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Mezid N. Keraga
Hans Lööf
Andreas Stephan

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Innovation and employment in sub-Saharan Africa: New evidence from the World Bank Enterprise Survey

Mezid N. Keraga[1], Hans Lööf[2], and Andreas Stephan[3]

[1]Ethiopian Civil Service University, Ethiopia, mezid-nasir.keraga@ju.se
[2]Royal Institute of Technology, Sweden, hans.loof@indek.kth.se
[3]Linnaeus University, Sweden, andreas.stephan@lnu.se

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Abstract

This paper presents new insights into the relationship between innovation and employment in low-income countries. We use firm-level data sourced from the World Bank Enterprise Survey (ES) and focus on six sub-Saharan African (SSA) economies over the period 2003-2019. The econometric results from difference-in-differences (DiD) estimations, in conjunction with propensity score matching show a positive influence of product innovation on both permanent and total firm-level employment. The evidence for employment impact of process innovations is weak. Considering relations between firms, we find a positive intra-industry spillover effect from both product and process innovation on employment in firms operating within the same two-digit industry, while the results for inter-industry spillovers are non-significant or negative.

Keywords: Innovation, Employment, Sub-Saharan, Spillover effects, DID, Matching approach

JEL: O30, J20

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1 Introduction

Innovation-driven growth is no longer limited solely to high-income countries. Promoting innovation has become a strategic imperative for many emerging and developing economies, including those with a strong agricultural base, a sizable informal sector, and a workforce predominantly engaged in micro- and small enterprises. This paper aims to shed light on the employment impact of innovation in one of the world's most impoverished regions, sub-Saharan Africa (SSA), by investigating how innovation affects employment at the firm level. While there is some variation within the region, countries in sub-Saharan Africa (SSA) are generally characterized by low levels of education, underdeveloped technology, limited research investments, and significant shortcomings in the institutional framework that supports innovation, such as access to financing and risk capital as well as the functioning of an effective innovation system.

Innovation surveys based on the so-called Oslo Manual (Data, 2005) have been an important source of knowledge to better understand the driving forces for and the significance of innovation activity in primarily Western economies. According to the manual, innovation should be interpreted as a broad range of activities including the implementation of a new or significantly improved product (good or service) or process, a new marketing method, a novel product design, or a new organizational method in business practices, workplace organization or external relations. Moreover, the definitions allow for both radical and incremental innovation as well as innovations new to the market or only new to the firm.

An important insight that can be drawn from literature analyzing innovation surveys across industries and countries is that a substantial share of the innovations is not a result of R&D-intensive technological breakthroughs and patentable inventions. Often, innovations are the outcome of incremental improvements of existing products or processes. The Oslo Manual also interprets innovation activities significantly wider than just R&D including also the acquisition of machinery, equipment, software, and licenses, engineering and development work, as well as design, training, and marketing undertaken to develop and implement a product or process innovation.

The fact that innovation can be associated with both high and low technology, R&D and non-R&D activities, manufacturing and service sectors, and different degrees of novelty have made innovation surveys and their guidelines attractive for adoption also among low-income countries in the global south.

Our paper benefits from the World Bank Enterprise Survey (ES) project, which repeatedly collects enterprise data in about 140 low- and middle-income countries with a standard methodology allowing for cross-country comparisons. The innovation-related part of the survey questionnaire follows the guidelines suggested by the Oslo Manual. We have compiled a dataset for the six SSA countries Cameron, Kenya, Niger, Mali, Rwanda, and Zambia for the period 2003 to 2019. Both manufacturing and service firms as well as process and product innovations are studied, and we consider spillovers within and between industries in our econometric model.

There have been major efforts recently to harmonize innovation data collection methods, enabling better comparison and analysis of drivers of innovation and innovation outcomes across countries. However, analyses of the innovation surveys are fraught with a series of complicated challenges making it difficult to establish a reliable statistical relationship between innovation on the one hand and productivity or employment on the other. This applies to low-income countries in particular. A pervasive problem is that the variables available often suffer from measurement errors of different origins, not to mention variables that are unavailable in parts or total. Moreover, the effects of innovation often occur with long lags, they may vary significantly from one firm or sector to another, and they may also be hidden by the effects of other factors of production and productivity, which occur simultaneously and sometimes dominate them.

