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Elvis Korku Avenyo, Maty Konte and Pierre Mohnen

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: info@merit.unu.edu | website: http://www.merit.unu.edu

Boschstraat 24, 6211 AX Maastricht, The Netherlands
Tel: (31) (43) 388 44 00

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The employment impact of product innovations in sub-Saharan Africa: Firm-level evidence

Elvis Korku Avenyo [*a], Maty Konte [†b], and Pierre Mohnen [‡c]

[a]University of Johannesburg, South Africa[§]
[b]United-Nations University (UNU-MERIT), The Netherlands
[c]Maastricht University and UNU-MERIT, The Netherlands

Abstract

Innovation has become a key interest in sub-Saharan Africa (SSA), as it is argued to be pervasive, and play eminent role in generating employment. There is, however, a dearth of empirical evidence assessing the impact of innovation on firm employment for SSA. This paper investigates the impact of product innovations on job creation using data from the recent waves of the Enterprise Survey merged with Innovation Follow-Up Survey for SSA countries for which both surveys are available. We apply the Dose Response Model under continuous and heterogeneous responses to treatment. The results reveal a positive impact of product innovations on total employment. This result is, however, found to hold only at specific intervals of product innovation intensities. Our analyses also show that product innovations tend to create both temporary and permanent jobs as well as skilled and unskilled jobs. However, the positive impact of product innovations on temporary and unskilled employment tends to outweigh that of permanent and skilled employment, raising questions about the security and quality of the new jobs generated by product innovations.

Keywords: Employment, Product Innovations, Dose Response Model, sub-Saharan Africa.

JEL Codes: J23, J3, O31, O33, L1.

[*]elvisa@uj.ac.za
[†]konte@merit.unu.edu
[‡]mohnen@merit.unu.edu
[§]DST/NRF South African Research Chair in Industrial Development, University of Johannesburg, Auckland Park, Johannesburg, South Africa; Corresponding author: elvisa@uj.ac.za

1 Introduction

Innovation is widely recognised as a primary driver of economic growth and productivity as well as a major source of employment (Fagerberg et al., 2005; van Dijk and Sandee, 2002; Verspagen, 1992; Schumpeter, 1934). Firm-level innovations, in particular, have been found to create new jobs in advanced countries (Harrison et al., 2014; Hall et al., 2008; Pianta, 2005). The effects of firm-level innovations and innovation activities have also been argued to be key to resolving some of the challenges faced by African countries today (NEPAD Planning and Coordinating Agency (NPCA)., 2010). One important question for African countries is how to 'link' innovation to employment creation (NEPAD Planning and Coordinating Agency (NPCA). (2014)). Yet, despite policy efforts in fostering innovation activities,[1] there is little empirical research on the relationship between innovation and employment in Africa.

This paper investigates the impact of product innovations on job creation using data from the Enterprise Survey (ES) merged with the Innovation Follow-Up Survey (IFS) for five sub-Saharan African (SSA) countries. The analysis includes SSA countries for which surveys on ES and innovation are conducted using the same data collection procedure. These countries are: the Democratic Republic of Congo, Ghana, Tanzania, Uganda and Zambia.

Advancing firm-level innovations, and promoting firm-level innovation activities arguably offer strong prospects for sustainable growth, improved productivity and consequently quality employment creation in developing countries, including those in SSA (Gault, 2010). The ample empirical literature examining the effect of innovation on employment remains mixed. Therefore, empirical analysis of this relationship still occupies centre place in the development literature (Peters, 2005). The innovation-employment literature also mainly focuses on manufacturing firms in developed countries, ignoring innovations in the service sector.[2] Yet, the service sector is the major contributor to GDP in most SSA economies, and it has been shown that innovations in the service sector have more beneficial effects on employment than innovations in the manufacturing sector (Gallouj and Djellal, 2010). It is then critical to consider and analyse the innovation activities of firms operating in the service sector. More importantly, innovation and employment policies may require a deep understanding of the direct and indirect mechanisms through which innovation affects employment at the firm-level (Hall et al., 2008).

Introducing new products on the market may be costly and risky. It is not guaranteed that the market is ready to buy the new good (or service). Small shares of innovative sales may be easy to obtain, but scaling up the sales of new products may require additional investments and a temporary cut of the number of workers to save costs. If the new product is successful on the market, then more workers can be hired to meet the increased demand until the market niche for the new product gets saturated. Firm-level evidence also suggests that product innovation is biased towards skilled labour in developing countries (Crespi et al., 2019; Cirera and Sabetti, 2019; de Elejalde et al., 2015).

[1] Lagos Plan, Khartoum declaration, Addis Ababa declaration, etc.
[2] Notable exceptions include Harrison et al. (2014) and Gebreeyesus (2011).

The empirical literature testing the skill-biased hypothesis of product innovation in SSA is scarce. Empirical evidence on whether product innovation is skill-biased or otherwise in SSA is particularly relevant because the region has insufficient 'skilled labour'. It is in the spirit of closing these evidence gaps and contributing to the understanding of how innovations impact employment that this paper becomes vital.

This paper contributes to the literature in three major ways. First, it contributes to the thin empirical literature in SSA by assessing the impact of firm-level product innovations on total employment, using newly available firm-level data. Existing evidence in the literature is mainly from developed countries and Latin America. This may be due to the scarce firm-level innovation data in SSA. With the availability of some innovation data in recent years, this paper contributes to the literature by providing empirical evidence that helps to better understand product innovations and their labour market implications in SSA.

Second, the paper goes beyond correlation analyses by employing a novel counter-factual perspective whereby innovative firms are assumed to have varying responses to sales from all innovative products (product innovation intensity). In modern micro-econometrics, counterfactual causal analysis is becoming widespread in establishing causal relationships between economic variables. However, the application of causal analysis remains scant in the innovation-employment literature with few exceptions including Van Roy et al. (2018). In this paper we model a firm's choice to introduce innovation or otherwise, and rigorously examine the impact of firm-level product innovations on employment under heterogeneous responses with varying innovation intensities. While an increase in product innovation intensity is shown to enhance employment creation (see for instance, Harrison et al. (2014)), our approach provides a deeper understanding of this causal relationship, and determines whether there are product innovation intensities whereby total employment is maximised or minimised.

Third, because the creation (compensation) and destruction (displacement) impact of product innovations may depend, for instance, on the skills of workers (de Elejalde et al., 2015; Harrison et al., 2014), this paper analyses the different impacts that product innovations may have on decent employment, specifically on job security and productive employment.

This paper uses comparable Enterprise Survey (ES) merged with Innovation Follow-Up Survey for the Democratic Republic of Congo (DRC), Ghana (GH), Tanzania (TZ), Uganda (UGA) and Zambia (ZAM). We apply the Dose Response Treatment (DRT) econometric model under continuous and heterogeneous responses to treatment recently developed by Cerulli (2015). The estimation results show that there is a compensation impact of product innovations on total employment. This conclusion is, however, found to be valid only within a sub-interval of firms' intensity of product innovations. Regarding decent employment, we find that product innovations create more temporary and unskilled employment than permanent and skilled employment.

The rest of the paper is organised as follows: Section 2 presents a brief literature review on the relationship between innovation and employment; Section 3 describes the DRT model and the data; Section 4 presents and discusses the findings. Section 5 presents the concluding remarks and recommendations.

2 Related literature

Development economics, by tradition, recognises innovation as a major driver of economic growth and a source of employment generation (Fagerberg et al., 2005; Dosi et al., 1988; Schumpeter, 1934; Verspagen, 1992, for a survey).[3] Conceptually, the theoretical analyses of the effect of innovation on employment are done from either the micro or macro strand or both (Vivarelli, 2014; Pianta, 2005). This review concentrates on the micro strand because innovations are introduced at the firm-level where their employment effects are manifested directly (Pianta, 2005).

The theoretical literature analysing the employment effects of innovation, essentially, classifies innovations into two main types: product and process.[4] This distinction is, however, not strict as complementarity is found to exist between the two types of innovations (Mohnen and Hall, 2013; Mairesse and Mohnen, 2010; Antonucci and Pianta, 2002).[5] The overall (direct and indirect) effects of both types of innovations on employment at the firm-level is still theoretically contrasting and ambiguous (Lachenmaier and Rottmann, 2011; Hall et al., 2008; Antonucci and Pianta, 2002). Process innovation is 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 level. The increase in productivity level can be passed on to customers 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 firms products, behaviour of agents in the firm as well as competition from other firms (Harrison et al., 2014). 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 intended to make firms more technologically competitive (Bogliacino and Pianta, 2010; Antonucci and Pianta, 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 (Antonucci and Pianta, 2002). This enables a direct positive relationship between innovation

[3] See Calvino and Virgillito (2018, for a recent survey of the literature).

