Journal of Economic Issues*, 48(1), 123–154. <http://doi.org/10.2753/JEI0021-3624480106>
- Wooldridge, J. M. (2013). *Introductory econometrics: a modern approach*. Mason, OH: South-Western Cengage Learning.

APPENDIX A

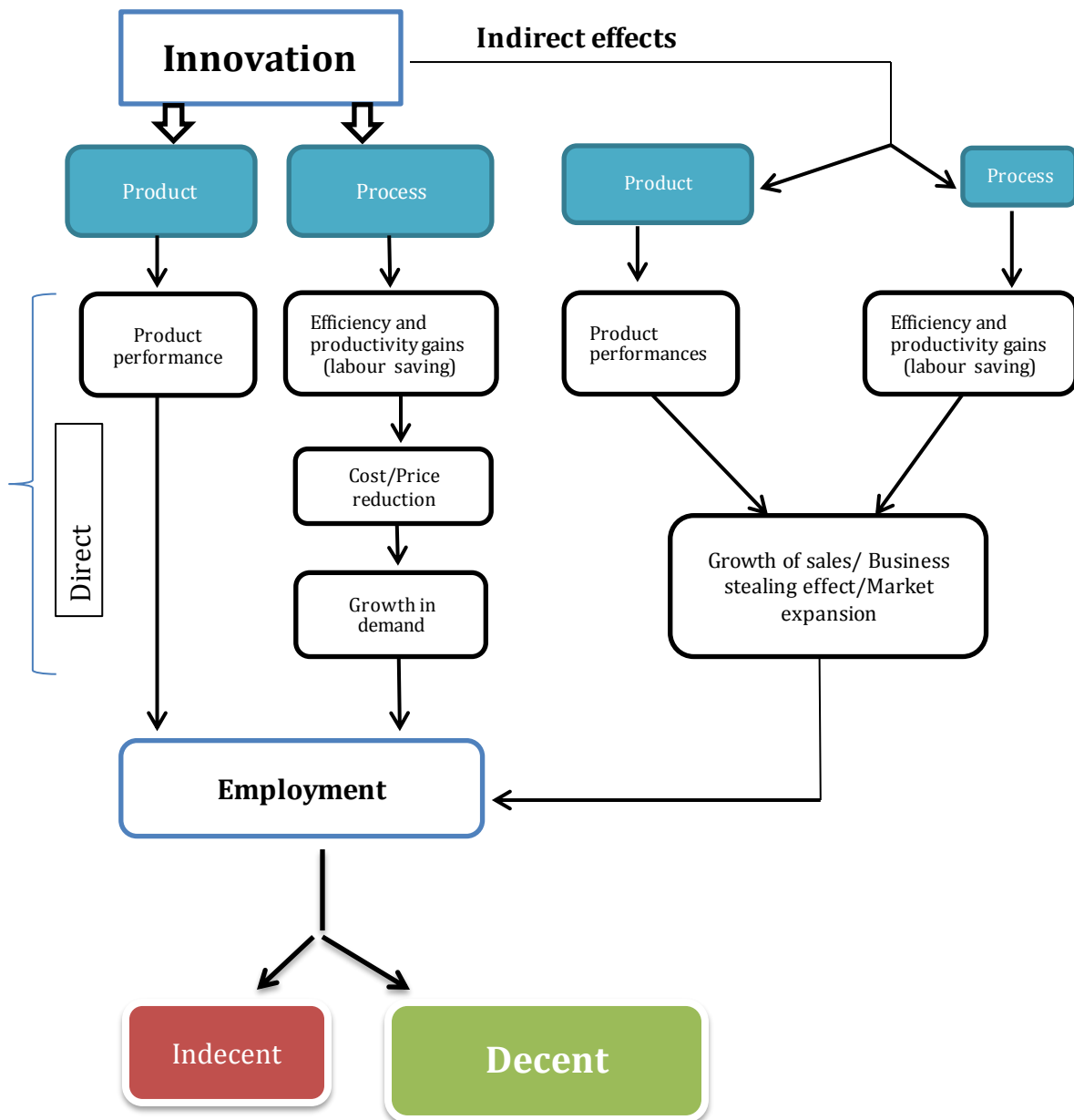


Figure 2: Relationship between innovation and employment at the firm level
Sources: Adapted from Evangelista & Vezzani (2010) and Gallouj & Djellal (2010)

APPENDIX B

Table 11: Population and sample representation of data by sector and size of firm