Our paper applies the following approaches to mitigate these challenges. First, we apply a panel data methodology utilizing several waves of the World Bank ES. Secondly, we adopt a quasi-experimental approach by applying difference-in-differences (DiD) estimations in combination with propensity score matching using the longitudinal cross-country data to identify the impact of innovation on firm-level employment. Thirdly, our research extends previous studies on innovation and employment in developing countries by including inter- and intra-industry spillover effects in the analysis. Thereby we can infer the aggregated impact of innovation on employment. Finally, the paper distinguishes innovation types and also various employment forms to obtain a more accurate picture of the relationship between innovation and employment in the context of developing countries.

The estimation results support the view that both product and process innovations have a positive impact on firm-level employment. The estimates for the intra-industry spillover effects from innovation show that there is an indirect positive effect on the employment of non-innovating firms in the same industry. In contrast, the inter-industry spillover effect is statistically not significant.

The paper proceeds as follows. Section 2 presents the background and related literature. The methodology, identification strategy, and sample construction are described in Section 3. Section 4 presents descriptive statistics and econometric results. Section 5 concludes.

2 Background and Related Literature

In this section, we provide a brief theoretical background and a review of related literature on the employment effects of firm-level innovation.

2.1 Theoretical innovation and employment perspective

The theoretical frameworks on the links between innovation and employment are mainly related to process innovations in the manufacturing sector and their links to technological change, productivity, and skills. A priori, we assume that the impact of innovation and knowledge spillovers does not differ between countries depending on their income status. In general, these theoretical views may apply also to the six SSA economies studied in the paper, despite the fact that 80% of employment in Africa and 85% in sub-Saharan Africa is informal and more than half of the African employment is situated in the agriculture sector.

In the seminal canonical model by Tinbergen (1974, 1975), demand for labor is assumed to take a factor-augmenting form complementing either high-skill or low-skill workers. However, historical evidence shows that process innovations can be both complementary and substitutable to workers' particular skills. While information and communication technologies coincide with an increased return to education, Goldin and Katz (1998) find that production technologies during the end of the second industrial revolution were skill complementary. Recent research on technical change and process innovations employs a richer and more micro-founded theoretical framework, useful to test hypotheses on issues such as occupational tasks (Acemoglu & Autor, 2011), routine-biased technical change (Autor et al., 2003), globalization and offshoring (Blinder, 2006), and spillovers (Mazzolari & Ragusa, 2013). Broadly, this research suggests that process innovations linked to technological change raise productivity by either complementing or replacing workers. Thus, the importance of process innovations for employment is an empirical rather than a theoretical question.

Regarding product innovations at the firm level, a main issue is market competition. There are theoretical arguments that predict both positive and negative effects on employment. Investing in research, development, and innovation is costly, and the market outcome depends on how the new product innovations compete with both competitors' and the firm's own products. The literature providing theories, views, and models, which facilitate our understanding of the links between product innovations and employment, started already by Schumpeter (2013) and has grown extensively over time; for recent contributions, see Acemoglu et al. (2018) and Harrison et al. (2014).

The impact of spillovers on economic development was first pointed out by Marshall (1890). Since then, a large body of theoretical work has developed models and studied both the role of innovation spillovers and the specific channels through which knowledge dissemination takes place. At the level of the entire economy, Say (1964) predicts that innovation may lead to the reallocation of jobs from one sector to another, while in the recombinant knowledge approach, Agarwal et al. (2007) consider spillovers as a wider ecosystem, where existing ideas are complemented and cross-fertilized. Consistent with this idea, Saviotti (2007) and Antonelli et al. (2010) suggest that flows of spillovers across firms add to a common knowledge pool exploited in a continued recombinatorial process. For individual firms, innovation spillovers can enhance or erode (business-stealing effect) competencies for the firm investing in new innovations.

2.2 Empirical Studies

The study closest to our paper is Avenyo et al. (2019), which uses data from the World Bank ES and an Innovation Follow-Up Survey in line with the Oslo Manual, both conducted in 2013. A treatment approach is applied to data for the five SSA countries DRC, Ghana, Tanzania, Uganda, and Zambia. Using a binary variable, taking the value of 1 if a firm has introduced at least one product innovation over the last three years, as the treatment variable, the paper reports the positive impact of product innovations on both temporary and permanent jobs as well as on skilled and unskilled jobs. The survey information on process innovation is only exploited as a covariate in the econometric model.