[4] See OECD and Eurostat (2005, paragraphs 156 & 168) for broad definitions of product and process innovations respectively.

[5] See Appendix A for the graphical representation of this theoretical relationship.

and employment. However, the market expansion that enables the positive direct effect could be a result of displacement (crowding-out effect) of other less competitive firms in the industry.[6] The effect of product innovation is, therefore, theoretically unclear and inconclusive.

The theoretical effect of introducing both types of innovations on employment depends on the size of the compensation and displacement effects emanating from both types of innovations. If product innovations have a larger compensation (positive) effect as compared to the displacement (negative) effect from process innovations, the joint introduction of both types of innovations is expected to generally have positive effect on employment and vice versa. The effects of innovation on employment also extend 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.

Despite the ambiguity in the theoretical literature, there exists some level of general consensus in the empirical literature about the relationship between product innovations and employment at the firm-level (Vivarelli, 2014; Pianta, 2005, for recent survey of the literature). Copious empirical works in the literature find a positive effect of product innovations on employment (Van Roy et al., 2018; Harrison et al., 2014; Meriküll, 2010; Peters, 2008; Hall et al., 2008; Piva et al., 2005). Harrison et al. (2014) analysed 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. The authors developed a simple theoretical framework that disentangles the effect of innovation (product and process) on output growth and employment growth from existing products. The major finding emanating is that product innovation is a major source of employment, and the compensation effects outweigh the displacement effects. Crespi et al. (2019), Cirera and Sabetti (2019), de Elejalde et al. (2015), Peters (2008) and Hall et al. (2008), using different adapted versions of the Harrison et al.(2014) earlier model, found similar results. Crespi et al. (2019) and de Elejalde et al. (2015) analysed the effect of product and process innovations on employment in Latin America using innovation survey data focusing on the manufacturing industry. The authors found product innovations to be skill-biased especially in high-tech manufacturing firms. Further analysis by de Elejalde et al. (2015) indicates that product innovation is skill biased but creates both skilled and unskilled jobs. Cirera and Sabetti (2019) using data from 53 developing countries obtained a higher effect of product innovation on low-skilled than on high-skilled labor. Dosi and Yu (2019) using Verdoorn-Kaldor model on Chinese data, also found a positive relationship between the introduction of new products and employment growth. Van Roy et al. (2018) further explored the impact of product innovation on employment using data covering about 20,000 European firms. Measuring product innovation as weighted patents and applying the system GMM, the authors'

[6] The crowding-out effect is, however, captured at firm-level analysis if firms in the data set are representative of the industry (see Harrison et al.(2014)).

main result is that product innovation has a positive and a significant impact on firm-level employment.

Empirical evidence analysing the relationship between innovation and employment in SSA is scant. The idiosyncratic nature of innovations in SSA - mainly incremental- and the structural characteristics of these economies might lead to invalid extrapolation of results from other regions. The known empirical evidence available includes Gebreeyesus (2011) and Konte and Ndong (2012). Using secondary survey data on informal micro-enterprises in Ethiopia, Gebreeyesus (2011) found innovation activities to contribute to employment growth. The author also found no bi-directional causality from employment growth to innovation. In a rare descriptive study that collected primary data on informal Information and Communication Technology (ICT) firms in Senegal, Konte and Ndong (2012) found innovation as a contributor to job creation and economic growth. Our paper adds to this thin literature by presenting a cross-country firm-level analysis using data from 5 SSA economies.

3 Methodology

3.1 Theoretical and empirical models

The Dose Response Model (DRM) employed in this paper is an econometric model for estimating continuous treatments under heterogeneous responses, where selection into treatment may be endogenous (Cerulli, 2015). A firm's decision to innovate may not be random, and may be influenced by confounders and vice versa. Cerulli and Poti (2014) applied this methodology to analyse the impact of public support intensity and firm R&D performance.[7] The DRM is an extension of the Hirano and Imbens (2005) model in two directions: it relaxes the selection-on-observables assumption, and it is applicable to data where lots of firms have not introduced any type of innovation (Baum and Cerulli, 2016; Cerulli, 2015; Cerulli and Poti, 2014).[8]

A criticism of the DRM, as noted by Cerulli (2015), is that the IV estimator is 'inconsistent in finite samples.' Due to the spike in our data, that is, a large number of non-innovators, estimates from our empirical analyses may have a bias. We, however, tried to improve the consistency of our results by merging two related data sets and appending all observations across 5 countries. The consistency of the IV estimator is found to improve as the sample size gets larger (Cerulli, 2015). In contrast to Cerulli (2015), and Baum and Cerulli (2016), we employed a full-information maximum likelihood (FIML) instead of an IV approach. The FIML approach, however, assumes a specific functional form and jointly normally distributed error terms.

[7] See Baum and Cerulli (2016) for a recent application.

[8] Fryges and Wagner (2008) applied the Hirano and Imbens (2005) model to investigate the relationship between exports and productivity growth.

3.1.1 Description of theoretical model

Assume there are two exclusive groups of firms: innovative firms (treated) and non-innovative firms (untreated). Let the innovation indicator, $W_i = \{0, 1\}$ shows whether a firm has introduced an innovation ($W_i = 1$) or not ($W_i = 0$). Firms are assumed to have different product innovation intensities (t) with non-innovative firms having $t = 0$. Innovative firms are assumed to take values greater than zero ($t > 0$) as these firms have, within the period under consideration, introduced at least one innovation. t is, therefore, assumed to take values strictly within the continuous range of [0:100].

Let the employment outcome of an innovative firm (treated) be defined as y_{1i} and the employment outcome of a non-innovative firm (untreated) be y_{0i}. Suppose a vector of M confounders as $X = \{x_{1i} \ldots x_{Mi}\}$ for all firms. Let N refer to the total number of firms, N_1 the total number of innovative firms and N_0 the total number of non-innovative firms with $N = N_1 + N_0$.

Following Cerulli (2015), the population employment outcomes can be written as:

$$w = 1 : y_1 = a_1 + f_1(x) + g(t) + e_1 \tag{1.1}$$

$$w = 0 : y_0 = a_0 + f_0(x) + e_0 \tag{1.2}$$

where y_1 and y_0 are the employment outcomes of innovative and non-innovative firms respectively, a_1 and a_o are two scalars, $f_1(x)$ and $f_0(x)$ are firms' responses to the vector of confounding variables (x) in terms of innovating versus not-innovating, $g(t)$ measures the responses of employment outcomes to the intensity or the level of product innovations taking a value of 0 if $w = 0$ and $\neq 0$ if $w = 1$. e_0 and e_1 have zero means.

Let us assume that $f_1(x)$ and $f_0(x)$ have linear parametric forms as $f_1(x) = x\delta_1$ and $f_0(x) = x\delta_0$. The causal parameters conditional on x and t can be written as:[9]

$$ATET(x, t > 0) = E(y_1 - y_0 \mid \text{x},\ \text{t} > 0) \tag{2.1}$$

$$ATENT(x, t = 0) = E(y_1 - y_0 \mid \text{x},\ \text{t} = 0) \tag{2.2}$$

$$ATE(x,t) = E(y_1 - y_0 \mid \text{x}, \text{t})) = \left\{ \begin{matrix} (a_1-a_0)+x(\delta_1-\delta_0)+g(t) & if\ t>0 \\ (a_1-a_0)+x(\delta_1-\delta_0) & if\ t=0 \end{matrix} \right\} = \left\{ \begin{matrix} a+x\delta+g(t) & if\ t>0 \\ a + x\delta & if\ \ t = 0 \end{matrix} \right. \tag{2.3}$$

[9] These assume that the treatment effect (TE)= $(y_1 - y_0)$.

where $a = (a_1 - a_0)$ and $\delta = (\delta_1 - \delta_0)$. $ATET$ 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 defined as the Average Treatment Effect.