	Total data population		In sample	
		Product	Process	JPP
No. of firms	4,955	1089	2057	1242
Sector				
Manufacturing (%)	40.59	51.97	42.68	53.06
Retail (%)	25.37	17.355	24.16	17.71
Services (%)	34.05	30.67	33.16	29.23
Size of firm				
Micro (%)	2.16		2.38	
Small (%)	62.72	65.66	63.98	65.14
Medium (%)	26.68	27.54	25.96	27.77
Large (%)	8.44	6.80	7.68	7.09

APPENDIX C

Variable definition

Growth of total employment: the percentage change in firm's total employment (permanent+ temporary) between last fiscal year and 3 fiscal years ago.

Growth of permanent employment: the percentage change in firm's total permanent full time employment between last fiscal year and 3 fiscal years ago.

Growth of temporary employment: the percentage change in firm's total full-time temporary employment between last fiscal year and 3 fiscal years ago. Full-time temporary employment 3 fiscal years ago is constructed assuming that the ratio of permanent and temporary employment in last fiscal year is the same 3 fiscal years ago.

Product innovation: a binary variable taking the value of 1 if the firm has introduced product innovation over the last 3 fiscal years and 0 if otherwise.

Process innovation: a binary variable taking the value of 1 if the firm has introduced any innovative methods; or innovative logistics, delivery, distribution methods; or any innovative supporting activity for processes over the last 3 fiscal years and 0 if otherwise.

JPP innovations: a binary variable taking the value of 1 if the firm has introduced both product and process innovations over the last 3 fiscal years and 0 if otherwise.

Product innovation intensity: a continuous variable indicating the percentage of total sales represented by sales from all innovative products or services. It assumes strict value between 0-100. Zero implies the firm has not introduced product innovation.

Process innovation intensity: the degree of process innovation constructed as the (total number of process innovations introduced by firm/3)*100. It is a continuous variable that assumes strict value within the range of 0-100. Zero implies the firm has not introduced any of the process innovations and 100 implying the firm has introduced all three types of process innovations under consideration. In the dataset, firms are asked whether they have introduced any of these 3 types of process innovations: any innovative methods of manufacturing products/offering services; any innovative logistics, delivery/distribution methods for products and services; any supporting activity for processes.

Joint Process and Product innovation intensity (JPP intensity): constructed as (Process innovation intensity+ Product innovation intensity)/2 for firms that have introduced both process and product innovations.

Growth of skilled (unskilled) employment: the percentage change in the firm's total full-time skilled (unskilled) workers between last fiscal year and 3 fiscal years ago. Full-time unskilled workers in last fiscal year and 3 fiscal years ago are constructed by dividing the total employment in each period by the ratio of unskilled employment to skilled employment plus 1. We assume the ratio of unskilled employment to skilled employment last fiscal year is approximately similar to ratio of unskilled employment to skilled employment 3 fiscal years ago.

Ratio of male to female employment: constructed as the total number of full-time male workers divided by the total number of full-time female workers at the end of last fiscal year.

Log of experience: the logarithm of the number of working years of the top manager.

Ownership: a dummy variable that takes value 1 if the firm is foreign owned and 0 if the firm is owned domestically.

Log of total employment (-3): the logarithm of total number of employees at end of 3 fiscal years ago.

Real growth of sales per worker: constructed as the difference in the logarithm of

deflated total sales of output per worker in last fiscal year converted to United States Dollars using exchange rate in corresponding fiscal year minus the logarithm of deflated total sales of output per worker in last 3 fiscal years converted to United States Dollars using exchange rate in the corresponding fiscal year. Sales are deflated using implicit deflators from United Nations System of Accounts with base year 2005.

R&D: a binary variable taking the value of 1 if the firm has spent on formal R&D activities during the last three years and 0 if otherwise.

Log of labour cost per worker (USD) the logarithm of labour cost per worker in United States Dollars constructed as total cost of labour/total permanent employees+0.5(temporary employees) converted using exchange rate in last fiscal year.

License: a dummy variable that takes value 1 if the firm purchased/licensed any patented or non-patented inventions over the last 3 fiscal years and 0 if otherwise.

Patent: a dummy variable that takes value 1 if the firm applied for a patent concerning a product innovation or concerning process innovation or both over the last 3 fiscal years and 0 if otherwise.

External R&D: a dummy variable that takes value 1 if the firm conducted extramural R&D over the last 3 fiscal years and 0 if otherwise.