A second paper using the ES to analyze the association between innovation and employment in Africa is the study by Okumu et al. (2019). The authors consider cross-sectional data on 6,400 manufacturing firms in 27 African countries. Combining different waves during the period 2011-2017, the paper reports employment growth is positively associated with both process and product innovations.

Cirera and Sabetti (2019) examine the impact of technological as well as organizational innovation on firm-level employment growth, also taking advantage of the World Bank survey. Their dataset contains information on employment growth and the share of current sales due to newly introduced or improved products in 53 countries across Africa, South Asia, the Middle East, North Africa, Eastern Europe, and Central Asia. Most firms were surveyed in 2013 or 2014, as well as 3 years prior to that. The study finds that product innovation correlates positively with increased employment. Notably, in low-income African countries, where innovations are considered to be more incremental, the impact on employment growth was found to be larger than in middle- and high-income countries.

Some recent studies on innovation and employment in Africa employ national innovation surveys, similar to the Community Innovation Survey (CIS) launched among the EU members biannually. Naidoo et al. (2023) apply pooled data on 1,698 manufacturing and service firms from three South African CIS waves of 2005–2007, 2010–2012, and 2014–2016. They report that process innovation tends to have a larger positive impact on employment than product innovation. The study also suggests that both process and product innovations have larger positive effects on employment growth for exporting firms relative to non-exporting firms. The third main finding is that firms that introduce radical innovations that are new to the market, experience a higher positive employment effect than firms that introduce innovations that are new to only the firm. Medase and Wyrwich (2021) consider two waves of Nigerian CIS surveys over the period 2005-2007 and 2008-2010, observing 1,359 firms in total. The study suggests a positive association between process innovation and employment in both manufacturing and services, while mixed evidence is provided for product innovation. The OLS estimate is positive and significant for manufacturing firms and negative and significant among services. Somewhat contrasting results are reported by Gyeke-Dako et al. (2016) estimating cross-sectional CIS data retrieved from 428 Ghanaian manufacturing firms in 2015. The empirical analysis indicates a positive correlation only between product innovation and employment, while the impact of process innovation is not statistically different from zero.

3 Empirical Methodology

3.1 Econometric Specification

To identify the impact of innovation on employment, we adopt the standard neoclassical model of profit maximization. The demand for labor is a derived demand from a firm's profit maximization function. Accordingly, the paper follows the Van Reenen (1997) specification of a competitive firm. A firm operating under a constant elasticity substitution (CES) production function is specified as follows:

$$Y = T[(A_l L)^{(\frac{\sigma-1}{\sigma})} + (B_K K)^{(\frac{\sigma}{\sigma-1})}]^{\sigma(\sigma-1)}, \tag{1}$$

where L is employment, K is capital, Y is output, T is the Hicks-neutral technology parameter, A_l is labor augmenting Harrod-neutral technology, and A_k is the Solow-neutral technical change. In a perfectly competitive market, the wage is equal to the marginal productivity of labor and given by:

$$MP_l = \frac{W}{P}, \tag{2}$$

where MP_l, is the marginal product of labor, W is the wage rate, and P is the price of product. Taking the first order condition for labor, substituting $Eq(2)$ by $Eq(1)$, taking the logarithm of $Eq(1)$, and then solving for L, we obtain the following:

$$\log L = \log Y - \sigma \log(\frac{w}{p}) + (\sigma - 1) \log A_l. \tag{3}$$

Next, substituting the marginal product of capital with the real price of capital and substituting in the labor demand function of $Eq(2)$, we obtain the following:

$$\log L = (\sigma - 1) \log(\frac{A_l}{A_k}) - \sigma \log(\frac{W}{P} + \log K + \sigma \log R), \tag{4}$$

where R is the price of capital. Van Reenen (1997) substituted the unobserved technology shock terms $(\sigma - 1)\log(A_L/A_K)$ with innovation and specified a stochastic labor demand function.