Rewriting equation 2.3 conditional on x, t, w gives:

$$ATE\left(x,t,w\right) = \{^{ATE(x,\ t>0)\ if\ \ w=1}_{ATE(x,\ t=0)\ if\ \ w=0} = w\left[a + x\delta + g\left(t\right)\right] + \left(1-w\right)\left[a + x\delta\right] \tag{3}$$

By the law of iteration, the unconditional ATE is obtained as:

$$ATE = E_{(x,t,w)}\left[ATE\left(x,t,w\right)\right] = p\left(w=1\right)\left(ATET\right) + p\left(w=0\right)\left(ATENT\right) \tag{4.1}$$

where

$$ATET = a + \overline{x}_{t>0}\delta + \overline{g} \tag{4.2}$$

$$ATENT = a + \overline{x}_{t=0}\delta \tag{4.3}$$

where $\overline{g}$ is the average response function taken over $t > 0$. p(w=1) is the probability to innovate and p(w=0) is the probability to not innovate.

Thus, the Dose Response Function (DRF) is derived algebraically by averaging $ATE(x,t,w)$ over x and w so that:[10]

$$ATE\left(t\right) = \begin{cases} ATET + \left(g\left(t\right) - \overline{g}\ \right) if\ \ t > 0 \\ ATENT\ \ \text{if}\ \ t = 0 \end{cases} \tag{5}$$

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

[10] See Cerulli (2012, p. 7&8 for proof).

3.1.2 Empirical model

Transforming[11] and assuming that $g\ (t)$ is a three degree polynomial, that is, $g\,(t) = bt + ct^2 + dt^3$,[12] the estimation equation can be derived as:[13]

$$E(y|x,w,t) = a_0 + \ x\delta_0 + wATE + w\left[x - \overline{x}\right]\delta + b\left[t - E\left(t\right)\right]w + c\left[t^2 - E\left(t^2\right)\right]w \\ +d\left[t^3 - E\left(t^3\right)\right]w + \varepsilon \tag{6}$$

where $\varepsilon = e_0 + w(e_1 - e_0)$. y is the employment outcome of firms. ATE indicates the average causal effect of introducing product innovations on employment. $w\left[x - \overline{x}\right]\delta$ captures the heterogeneous average deviations of exogenous confounders from their means. Equation (6) estimates the average employment responses to product innovations (ATE) while controlling for exogenous factors (x) as x and the intensity of product innovations (t) deviate from their means. Under Conditional Mean Independence (CMI), OLS estimation of equation (6) would provide consistent estimates of the parameters of interest (Cerulli, 2015, 2014).

The Dose Response Function can be estimated as:

$$\widehat{ATE}(t_i) = w\left[\widehat{ATET} + \hat{b}\left(t_i - \frac{1}{N}\sum_{i=1}^{N} t_i\right) + \hat{c}\left(t_i^2 - \frac{1}{N}\sum_{i=1}^{N} t_i^2\right) + \hat{d}\left(t_i^3 - \frac{1}{N}\sum_{i=1}^{N} t_i^3\right)\right] \\ +(1-w)\widehat{ATENT} \tag{7}$$

where $\widehat{ATE}(t_i)$ is a consistent Dose Response Function with $\widehat{ATE}(t_i) = ATE(t_i)_{t_i>0}$. $\widehat{ATET}$ and $\widehat{ATENT}$ refer to the estimated Average Treatment Effect on the Treated (innovative firms) and the estimated Average Treatment Effect on Non-Treated (non- innovative firms) respectively.

However, empirical evidence from the innovation literature indicates that the decision to innovate or not (w), and the intensity or the level of product innovation (t) are likely to be endogenous (see Harrison et al. (2014)). The assumption of Conditional Mean Independence (CMI), therefore, breaks down and estimation of equation (6) with OLS gives biased estimates. That is, $E(\varepsilon|x,w,t) \neq E(e_0 + w(e_1 - e_0)|x,w,t)$ (Cerulli, 2014, p. 9). Following Cerulli (2015), equation (6) is re-written as an estimation equation as:

$$y = a_0 + \ x\delta_0 + wATE + w\left[x - \overline{x}\right]\delta + bwT_1 + cwT_2 + dwT_3 + \varepsilon_y \tag{8.1}$$

[11] The transformation is done by substituting equations 2.1 and 2.2 into the Potential Outcome Model (POM), $y = y_0 + w\ (y_1 - \ y_0)$.

[12] According to Cerulli (2012) and Cerulli and Poti (2014), g (t) can be assumed to have linear, partial linear or polynomial regression forms. We assumed a polynomial regression form here to control for possible non-linearity of the intensity of product innovation. We checked the robustness of our results by also assuming a linear regression form.

[13] Cerulli (2012, p. 8&9 for proof).

$$w = \left\{ \begin{array}{c} 1\ if\ w^* = \eta_1 x_1 + \varepsilon_w\ > 0 \\ 0\ if\ w^* \leq 0 \end{array} \right\} \tag{8.2}$$

$$t = \left\{ \begin{array}{c} \eta_2 x_2 + \varepsilon_t \quad if\ w^* > 0 \\ 0\ if\ w^* \leq 0 \end{array} \right\} \tag{8.3}$$

where $T_1 = [t - E(t)]$, $T_2 = \left[t^2 - E\left(t^2\right)\right]$ and $T_3 = \left[t^3 - E\left(t^3\right)\right]$ are considered to be endogenous together with w. ε_y is an error term with zero mean and constant variance. y refers to total employment in logs. δ is the average heterogeneous employment among product innovators due to deviations from main cities of business and also serves as an additional exclusion restriction (see Baum and Cerulli (2016)). w^* is the unobservable latent variable of innovative and non-innovative firms. The intensity of product innovation is only observed when a firm introduces an innovation ($w = 1$), otherwise it is assumed to be unobserved (Amemiya, 1985, p. 384 & 385). Equations (8.2) and (8.3) are specified as a Type II Tobit model (Amemiya, 1985) where (8.2) shows the selection equation with x_1 as a vector of covariates that influences the decision of a firm to innovate or not, while (8.3) defines the vector of covariates x_2 that determines the intensity of product innovation. Covariates included in x_1 and x_2 are suggested by the recent empirical literature including Gebreeyesus (2011) and Classen et al. (2014).

From equation 8.1, we are not only interested in the direct impact of product innovation (ATE) on total employment, but also how this impact is mediated by the intensity of product innovation given other covariates. b, c and d capture these heterogeneous effects of product innovation on total employment due to deviations of innovation intensities from their means. While the theoretical and empirical evidence from the innovation-employment literature suggest that product innovation (ATE) should have a positive impact on employment (Meriküll, 2010; Piva et al., 2005, among others), empirical findings from Harrison et al. (2014) and Peters (2008) indicate that the positive employment effect of product innovations is generated from the sales of new products. We, therefore, hypothesise that the total employment impact of product innovation is positive, but the positive effect is moderated by the intensity of product innovation.

3.1.3 Estimation/Identification procedure

For reasons of identification, we followed Cerulli (2015, 2014) to specify the vector of covariates in equations (8.2) and (8.3) as:

$$x_1 = (x,\ q_1) \tag{9.1}$$

$$x_2 = (x,\ q_2) \tag{9.2}$$

where q_1, q_2 are vectors of variables that appear and explain the probability of a firm to innovate and the intensity of product innovations respectively, thereby satisfying the exclusion restriction

(Wooldridge, 2013).

One difficulty, as well established in the econometric literature, is the identification of valid exclusion restrictions. The theoretical and empirical literature on employment and innovation have suggested several variables such as 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 et al., 2019). We considered the presence of licenses and patents as valid exclusion restrictions for product innovation intensity and product innovation occurrence respectively. Both licenses and patents are innovation activities that are not expected to be correlated with firms' total employment, except via product innovation. They are, however, expected to have a high correlation with our innovation variables. Licensing, for example, comes with risks. In the context, it is believed that firms only acquire a license that is 'successful' and one they have already 'imitated'. Expecting a high market return, they purchase the license to enable them sell their 'new', 'imitated' products on the domestic market, leading to high sales of innovative products. Regression results of our innovation variables yield significant coefficients for our two exclusion restrictions, indicating their validity.[14]

The estimation is performed using the conditional mixed process *(cmp)* (Roodman, 2011) econometric package in *Stata SE/15.1*, which performs FIML estimation of the system of equations in (8.2), (8.3) and (8.1), instead of using a two-stage IV estimation procedure as in Cerulli (2015), and Baum and Cerulli (2016).

3.2 Data and measurement

The empirical investigation in this paper uses data from the Enterprise Survey (ES) and the Innovation Follow-Up Survey of the World Bank.[15] The ES is a World Bank project that collects enterprise data in 139 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 Survey is a follow-up survey to the ES and collects nationally representative firm-level data on innovation and innovation activities of firms between the last fiscal year and three fiscal years ago.[16] The Innovation Follow-Up Survey follows the Oslo Manual (OECD and Eurostat, 2005) and covers 19 countries between 2011-2014, out of which 15 are in Africa.