Internal R&D: a dummy variable that takes value 1 if the firm conducted intramural R&D over the last 3 fiscal years and 0 if otherwise.

Increased range: a dummy variable that takes value 1 if the firm introduced product innovations to extend the range of products or service offered by firm over the last 3 fiscal years and 0 if otherwise.

Age: the number of years the firm has being operating.

Age square: the square of the number of years the firm has being operating.

Industry: sectors according to the group classification of ISIC Revision 3.1: group D, construction sector (group F), services sector (groups G and H), and transport, storage communications sector (group I) and IT (group K sub-sector 72).

Sector: a categorical variable that takes value 0 if the firm is engaged in manufacturing, 1 if firm is engaged in retail and 2 if firm is engaged in services.

Size of firm: a categorical variable that takes value 0 if the firm is micro (<5), 1 if the firm small (≥ 5 and ≤ 19), 2 if the firm is medium (≥ 20 and ≤ 99) and 3 if large (100 and over).

Support: a dummy variable that takes value 1 if the firm receives government support and 0 if otherwise.

Year: year of data collection.

APPENDIX D

Table 12: First stage estimations for product innovations

Heckman selection

(regression model with sample selection)

Log likelihood = -2686.801

Number of observations = 1091

Censored obs = 637

Uncensored obs = 454

Wald chi2 (31) = **131.69**

Prob > chi2 = 0.000

Percentage sales from all product innovations	Coef.	Std. Err.	P>z	Introduce product innovations	Coef.	Std. Err.	P>z
Log of experience	-1.719	2.098	0.413	Log of experience	0.004	0.083	0.963
Log of total employment (-3)	-0.727	1.484	0.624	Log of total employment (-3)	0.189	0.065	0.004
Real growth of sales per worker	0.651	0.854	0.446	Real growth of sales per worker	-0.063	0.036	0.077
R&D	1.403	2.641	0.595	R&D	0.386	0.102	0.000
Log of labour cost per worker (USD)	-1.414	0.711	0.047	Log of labour cost per worker (USD)	0.004	0.028	0.880
Ghana	-4.630	4.015	0.249	Ghana	-0.262	0.129	0.042
Tanzania	-1.963	6.228	0.753	Tanzania	-0.525	0.191	0.006
Uganda	-7.580	4.020	0.059	Uganda	0.519	0.159	0.001
Zambia	-14.992	6.481	0.021	Zambia	0.381	0.248	0.124
Age	-0.292	0.205	0.155	Age	0.009	0.009	0.289
Age Square	0.001	0.002	0.622	Age Square	0.000	0.000	0.322
License	6.806	3.874	0.0079	Patents	0.609	0.115	0.000
Constant	62.112	10.755	0.000	External R&D	0.403	0.162	0.013
				Constant	-0.870	0.395	0.028
/athrho	-0.104	0.206	0.615				
/lnsigma	3.100	0.036	0.000				
rho	-0.103	0.204					
sigma	22.189	0.789					
lambda	-2.289	4.553					

All regressions include country, size, year, sector and location fixed effects.

APPENDIX E

Table 13: First stage estimation for process innovation

Heckman selection
(regression model with sample selection)