Apart from that, we follow a similar method like Stare and Damijan (2015), but we adapt it to our context to capture the spillover effect of innovations. They are very interested in vertical innovations' spillover effect. Accordingly, the innovation spillover effect is constructed as follows:

$$Z^{kmt} = \sum_{m,j=1}^{n} (\alpha_{mjt} \times sIN_{mt}^{k}), m, j = 1, \ldots, n, \tag{5}$$

where Z^{kmt} is the weight of the sum of the share of innovative firms in the total population of firms in the two-digit industry of (m), and sIN_{mt}^{k} is the share of innovative firms in the total population of firms in the two-digit industry of (m). Further, α_{mjt} is a weight measurement, which is the share of output of industry (m) purchased by firms in the industry (j). Unfortunately, we do not have data on transactions that take place between two or multiple industries to attach weights for each. Therefore, our spillover-effect measurement considers the share of innovative firms to the total population only. Our empirical identification strategy that examines the impact of innovation and its spillover effect on employment in Africa is described below.

The variables included in our empirical model specification are based on the standard empirical innovation literature, resulting in the following equation:

$$Emp_{it} = \alpha_1 Innov_{it} + \alpha_2 Splov_{jt} + X_{it}'\beta + \gamma_i + \eta_j + \delta_c + \vartheta_t + \mu_{it}, \tag{6}$$

where Emp_{it} is employment indexed for a firm (i) at time (t). $Innov$ is innovation and represents both types of innovations (process and product). $Splov$ are industry-level innovations to capture the spillover effect. To capture inter-industry spillover effects of innovation, we estimated innovations in the two-digit industry (h) on employment of firm's (i) in industry (j), where ($j \neq h$). Similarly, intra-industry spillover effects of innovations are included to highlight their impact on the employment of rival firms in the same industry. X'_{1ijct} is the vector of predetermined variables that affect employment (like annual sales revenue, wage, and other firm-specific characteristics), and β is the associated vector of coefficients. Finally, firm-, industry-, and country-specific unobserved heterogeneities are captured by γ, η, and δ, respectively, and ϑ is the time effect capturing common macroeconomic shocks. Finally, μ represents the random error term of the model.

3.2 Identification Strategy

To identify the impact of innovations on employment, we apply the two-way fixed effect (FE) estimator after matching. FE estimation with matching is executed in a two-step procedure. First, the matching of treated (innovative) firms with control (non-innovative) firms is done based on the variables included in the empirical specification that influence the outcome variable, i.e., employment. In our case, matching is done based on the following variables: log of firm age, log of sale, log of wage, log of capital, proportion of skilled labor, firm size, share of export, share of foreign ownership, and location dummy.

A nearest-neighbor matching algorithm is used to match the treated and control firms. Employing a matching estimation method in combination with DiD can reduce the concern of model dependence of the obtained estimates (Ho et al., 2007). Second, based on the matched sample, two-way FE estimation is applied. Indicators of spillover effect variables are added in the second regression model. To assess the sensitivity of results, the empirical model has been estimated by using the FE estimator without prior matching. Finally, pooled OLS is used ignoring the repeated cross-sectional dimension of the dataset as a mechanism to check the sensitivity and robustness of our findings.[1]

[1]The validity of the DiD approach for identifying the effect of interest rests on the parallel trend assumption. Initially, we estimated the model using a more flexible double difference model. However, it is not possible to obtain the estimate of the innovation impact on employment with this approach. Consequently, we adopted the FE estimation in combination with matching to fit the model to the data as described in the text.

Since innovation, the treatment variable, is measured at different times in each country, and the time gap between two survey periods is also not constant across all countries included in the sample, the FE estimator in combination with matching is the most appropriate approach.

3.3 Data and Variable Description

We use the ES dataset, which is firm-level data collected by the World Bank. The ES collects data from enterprises in manufacturing and key service sectors in every region of the world by standardized survey instruments and a uniform sampling methodology. The survey sample frame is constructed from a list of enterprises made available by the Central Statistical Agency (CSA), the country's statistical office, the Tax and Business Licensing Authority, and Business Associations and Marketing Database. A stratified random sampling approach is applied to select the enterprises for the ES, using firm size, the business sector, and geographic region. Firm size is categorized based on the number of employees working in the firm: 5-19 (small), 20-99 (medium), and 100 and above employees (large firms). Large-sized firms are over-sampled to reduce the negative proportion effects while underscoring the importance of large firms for employment and growth. Furthermore, the sectoral strata defined are manufacturing, retail, and other services, while geographic regions within a country are selected based on which cities/regions collectively contain most of the economic activity.