For compatibility of surveys, we considered only countries that conducted the ES and the innovation survey in 2013.[17] Due to large missing observations for most of our variables of interest, the ES and the Innovation Follow-Up Survey were merged at the country level using

[14] See Appendix B.
[15] Both data sets cover manufacturing and service sector firms.
[16] See OECD and Eurostat (2005) for measurement and definition of these concepts.
[17] Ethiopia, Rwanda, and Zimbabwe are also excluded as the sampling methodologies employed in the follow-up survey differ from the ES global methodology.

a unique country identifier. All merged country data sets were then appended using a global unique identifier for larger sample size. Appending all the data sets across countries guarantees a larger sample size and also offers us the opportunity to cross-check responses across the 2 surveys. In total, data for five SSA countries (DRC, Ghana, Tanzania, Uganda and Zambia) totaling 2,466 firms were obtained.

To standardise our data for cross-country comparison, we converted nominal sales values to United States Dollars (USD) using exchange rate data in the corresponding fiscal year from the World Bank's World Development Indicators.

We explain below how we measure our key variables.

Innovation: In line with Harrison et al. (2014), among others, we use two related measures to capture innovation: product innovation and product innovation intensity. Product innovation is a dummy variable capturing whether a firm introduced any innovative good or service over the last 3 fiscal years, that is, between 2010 and 2012. Product innovation intensity captures the percentage of sales from all product innovations in the last fiscal year (2012). It assumes strict values between 0-100.

Employment outcomes: As a dependent variable, the literature commonly measures changes in employment in terms of growth rates (see for example Ross and Zimmermann (1993); Carree and Thurik (2008); Gebreeyesus (2011); Audretsch et al. (2014); Harrison et al. (2014)). Our key independent variable, product innovation intensity, is measured at the end of 2012. As a result, predicting the impact of product innovation intensity on employment growth that occurred between 2012 and 2010 is time-wise inconsistent. We, therefore, use five main employment variables all measured in full-time employment levels at the end of 2012: permanent employment, temporary employment, skilled employment, unskilled employment, and total employment.[18] Total employment is the addition of permanent employment and temporary employment. All outcome variables are logged in our empirical analysis. The log of temporary employment is generated by adding 1 to the number of temporary employees before taking logs to avoid missing firms that do not have temporary employees.

In addition to our innovation variables, we controlled for other key covariates such as cost of labour, age, lagged total sales and lagged size. Following Ross and Zimmermann (1993) and Brouwer et al. (1993), we expect higher wage bills to be associated with decreases in employment, and we also expect larger firms (in terms of employment) and firms with higher demand (in terms of sales) two years earlier to remain larger in 2012. Following Gebreeyesus (2011), we expect a convex relationship between total employment at the end of 2012 and firm age. Table 1 provides a detailed definition and measure of all variables used in our analysis.

[18] Our analyses focus on these due to measurement problems with other classifications of employment, such as female versus male workers.

Table 1: Definition and measurement of all variables.

Total employment(log)	The logarithm of the addition of permanent employment and temporary employment.
Permanent employment(log)	The logarithm of total number of permanent, full-time employees at the end of the last fiscal year.
Temporary employment(log)	The logarithm of total number of full-time temporary employees at the end of the last fiscal year. Temporary employment(log) is constructed by adding 1 to the number of temporary employees before taking logs to avoid missing firms that do not have temporary employees.
Skilled employment(log)	The logarithm of total number of full-time skilled employees at the end of the last fiscal year.
Unskilled employment(log)	The logarithm of total number of full-time unskilled employees at the end of the last fiscal year. Unskilled employment (log) is constructed by adding 1 to the number of full-time unskilled employees before taking logs to avoid missing firms that have zero unskilled employees.
Product innovation	A binary variable taking the value of 1 if a firm has introduced at least one product innovation over the last 3 fiscal years and 0 if otherwise.
Technological product and process (TPP) innovation	A binary variable taking the value of 1 if a firm 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 at the end of the last fiscal year. It assumes strict values between 0-100. Zero implies the firm has not introduced product innovation.
Log of experience	The logarithm of the number of working years of the top manager at the end of the last fiscal year.
Log of total employment (-2)	The logarithm of total number of employees at the end of 3 fiscal years ago.
Log of sales (USD) (-2)	The logarithm of total sales in last 3 fiscal years converted to United States Dollars using exchange rate in corresponding fiscal year.
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 (USD)	The logarithm of labour cost in United States Dollars in the last fiscal year. This is constructed as total cost of labour converted using exchange rate in the last fiscal year.
License	A dummy variable that takes value 1 if the firm purchased 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.
Age	The number of years the firm has been operating at the end of the last fiscal year.
Age square	The square of the number of years the firm has been operating at the end of the last fiscal year.
Size of firm	A categorical variable that takes value 0 if the firm is micro (<5), 1 if the firm is small (≥ 5 and ≤ 19), 2 if the firm is medium (≥ 20 and ≤ 99) and 3 if large (100 and over).
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 other services.
Region	A categorical variable that indicates the region a firm is located.
City	A dummy variable that takes value 1 if the firm is located in the main city of business and 0 if otherwise.

3.2.1 Descriptive analysis

Due to the large number of cross missing values, there were large drops in the number of firms across our regressions. Despite the enormous drop in the number of firms, the representativeness of the population was relatively maintained in terms of sector and size.[19] Table 2 shows the descriptive statistics for our main variables based on 1,158 observations used in our extended regression in Table 3 (columns 2 and 4). For each variable, we sub-divided the sample into innovators and non-innovators across all countries under consideration. Out of 1,158 observations used, 504 firms representing about 43.5% of firms introduced product innovations with mean percentage sales from all product innovations (product innovation intensity) of about 35.38%. Our data also shows that 376 firms introduced both product and process (TPP) innovations as compared to 782 non-innovators. Our data also suggests that TPP innovations on average have a higher innovation intensity as compared to innovation intensity from product innovation only. In terms of total employment, product innovators, on one hand, employ about 74 workers on average while non-product innovators employ on average 33 workers. The above descriptive statistics indicate that in our sample, total employment tends to be statistically lower for non-product innovators as compared to product innovators. A closer look across each country's descriptive statistics, however, indicates mixed employment outcomes. For example, innovators in Tanzania, on average, employed fewer workers as compared to non-product innovators. Our data also show higher permanent employment across all countries for product innovators, with mean of about 63 workers. In terms of temporary employment, product innovators across all countries, with the exception of Tanzania, employed more temporary workers in comparison with non-product innovators. Non-innovative firms in Tanzania, however, employed about 28 temporary workers while product innovators employed about 13 temporary workers. Both product and non-product innovative firms, on average, employ about 3 skilled workers. Product innovators, on the other hand, employ about 2 unskilled workers while non-product innovators employ about 1 unskilled worker, on average. Firms may also hire new workers for developing new innovative products. Our data indicates that about 159 innovative firms, making up about 32%, indicated to have hired employees for developing the main innovative product, while 340 innovative firms, representing about 68%, indicated otherwise.

In terms of innovation activities such as patent and license, we observe that the majority of product innovators do not undertake these activities. For instance, 123 product innovators responded to have applied for patent over the period under consideration while 381 product innovators responded otherwise. About 67 non-product innovators also responded to have patented over the period. With regards to licensing activity, 46 (26) product innovators (non-product innovators) responded to have purchased an invention over the last 3 fiscal years. These indicate that innovation activities do not always lead to innovations, and innovation activities are not only done by innovators.

[19] See Appendix C.

Table 2: Descriptive statistics of innovation and employment variables.