Log likelihood = -1307.124

Number of observations = 2073

Censored obs = 1045

Uncensored obs = 1028

Wald chi2 (31) = **125.32**

Prob > chi2 = 0.000

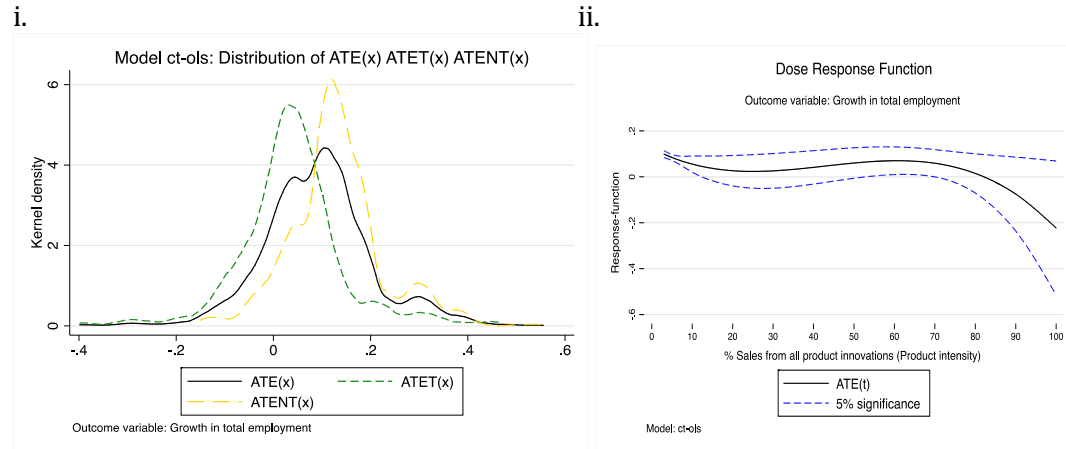
Process intensity	Coef.	Std. Err.	P>z	Introduce process innovation	Coef.	Std. Err.	P>z
Support	0.045	0.035	0.195	Support	0.084	0.133	0.527
Log of total employment (-3)	0.025	0.013	0.053	Log of total employment (-3)	0.091	0.047	0.053
Real growth of sales per worker	-0.004	0.006	0.554	Real growth of sales per worker	-0.011	0.021	0.600
R&D	0.004	0.020	0.843	R&D	0.255	0.073	0.000
Log of labour cost per worker (USD)	0.000	0.003	0.975	Log of labour cost per worker (USD)	0.010	0.011	0.344
Ghana	-0.025	0.038	0.506	Ghana	0.085	0.118	0.473
Malawi	0.058	0.055	0.292	Malawi	0.391	0.175	0.026
Namibia	0.106	0.057	0.062	Namibia	0.422	0.189	0.026
Nigeria	0.118	0.051	0.021	Nigeria	0.629	0.157	0.000
South Sudan	0.020	0.049	0.685	South Sudan	0.642	0.150	0.000
Sudan	0.230	0.065	0.000	Sudan	-0.002	0.186	0.991
Tanzania	-0.001	0.048	0.985	Tanzania	0.032	0.155	0.835
Uganda	-0.042	0.044	0.339	Uganda	0.166	0.150	0.269
Zambia	0.045	0.041	0.265	Zambia	0.713	0.145	0.000
External RD	0.139	0.026	0.000	License	0.482	0.117	0.000
Constant	0.449	0.116	0.000	Patents	0.752	0.082	0.000
/athrho	-0.587	0.110	0.000	Constant	-0.557	0.395	0.159
/lnsigma	-1.279	0.036	0.000				
rho	-0.528	0.080					
sigma	0.278	0.010					
lambda	-0.147	0.026					

All first stage regressions include sector, year, size, location fixed effects; log of age and log of age squared.

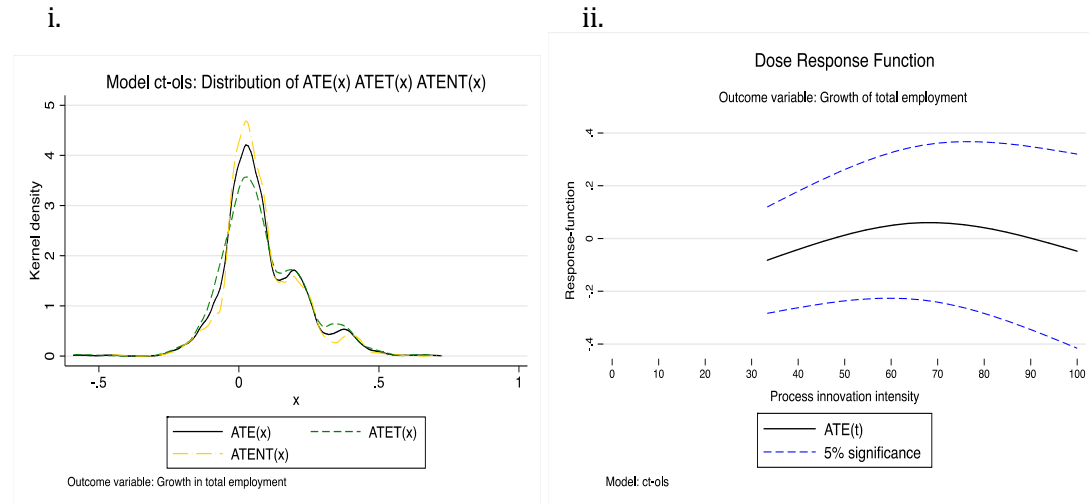
APPENDIX F.

Figure 3: OLS Kernel density estimations and Dose Response Functions

A: Product innovation



B: Process innovation



C: JPP innovation