The survey targets establishments that are formal (registered) companies and have 5 or more employees. All the sample firms are either fully or partially owned by the private sector. The survey is conducted at the establishment level, which is advantageous for micro-level analysis. The survey instrument has 15 sections (A-N) organized by topics. Section (H) is entirely dedicated to innovation-related issues. However, the ES uses two instruments that are designed for manufacturing and key service sectors separately.

About 146 countries are covered by the World Bank ES but the survey is not conducted in the same year across countries. Some countries have rich datasets while others were included in fewer rounds. For this study, we consider countries that have at least three rounds in the survey dataset. We found seven African countries that meet this criterion–namely, Cameroon, Kenya, Mali, Niger, Nigeria, Rwanda, and Zambia. However, Nigeria was dropped from our sample because it has only one-period observation for our key variable, innovation. Accordingly, our sample firms are drawn from six SSA countries. The values of sales revenue, capital, and labor cost of each country are changed into their equivalent in USD for each year, and extreme values of the top one percent are trimmed using the $Winsor$ outlier fixation technique. Details of the variables we used for this study are presented in Table 1.

In the ES dataset, a binary question addresses whether a firm has introduced new or significantly improved products or processes over the last three years. In our study, we use this information as an indicator of innovation activities by the firm.

4 Results

4.1 Descriptive Statistics

A summary of the sample size in each country and the survey year is presented in Table 2. In total, we observe $7,736$ firms over the period 2003-2019, of which Kenya accounts for about 30%. Mali is observed in four surveys and the others in three.

Table 3 displays employment growth for the observed firms grouped into three sizes: small (less than 20 employees), medium (20-99 employees), and large (above 99 employees). The average growth rate is surprisingly similar across the different size categories.

Table 4 reports descriptive statistics for the variables included in the empirical analysis. Separating between innovators and non-innovators, except for the share of foreign ownership, all variables included in the empirical model have a significant difference between innovative and non-innovative firms before matching (column 1, overall sample).

The upper part of the table shows that innovative firms have more permanent, temporary, and total employment, with some variations across the six countries. The lower part of the table reports that innovators have more exports, a larger market share, and larger firm size. No differences in corporate ownership can be found, while the average wage level is higher in non-innovative firms (overall sample).

From Table 5, after matching, no statistically significant difference in mean distribution can be identified between treated[2] and control groups of firms for all covariates included in our empirical model specification. Our final estimation is based on these matched sample firms. As a result, to some extent, our regression estimates are less likely to be affected by self-selection bias. Moreover, our sample meets the basic assumption of randomness in providing treatment. In other words, one of the two basic assumptions of propensity score matching is conditional independence, i.e., the outcome variable is independent of the treatment given the covariates. Based on the test statistics, our estimation result based on the above sample firms is statistically desirable. The findings of this sample can be considered as a quasi-experimental investigation.

If we look at the two figures closely, after matching (see Figure 2) the propensity score distribution for control firms is relatively smoothed compared to before matching (see Figure 1). The distribution of the propensity score for treated and control firms looks similar after matching. We have already shown in descriptive statistics that after matching treated and control firms have similar characteristics.

As can be seen from Table 6 above, from the total of sample firms, more than 725 firms are found on the common support region either for permanent or total employment as an outcome variable. Both types of innovations (product and process) have a significant impact on both types of employment (permanent and total). The size of the Average Treatment Effect (ATE) of innovation is higher for overall employment. More precisely, firms that are engaged

[2]Here, "treated firms" refers to firms that introduce new or significantly improved goods and services, i.e., product-innovative firms. Similarly, we have done a test for firms that are engaged in process innovations. The descriptive statistics are similar to what we have presented here in Table 5. Hence, to save space and avoid redundancy of information, we prefer to skip presenting the results here.

in product innovations create 54.6 and 57.6 percentage points more job opportunities for permanent and total employment than their counterparts, respectively. Process innovations have a positive impact on both categories of employment with a higher magnitude of impact compared to product innovations.