	ALL	DRC	GH	TZ	UGA	ZAM
No. of firms	1,158	238	320	107	149	344
Product innovation						
Innovators	504	92	89	23	95	205
Non-innovators	654	146	231	84	54	139
Innovation Intensity (Mean % sales)	35.38	47.67	34.83	47.0	42.22	25.92
Technological product & process (TPP) innovation						
Innovators	376	72	56	13	59	176
Non-innovators	782	166	264	94	90	168
Innovation Intensity (Mean % sales)	36.18	47.28	37.29	49.75	50.04	25.98
Total employment (Mean)						
Product Innovators	74.23	76.25	44.52	60.35	152.34	51.59
Non-Product Innovators	32.8	34.21	27.10	61.23	23.96	25.57
Significance (Mean Difference)	***		***	**	**	***
Permanent employment (Mean)						
Product Innovators	63.07	65.64	32.39	47.74	133.57	44.29
Non-Product Innovators	25.67	29.16	24.47	33.58	17.83	22.29
Significance (Mean Difference)	***					***
Temporary employment (Mean)						
Product Innovators	11.16	10.61	12.13	12.61	18.77	7.30
Non-Product Innovators	7.13	5.05	3.53	27.65	6.13	3.28
Significance (Mean Difference)	***		***		***	**
Skilled employment (Mean)						
Product Innovators	32.56	30.49	16.46	30.68	54.40	29.64
Non-Product Innovators	30.08	25.30	24.26	54.57	22.08	24.19
Significance (Mean Difference)	***					
Unskilled employment (Mean)						
Product Innovators	41.67	45.76	28.06	29.67	97.94	21.9
Non-Product Innovators	2.72	8.91	2.84	6.66	1.88	1.38
Significance (Mean Difference)	**				*	
Hired for main product innovation						
Yes	159	37	24	4	36	58
No	340	54	64	19	59	144
Patent (No. of respondents)						
Product Innovators						
Yes	123	25	17	9	21	51
No	381	62	72	14	74	154
Non-Product Innovators						
Yes	67	7	10	23	5	22
No	587	139	221	61	49	117
License (No. of respondents)						
Product Innovators						
Yes	46	13	2	6	13	12
No	458	74	87	17	82	193
Non-Product Innovators						
Yes	26	1	6	14	2	3
No	628	145	225	70	52	136

Source: ES and Innovation Follow-up surveys. Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 Empirical results and discussion

4.1 Estimation results

Table 3 below presents the estimation results showing the impact of product innovations on total employment in logs. We estimated different model specifications where we sequentially added different sets of control variables to extend the basic specification for a robustness check. We included in all extended regressions sector and location dummies. It is also worth mentioning that the estimated coefficient on product innovation is our estimate of the Average Treatment Effect (ATE) as indicated in the estimation equation (8.1). In other words, the estimated coefficient on product innovation indicates, ceteris paribus, the average effect of firms' innovative products on total employment.

Our results indicate a significantly positive impact of product innovations on total employment. The stability of this result across all specifications suggests that firms, during the period under consideration, favoured and adopted technological competitive strategies with product quality and market expansion advantages leading to compensation impacts on total employment. This may be due to the rise of the middle class with incessant demand for new products in SSA. This result fits with existing empirical findings by Van Roy et al. (2018); Harrison et al. (2014); Meriküll (2010); Hall et al. (2008); Peters (2008); Piva et al. (2005, 2003). These studies find product innovations to generally have positive job creation effects. Our polynomial terms (T_1w, T_2w, T_3w) are all statistically significant in the extended model (column 2), although, economically speaking, they are close to zero. Nevertheless, as we shall illustrate in the next section, this result implies that product innovation intensities impact total employment differently.

Other significant predictors across the extended specification (column 2) include log of total employment two years earlier, age, log of sales in US dollars two years earlier, R&D and log of labour cost (in USD). The total employment of the firm, at the beginning of the period, is found to have a positive impact on the total employment of firms across all specifications. Firms that engage in R&D activities are also found to have higher total employment than firms that do otherwise. This suggests that investments in R&D-related activities lead to employment of more workers. In addition, total sales (in USD and lagged by two periods) is found to have a positive impact on total employment across all specifications, suggesting that larger firms tend to employ more workers. Our results show a convex relationship between firm age and employment activity, suggesting that total employment decreases at a younger age but tends to increase as firms grow in age. An increase in the cost of labour is also found to discourage firms from hiring workers.

Table 3: Employment impact of firm-level product innovations.

Estimation method	Full-information maximum likelihood (FIML)			
	(1)	(2)	(3)^a	(4)^a
	Total employment (log)			
Product innovation (w)	0.121***	0.123***		
	(7.11)	(4.28)		
TPP (w)			0.393***	0.387***
			(4.14)	(4.26)
T_1w		-0.007*		0.002
		(-1.87)		(0.28)
T_2w		0.000*		0.000
		(1.80)		(0.44)
T_3w		-0.000**		-0.000
		(-2.00)		(-0.90)
Log of experience	-0.010	-0.011	-0.016	-0.020
	(-0.68)	(-0.66)	(-0.80)	(-0.95)
Log of total employment (-2)	0.707***	0.713***	0.700***	0.701***
	(24.50)	(21.40)	(18.96)	(18.74)
Log of sales (USD) (-2)	0.039***	0.037***	0.041***	0.038***
	(6.26)	(5.34)	(5.44)	(5.02)
R&D	0.049***	0.042*	-0.014	-0.036
	(2.73)	(1.83)	(-0.41)	(-0.85)
Log of labour cost (USD)	-0.035***	-0.035***	-0.037***	-0.036***
	(-4.45)	(-3.84)	(-3.76)	(-3.56)
Age	-0.003**	-0.003*	-0.002	-0.002
	(-2.39)	(-1.76)	(-0.71)	(-0.75)
Age square	0.000***	0.000***	0.000	0.000
	(4.73)	(2.90)	(0.95)	(1.02)
Country fixed effect	Yes	Yes	Yes	Yes
N	1160	1158	1160	1158
Wald chi^2	5381.654	5400.923	5768.868	5749.060
Prob >chi^2	0.000	0.000	0.000	0.000

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.
^{a}Used TPP as the dependent variable in the selection equation.

In the presence of complementarity, the introduction of product and process (TPP) innovations is expected to imply a strictly higher positive impact on firms' total employment than the mere introduction of product innovation, including firms that do product innovation only. In other words, the causal parameter, ATE, of TPP innovation is expected to be strictly higher than the ATE of the separate introduction of product innovation on total employment. The results shown in columns 3 and 4 show a significantly positive effect of TPP on total employment, with a coefficient larger than for firms that introduced product innovation only. This net compensation effect from TPP may be explained by the employment stimulating effects emanating from product innovation with reinforcing effects from process innovation through productivity gains, which lead to price reductions thereby stimulating demand and employment. In this case, however, there are no significant moderating effects of product innovation intensity through TPP on total employment.

4.1.1 Employment responses

As noted, innovative firms have different product innovation intensities that may have different impacts on employment outcomes. We, therefore, estimated the Dose Response Function (DRF) in this section to analyse the impact of different levels of product innovation intensities on the total employment of the firm. Based on the regression results in Table 3, we determined the average expected conditional total employment given the product innovation intensity and the other covariates. The DRF derived from the estimation in column 2 of Table 3 is plotted in Figure 1 below.

Figure 1 shows the different total employment responses of firms, evaluated across all product innovation intensities. The shape of the relationship implies that, on average, product innovation is associated with a 10 percent higher level of total employment. But this increase in employment decreases and becomes insignificant as product innovation intensities range from 20% to 40% and when they exceed 90%. This result may be due to uncertainty posed by 'dual' competition in the market, and the type of product innovations introduced. Firms whose sales from product innovations constitute a large portion of total sales may be first-time mono-product innovators. Due to uncertainty in the product market, these firms may be reluctant to employ new workers and may as well lay-off workers with the introduction of product innovations. And when innovation intensities are not yet sufficiently high (below 40%) it may be that the cost of introducing them is so high that labour needs to be saved to cut down costs in order to survive. Our DRF suggests that the general conclusion in the literature, that product innovation boosts employment, may only hold within a sub-interval of percentage sales from all new product innovations.