4.2 Estimation Results

This part reports estimation results concerning the dummy variables that indicate whether a firm has implemented a new or significantly improved product or process within the past three years. From a theoretical perspective, a positive estimate suggests that the compensation effect of product innovations through pricing mechanisms might outweigh the displacement effect caused by reduced demand for older products.

Three different models are estimated to disentangle the impact of innovation (product and process) on employment (permanent and total). Columns (1) and (4) in Table 7, report FE estimates using the matched sample regarding the impact of product innovations on permanent and total employment, respectively. Results reported in columns 2 and 5 are the FE estimates for the whole sample without applying matching. Finally, columns 2 and 3 report pooled OLS estimates ignoring the repeated cross-sectional nature of the panel.

Column (1) reports a positive and statistically significant estimate of product innovation. The magnitude of the coefficient is 0.23, which suggests that firms introducing at least one product innovation have a causal impact on permanent employment corresponding to 26%[3] when the reference are firms without product innovation.

Considering the positive and statistically significant coefficient estimate of 0.26 (30%) for total employment in column (4), we can conclude that the innovation also encourages temporary employment.

Notably, the estimates for product innovation remain consistently positive and significant across all three models, encompassing both permanent and total employment.

[3] $100*(e^{\alpha}-1)$

Our findings align with the empirical evidence reported by Medase and Wyrwich (2021) concerning Nigeria's manufacturing firms, which utilized the national innovation survey. Our study corroborates also with Okumu et al. (2019) and Cirera and Sabetti (2019), which, similar to this paper, exploit data from the ES.

This paper introduces a novelty by constructing spillover variables derived from national and yearly data obtained from the ES, measured by the ratio of the total number of innovative firms in a two-digit industry to the total number of innovative firms in the country (inter-industry spillovers), and the ratio of total number of innovative firms in the two-digit industry to the total number of innovative firms in the same industry in each country and year (intra-industry spillovers).

Column (1) of Table 7 reports a negative and statistically significant estimate for the inter-spillover variable on permanent employment, while no effect can be found for total employment in column (4). In contrast to these results, we document a positive spillover effect between firms within the same industry. The estimates are significant for both permanent and total employment.

How can these spillover estimates be interpreted? The negative impact on permanent employment of a larger share of product innovators in the economy is somewhat puzzling.

One potential explanation might be attributed to a phenomenon akin to creative destruction. This concept involves new products in an industry competing with older ones, potentially resulting in the erosion of market shares, even for innovative companies in other industries. This dynamic could potentially exert a negative impact on overall permanent employment. As an example of conflicting outcomes, consider the study conducted by Stare and Damijan (2015), which, through a macro-level analysis, suggests a positive impact of product innovation on the employment of vertically connected firms in Spain.

Within industries, the results provide evidence that product innovations stimulate both permanent and total employment across innovative firms. This may be due to the diffusion of ideas and knowledge through worker and managerial mobility, external knowledge sourcing through patents, imitation collaborations, spin-outs, spin-offs, and other kinds of start-ups. For a more recent study, see Baum et al. (2022).

In Table 8, the impact of process innovation and spillovers on employment are presented. The matched model indicates a positive effect only at the lowest acceptable significance level for permanent employment while demonstrating no discernible effect on total employment. This finding is in line with Álvarez et al. (2011) and Benavente and Lauterbach (2008) for Chile, Gyeke-Dako et al. (2016) for Ghana, and De Elejalde et al. (2015) for Argentina, all stating that process innovations do not have a significant impact on employment. Only our pooled model without matched sample reports positive and highly significant estimates in alignment with evidence reported by Medase and Wyrwich (2021), Castillo et al. (2014), and Zhu et al. (2021) using firm-level data for Nigeria, Argentina, and Chile respectively. Our conclusion here is that the matching estimators, which do not require specifying the functional form of the outcome equation and are, therefore, not susceptible to misspecification bias along that dimension in a panel setting, yield more reliable estimates than the pooled models as well as cross-sectional approaches.

Our spillover estimates indicate a positive employment effect of process innovation within industries. This outcome may be explained by the inherent link between process and product innovations. The introduction of new or enhanced products often necessitates investments in corresponding production processes. Consequently, a higher prevalence of companies adopting process innovations within an industry may denote a dynamic process that, in turn, surpasses the current demand for labor. We do not observe a corresponding effect across industries.

5 Conclusions

The introduction of harmonized innovation surveys at the firm level provides opportunities to conduct micro-studies on the innovation outcome of companies both within and between industries, even in the developing country context.

One major challenge for conducting innovation studies in regions such as SSA is the quality and availability of data, which may affect the precision of the estimated coefficients both in terms of sign and significance. This is also the main reason for the low number of econometric innovation studies for firms in low-income regions.

Our paper aims to address this research gap and to provide reliable estimates on the causal link between innovation and employment in the SSA region. To construct a panel dataset of firms, only countries participating in at least three waves of the World Bank Enterprise Survey (ES) are selected. This results in a dataset with about 4,000 firms from six countries of which 725 firms constitute a treatment group of innovators. Firms that are in the support region are used for our estimation. Then a quasi-experimental approach is adopted by applying DiD estimations in combination with propensity score matching using the longitudinal dimension of cross-country data to identify the impact of innovation on firm-level employment.

Theoretical considerations suggest that the effect of innovation on firms' employment can be positive, neutral, or negative depending on factors such as skill category, technology, competition, and market success. Our econometric results show a positive influence of product innovation on both permanent and total firm-level employment. The evidence for a positive employment effect from process innovations is weak. We find a positive intra-industry spillover effect from both product and process innovation on employment in firms operating within the same two-digit industry, while the results for inter-industry spillovers are negative or non-significant.

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Appendices

A Tables

Table 4: Descriptive statistics before matching

	1 Overall	2 Cameroon	3 Niger	4 Rwanda	5 Zambia	6 Mali	7 Kenya
Permanent Emp							
Innovators	61.419***	54.405*	33.34	45.2	53.3***	32.8	72.646***
	(2264)	(200)	(50)	(145)	(548)	(131)	(1190)
Non-innovators	40.512	39.594	35.10	59.78	36.5	24.573	46.587
	(2089)	(293)	(58)	(46)	(694)	(164)	(834)
Temporary Emp							
Innovators	17.349***	8.31	15.16	16.79	9.1***	7.633	23.776***
	(2286)	(200)	(49)	(144)	(560)	(120)	(1213)
Non-innovators	8.928	8.728	10.17	6.69	5.7	4.973	12.367
	(2139)	(286)	(58)	(46)	(726)	(147)	(876)
Total Emp							
Innovators	83.919***	62.672	49.38	68.32	66***	38.779	103.44***
	(2189)	(186)	(48)	(142)	(532)	(118)	(1163)
Non-innovators	54.004	49.428	45.28	87.93	47.5	27.717	64.433
	(2032)	(269)	(58)	(45)	(694)	(145)	(821)
Sales in (1000)							
Innovators	625.3***	4208.3	6620.5	3486.1	245400***	4762.5	10347.3**
	(2126)	(203)	(38)	(128)	483)	(127)	(1147)
Non-innovators	370.7	2192.7	5512.2	25239.2	103276.6	1389.5	5231.8
	(2003)	(307)	(44)	(49)	(658)	(158)	(797)
Wage							
Innovators	277617.4	7263.7	2459.1	11520.1	1149548.8***	3494	5042
	(2389)	(216)	(51)	(149)	(568)	(136)	(1269)
Non innovators	345600.4***	7624	2978**	12822.2	1061751.2	3173.5	4981.7
	(2,202)	(312)	(58)	(50)	(709)	(170)	(903)
Ownership							
Innovators	0.143	0.106	0.108	0.159	0.264	0.096	0.098
	(2375)	(213)	(49)	(148)	(574)	(136)	(1255)
Non-innovators	0.148	0.091	0.184	0.130	0.234	0.144	0.099
	(2,218)	(312)	(56)	(50)	(731)	(169)	(900)
Export							
Innovators	0.071***	0.037	0.04	0.059	0.044***	0.026	0.095***
	(2,367)	(215)	(47)	(148)	(570)	(132)	(1255)
Non-innovators	0.050	0.067	0.049	0.036	0.021	0.044	0.071
	(2,201)	(308)	(57)	(50)	(730)	(165)	(891)
Market share							

cont.