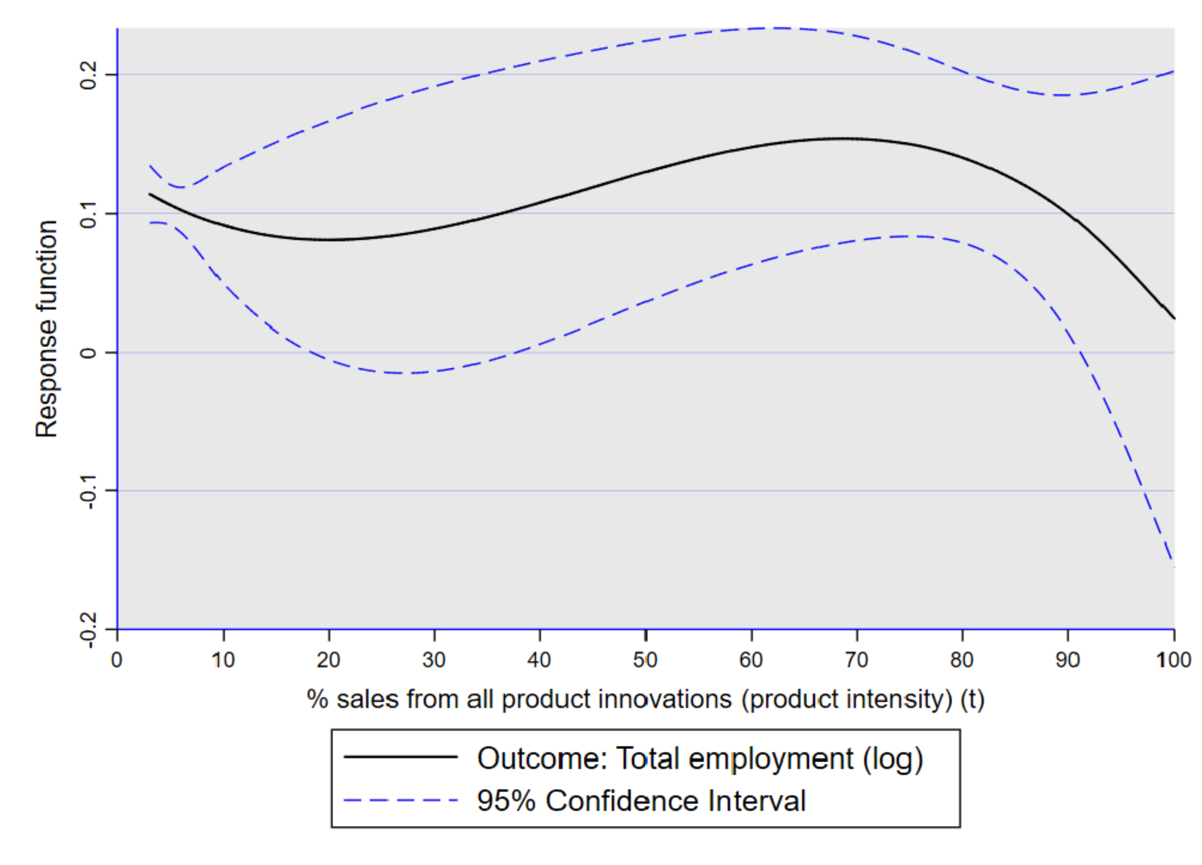

Figure 1: Dose Response Function for total employment(log).

4.2 Extension to decent employment

Productive[20] and decent[21] employment are widely recognised in the growth-poverty nexus literature as critical mechanisms through which the benefits of growth are distributed (Islam, 2013, 2004; Martins and Takeuchi, 2013; International Labour Organization (ILO)., 2012; Osmani, 2005). 'Decent work and economic growth' is the 8^{th} goal of the Sustainable Development Goals (SDGs) adopted in 2015. Achieving decent work for all has been found to be important in achieving other goals such as 'no poverty' (SDG 1), 'zero hunger' (SDG 2) and 'quality education' (SDG 4), through income earned both in the wage sector and self-employed activities (International Labour Organization (ILO)., 2012). As a result, there is a renewed policy interest, particularly in developing countries, on how to nurture and generate decent employment. In this light, the role of innovation (SDG 9) is well emphasised in development economics. Using permanent versus temporary, and skilled versus unskilled employment as proxies for job security and 'productive' employment respectively, we extend our analysis in this section to examine the impact of innovation on decent employment in SSA.

[20] The International Labour Organization (ILO). (2012, p. 3) 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.'

[21] Decent employment/work in this context, refers to work that is secured. See International Labour Organization (ILO). (2013, p. 12) for a broader definition.

Table 4 and figure 2 present estimates for both permanent and temporary employment used as proxies for employment security. Results indicate compensation impact of product innovations on both permanent employment (A-(2)) and temporary employment (B-(4)). Our findings, however, indicate that the compensation impact of product innovation on temporary employment tends to outweigh that of permanent employment. These results are robust and suggest that product innovators prefer to hire more on a temporary basis rather than on a permanent basis. One explanation for this may be the labour cost differences. Firms that employ temporary workers are not required by law to pay social security and income tax for their temporary employees. For permanent workers, however, firms are required to pay social security for each worker which may lead to higher cost burdens. Another explanation may be due to the risk associated with innovation and the uncertainty about the performance of product innovations. Uncertainty may come from the fact that firms do not absolutely know how their new products would perform in product markets in the short-term and, as a result, may prefer to offer temporary contracts rather than permanent contracts.

Our polynomial terms are also significant for both permanent employment and temporary employment. The implication of their opposite signs is that product innovative firms, on average, substitute temporary employment for permanent employment at very low and at very high intensities of product innovation while substituting permanent employment for temporary employment at intermediate product innovation intensities. This may be due to the uncertainty associated with the performance of product innovations on the market.

Table 5 presents the estimation results for both skilled and unskilled employment used as proxies for quality of employment (productive employment). The results indicate significantly positive impact of product innovations on both skilled and unskilled employment. However, the findings suggest that product innovation is skill-biased. This may be explained by the high cost of hiring skilled workers that are generally scarce in SSA. These results enlarge the relatively limited existing findings by scholars such as de Elejalde et al. (2015) and Crespi et al. (2019). Our three-degree polynomial terms for both skilled and unskilled employment are all significant and with the same signs at each level. The shape of skilled and unskilled employment responses evaluated across all product innovation intensities are similar to that shown in Figure 1.

Table 4: Permanent vs. temporary employment impact of product innovations.

Estimation method	Full-information maximum likelihood (FIML)			
	A		B	
	(1)	(2)	(3)	(4)
	Permanent employment		Temporary employment	
Product innovation (w)	0.035	0.052***	0.213***	0.398***
	(1.27)	(3.70)	(5.89)	(4.14)
T_1w		-0.274**		0.040**
		(-1.98)		(2.16)
T_2w		0.006*		-0.001*
		(1.87)		(-1.78)
T_3w		-0.000*		0.000*
		(-1.79)		(1.84)
Log of experience	0.023	0.059	-0.074	-0.074
	(0.89)	(1.55)	(-1.50)	(-1.33)
Log of total employment (-2)	0.551***	0.573***	0.754***	0.770***
	(12.60)	(13.50)	(21.71)	(11.48)
Log of sales (USD) (-2)	0.048***	0.069***	0.009	0.008
	(5.00)	(4.48)	(0.50)	(0.38)
R&D	0.011	0.000	0.211***	0.145*
	(0.35)	(0.00)	(2.82)	(1.77)
Log of labour cost (USD)	-0.028**	-0.037**	-0.034	-0.029
	(-2.36)	(-2.14)	(-1.40)	(-1.01)
Age	-0.001	-0.008	-0.007	-0.008
	(-0.41)	(-1.61)	(-1.15)	(-1.26)
Age Square	0.000	0.000	0.000	0.000
	(1.15)	(1.62)	(0.63)	(0.85)
Country fixed effect	Yes	Yes	Yes	Yes
N	1158	1158	1158	1158
Wald chi^2	5721.66	6072.68	6643.65	8802.2426
Prob >chi^2	0.000	0.000	0.000	0.000

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.

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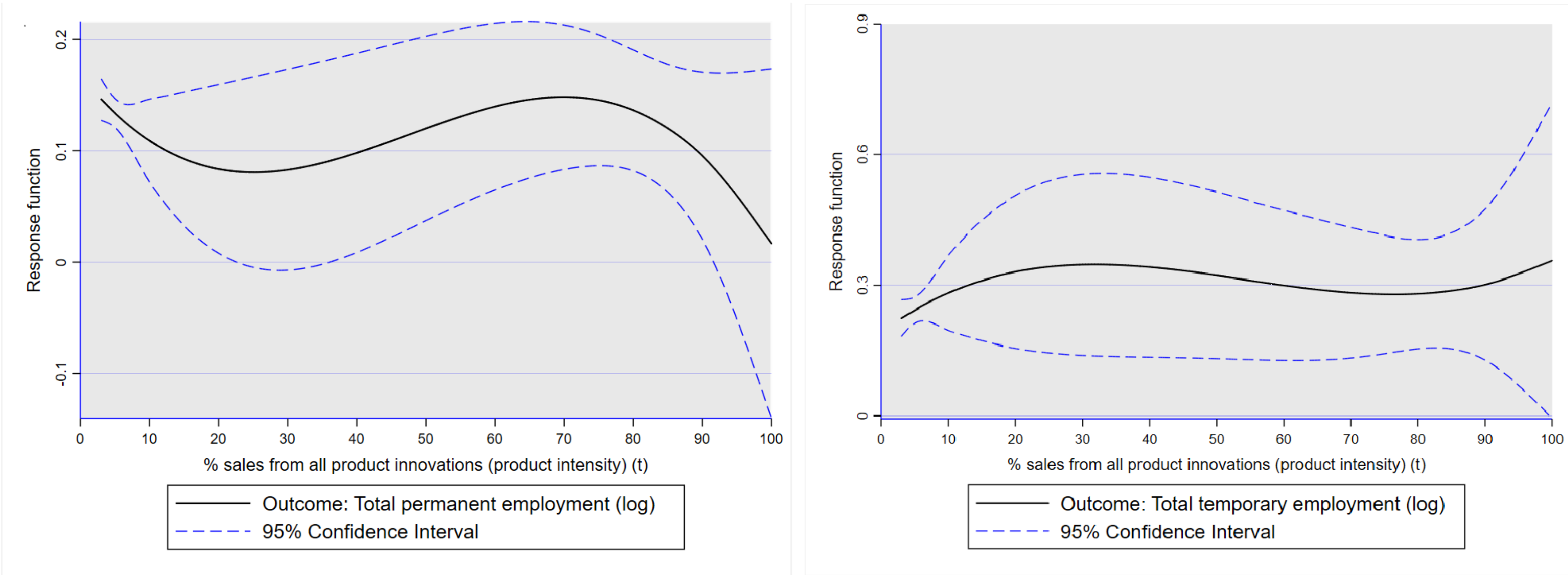

Figure 2: Dose Response Functions for total permanent and temporary employment.

Table 5: Skilled vs. unskilled employment impact of product innovations.

Estimation method	Full-information maximum likelihood (FIML)			
	A		B	
	(1)	(2)	(3)	(4)
	Skilled employment		Unskilled employment	
Product innovation (w)	0.059*	0.094*	0.303***	0.616***
	(1.84)	(1.87)	(4.24)	(4.59)
T_1w		-0.017**		-0.064***
		(-2.44)		(-3.21)
T_2w		0.000**		0.002***
		(2.32)		(3.11)
T_3w		-0.000**		-0.000***
		(-2.52)		(-2.96)
Log of experience	-0.027	-0.036	-0.051	-0.006
	(-0.89)	(-1.21)	(-0.68)	(-0.08)
Log of total employment (-2)	0.608***	0.617***	0.476***	0.503***
	(14.35)	(15.13)	(7.63)	(5.96)
Log of sales (USD) (-2)	0.048***	0.043***	0.037	0.041
	(4.57)	(4.19)	(1.54)	(1.59)
R&D	0.361***	0.401***	0.070	0.120
	(4.48)	(4.52)	(0.84)	(1.28)
Log of labour cost (USD)	-0.021	-0.022	-0.044	-0.047
	(-1.61)	(-1.60)	(-1.25)	(-1.31)
Age	-0.004	-0.005	0.030***	0.021*
	(-1.19)	(-1.50)	(2.98)	(1.91)
Age square	0.000	0.000	-0.001***	-0.000**
	(1.07)	(1.34)	(-3.32)	(-2.37)
Country fixed effect	Yes	Yes	Yes	Yes
N	1158	1158	1158	1158
Wald chi^2	4646.14	4615	5752.434	5722.884
Prob >chi^2	0.000	0.000	0.000	0.000

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.

4.3 Additional robustness check

As a further robustness check, we estimated our system of equations (8.1-8.3) accounting for sampling weights (see Table 8 in appendix D). Our estimation results remain similar between our main results (Table 3: column 2 and Table 4: columns 2 and 4) and the weighted estimates shown in Table 8. Our polynomial terms, however, become insignificant in the total employment specification (Table 8: column 1).

In order to further check the robustness of our results, we assumed that $g\left(t\right)$ follows a linear form ($g\left(t\right) = bt$) rather than a three degree polynomial, that is, $g\left(t\right) = bt + ct^2 + dt^3$. As a result, our estimation equation from (8.1) becomes:

$$y = a_0 + \ x\delta_0 + wATE + w\left[x - \overline{x}\right]\delta + bwT_1 + \varepsilon_y \tag{10}$$

Our estimation results showing the impact of product innovations on total employment as well as on the proxies of decent employment assuming a linear form are shown in Table 9 in Appendix E. Results are generally consistent in terms of significance and sign of variables as compared with our earlier results. We, however, found in Table 9 (column 1) that the ATE of introducing product innovations increased in size. This suggests that our linear model overestimates the impact of product innovations, and also fails to capture appropriately the non-linearity of product innovation intensities. The contrary holds when we employed our proxies for decent employment. The results suggest that our linear model underestimates the impact of product innovations on both permanent and temporary employment (see Table 9: columns 2 and 3).[22]

5 Conclusion

The relationship between innovation and employment remains central, especially in sub-Saharan African (SSA) economies where 'innovation-led' development thinking is emerging. In this paper, we sought to contribute to the deeper understanding of the causal relationship between product innovations and employment in SSA, by employing a counterfactual stance where we considered varying innovation intensities.

The paper adapted the Dose Response Model (DRM) under continuous treatment, and used the World Bank's Enterprise Survey (ES) merged with the Innovation Follow-Up Survey data for 5 countries in SSA, namely Democratic Republic of Congo, Ghana, Tanzania, Uganda and Zambia. Our results highlight the critical importance of product innovation activities in stimulating total employment of firms in SSA. We have shown that this conclusion only holds within specific sub-interval of firms' intensities of innovation. In other words, the impact of firms' innovation activities on total employment varies and depends on the market performance of 'new or significantly improved' goods and services. In extensions to decent employment, we employed proxies for security and quality of job, and our results suggest that product innovations lead to the creation of both permanent and temporary jobs on the one hand, and skilled and unskilled jobs on the other hand. Our results, however, indicate that product innovations tend to create more temporary jobs than permanent jobs as firms trade between permanent and temporary jobs at different intensities of product innovation.

The policy implications of these results cannot be overemphasised. In a continent where policy is being directed towards enhancing innovations at the firm-level, our results reveal that policy makers need to be wary if the primary motive of the innovation policies is to generate decent employment. This is because, the intensity of product innovations is not homogeneous but heterogeneous across firms with different compensating and displacement impacts depending on the type of employment. Based on these findings, the paper suggests policy efforts that

[22] These conclusions are confirmed by the Likelihood-ratio test with LR $chi^2(3)=21.23$ with Prob > $chi^2=0.00$ and LR $chi^2(3)=10.84$ with Prob > $chi^2=0.00$, respectively.

promote product innovations, but also offer some form of security to all types of workers, be it temporary, permanent, unskilled or skilled.

The analyses in this paper could be extended in several other ways. The analysis only focuses on total employment, with permanent employment versus temporary, and skilled versus unskilled employment differentiation. This is due to the large number of missing observations in other dimensions of employment such as male versus female, full time production versus full time non-production, full time production male workers versus full time non-production female workers, among others. An important area for future investigation regards product innovation novelty. Due to low sample sizes of measures of product innovation novelty - new to local market, new to national market, and new to international market - the paper failed to examine the different impacts product innovation differentiated by its novelty may have on employment. The nature of the data used also poses issues of time inconsistency between employment outcomes and our innovation variables. As a result, the analyses failed to consider employment growth. Further research could extend the analyses in this paper by using quality and comparable panel data when it becomes available. Recent empirical evidence also indicates that the impacts of product innovation and product innovation intensity on a firm's employment may differ over time, and may depend on the life cycle of the firm (the so-called 'three-stage model'). Based on the nature of our data (cross-section), the paper could not examine the 'three-stage model.' A natural extension of this paper would also be to examine the lag structure of innovation and how it impacts firm-level employment outcomes in sub-Saharan Africa, with the availability of time series/panel data.

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Appendices

Appendix A

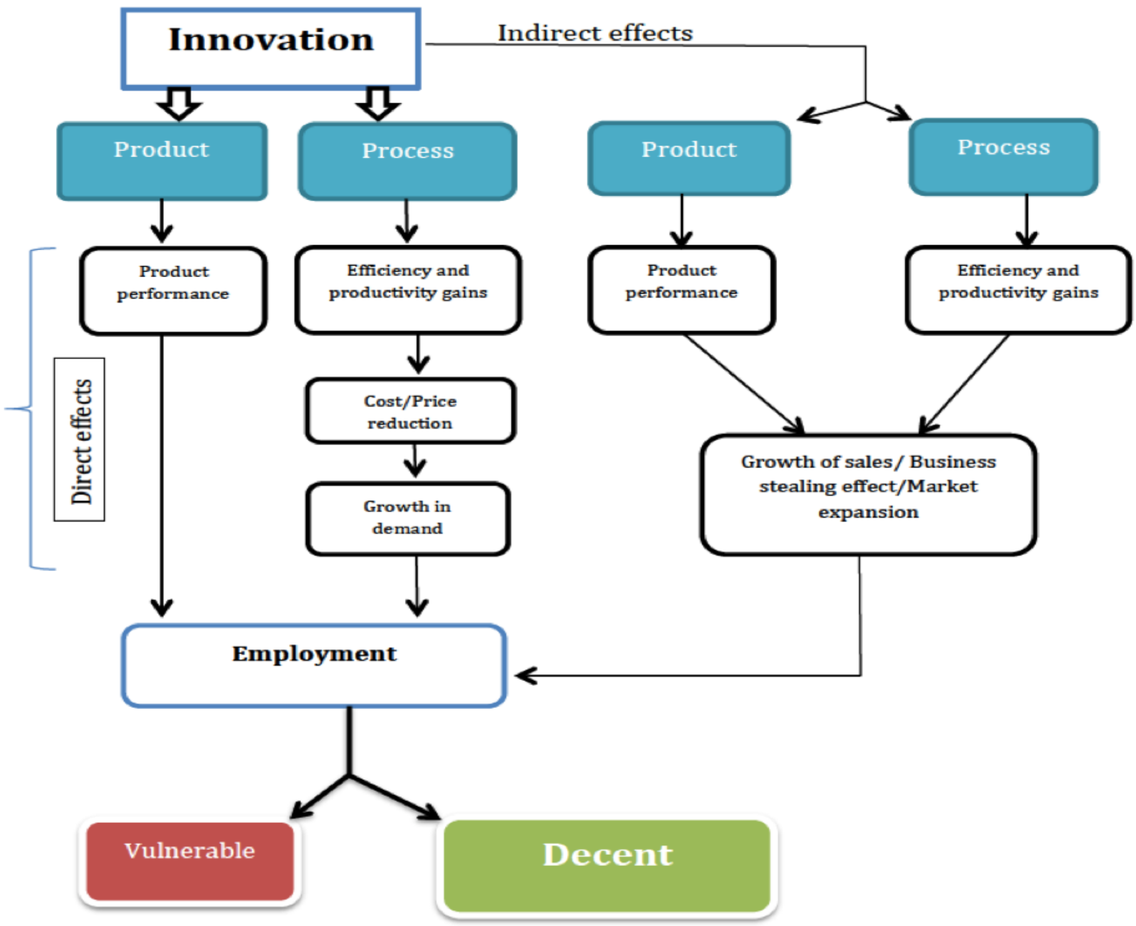

Figure 3: Simple theoretical relationship between product and process innovations and employment at the firm-level

Sources: Adapted from Evangelista &Vezzani (2010) and Gallouj & Djellal (2010)

Appendix B

Table 6: Estimation results for product innovation [a]

Estimation method	Full-information maximum likelihood (FIML)			
	(1)	(2)	(3)	(4)
	Sales from innovation (t)		Introduce innovation (w)	
Log of experience	0.464	0.416	0.075	0.076
	(0.52)	(0.47)	(1.00)	(1.01)
Log of total employment (-2)	3.269***	3.232***	0.182**	0.185**
	(4.65)	(8.33)	(2.43)	(2.45)
Log of sales (USD) (-2)	-0.496*	-0.503*	-0.008	-0.008
	(-1.72)	(-1.78)	(-0.30)	(-0.32)
Log of labour cost (USD)	0.327	0.343	0.056*	0.057*
	(0.92)	(1.59)	(1.65)	(1.68)
Age	0.064	0.063	-0.007	-0.008
	(1.03)	(1.15)	(-0.87)	(-0.87)
Age square	-0.002***	-0.002***	0.000	0.000
	(-3.50)	(-3.75)	(0.55)	(0.55)
R&D	8.549***	8.633***	0.505***	0.506***
	(10.01)	(13.40)	(5.00)	(5.01)
License	4.299***	4.075***		
	(2.82)	(3.17)		
Patents			0.518***	0.518***
			(4.82)	(4.87)
Polynomial terms	No	Yes	No	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	1160	1158		
Wald chi^2	5381.654	5400.923		
Prob >chi^2	0.000	0.000		

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.
[a] Results from equations 8.2 and 8.3 estimated together with results in Table 2 (8.1).

Appendix C

Table 7: Population and sample representation of data

	Population	Sample
No. of firms	2,466	1,158
Country		
Congo, DR (%)	15.61	20.55
Ghana (%)	22.26	27.63
Tanzania (%)	22.02	9.24
Uganda (%)	18.21	12.87
Zambia (%)	21.90	29.71
Sector		
Manufacturing (%)	49.31	52.16
Retail (%)	19.79	17.44
Other services (%)	30.90	30.40
Size of firm		
Small (%)	65.73	64.68
Medium (%)	26.89	28.07
Large (%)	7.38	7.25

Source: ES and Innovation Follow-up surveys.
Note: The sample data is based on the extended regression in column (2) of Table 3.

Appendix D

Table 8: Employment impact of firm-level product innovations - Weighted with sampling weights

Estimation method	Full-information maximum likelihood (FIML)		
	(1)	(2)	(3)
	Total employment	Permanent employment	Temporary employment
Product innovation (w)	0.112**	0.077***	0.509***
	(2.34)	(3.31)	(16.04)
T_1w	-0.005	-0.005*	0.013***
	(-0.48)	(-1.88)	(3.88)
T_2w	0.000	0.000**	-0.001**
	(0.68)	(2.02)	(-2.22)
T_3w	-0.000	-0.000**	0.000*
	(-0.77)	(-2.39)	(1.81)
Log of experience	-0.032	0.029	-0.023
	(-1.26)	(0.81)	(-0.46)
Log of total employment (-2)	0.637***	0.475***	0.687***
	(13.56)	(9.45)	(10.83)
Log of sales (USD) (-2)	0.029**	0.028**	0.030
	(2.48)	(2.46)	(1.23)
R&D	0.022	0.020	0.092
	(0.50)	(0.38)	(0.89)
Log of labour cost (USD)	-0.036**	-0.012	-0.090***
	(-2.19)	(-0.69)	(-3.36)
Age	-0.003	-0.001	-0.007*
	(-0.97)	(-0.17)	(-1.81)
Age square	0.000*	0.000	0.000**
	(1.86)	(1.28)	(2.10)
Country fixed effect	Yes	Yes	Yes
N	1158	1158	1158
Wald chi^2	19725.547	20804.29	23908.78
Prob $>chi^2$	0.000	0.000	0.000

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.

Appendix E

Table 9: Employment impact of product innovation with linear dose response function

Estimation method	Full-information maximum likelihood (FIML)		
	(1)	(2)	(3)
	Total employment	Permanent employment	Temporary employment
Product innovation (w)	0.132***	0.048*	0.285***
	(6.39)	(1.92)	(3.51)
T_1w	-0.001	-0.003***	0.003*
	(-1.52)	(-2.71)	(1.70)
Log of experience	-0.012	0.012	-0.066
	(-0.75)	(0.46)	(-1.18)
Log of total employment (-2)	0.708***	0.573***	0.760***
	(24.34)	(13.44)	(11.28)
Log of sales (USD) (-2)	0.037***	0.044***	0.014
	(5.14)	(0.32)	(0.66)
R&D	0.044**	0.020	0.158*
	(2.02)	(0.59)	(1.94)
Log of labour cost (USD)	-0.037***	-0.027**	-0.033
	(-4.99)	(-2.43)	(-1.14)
Age	-0.002	0.000	-0.009
	(-1.50)	(0.05)	(-1.31)
Age square	0.000	-0.000	0.000
	(1.62)	(-0.72)	(0.82)
Country fixed effect	Yes	Yes	Yes
N	1158	1158	1158
Wald chi^2	5388.67	6801.03	2156.80
Prob $>chi^2$	0.000	0.000	0.000

Notes: Robust t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Used *cmp* Stata package for FIML estimation.
All regressions include sector, 23 industry, region and city fixed effects.
All t statistics are robust to heteroskedasticity.

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