	1 Overall	2 Cameroon	3 Niger	4 Rwanda	5 Zambia	6 Mali	7 Kenya
Innovators	0.015***	0.022	0.059	0.031	0.012***	0.022	0.012***
	(2145)	(208)	(39)	(128)	(494)	(130)	(1146)
Non-innovators	0.009	0.018	0.040	0.018	0.006	0.018	0.005
	(1,961)	(308)	(43)	(37)	(619)	(158)	(796)
Firm size							
Small firms							
Innovators	1,046	94	32	90	322**	78	430***
	(2,309)	(146)	(51)	(149)	(582)	(112)	(1269)
Non-innovators	1,201	147	37	28	349	93	442
	(2,095)	(213)	(58)	(50)	(734)	(123)	(903)
Large firms							
Innovators	1,263***	52	19	59	261	34	839
	(2,309)	(146)	(51)	(149)	(582)	(112)	(1269)
Non-innovators	894	66	21	22	284	40	461
	(2,095)	(213)	(58)	(50)	(734)	(123)	(903)

Notes: Sample size in parentheses, t-test on mean difference innovators and non-innovators, *** p<0.01, ** p<0.05, * p<0.1.

Table 1: Variable Definitions

Variables	**Definition**
Product innovations	Dummy coded 1 if firm i has introduced products or services that are new or have significant improvements in capabilities, user-friendliness, components or subsystems in the last three years
Process innovations	Dummy coded 1 if firm i has introduced new or significantly improved processes in the last three years
Inter-industry spillovers	The ratio of the total number of innovative firms in the two-digit "(J)" industry to the total number of innovative firms in the country in each year
Intra-industry spillovers	The ratio of total number of innovative firms in the two-digit "J" industry to the total number of innovative firms in the same industry in each country and year
Firm's characteristics	
Age	Years of operating in the market in logarithm
Employment	Number of employees in firm (i) in logarithm
Export orientation	Firm (i)'s share of exports in its total sales for a given year
Sale	Annual sale of firm (i) measured in USD
Firm size	Dummy coded 1 if firm (i) is in the large category and 0 otherwise
Wage	The total amount of wage paid to labor in USD in logarithm
Capital	The book values of a firm (i)'s total assets in USD in logarithm
Manager-owner's characteristics	
Foreign ownership	Share of foreign capital in firm i's total capital
Business environment	
Market share	Share of firm (i)'s total sales in the total sales of industry (j) in country (c)
Location	Dummy coded 1 if firm (i) is not located in capital county (c) and 0 otherwise
Year	The survey year, which varies from country to country

Table 2: Summary of sample size in each country and survey period

Survey Year	Selected Countries Cameroon	Niger	Rwanda	Zambia	Mali	Kenya	Total
2003	-	-	-	-	155	-	155
2005	-	138	-	-	-	-	138
2006	207	-	212	-	-	-	419
2007	-	-	-	603	490	657	1750
2009	363	150	-	-	-	-	513
2010	-	-	-	-	360	-	360
2011	-	-	241	-	-	-	241
2013	-	-	-	720	-	781	1501
2016	361	-	-	-	185	-	546
2017	-	151	-	-	-	-	151
2018	-	-	-	-	-	1001	1001
2019	-	-	360	601	-	-	961
Total	931	439	813	1924	1190	2439	7736

Table 3: Employment growth vis-à-vis firm size

Firm size	Obs	Mean	Median	Std.Dev.	Min	Max
Small	3337	.139	.00	0.391	-2.526	2.639
Medium	2003	.126	.083	0.377	-2.303	3.401
Large	924	.152	.095	0.326	-2.408	2.303

Table 5: Descriptive statistics after matching

	mean			t-test		
Variable	Treated	Control	bias	T	p>t	V(T)/V(C)
Log of annual sale	14.722	14.554	5.8	1.040	0.296	1.030
Log of labor costs	12.503	12.345	5.5	1.000	0.318	1.060
Percentage of export	0.090	0.089	0.6	0.100	0.917	0.880
Foreign ownership	0.122	0.131	-2.900	-0.460	0.646	0.890
Log of capital	13.203	13.046	5.3	0.950	0.344	1.20*
Log of firm's age	2.902	2.974	-8.800	-1.520	0.128	1.040
Percentage of skilled labor	0.635	0.601	11.100	1.860	0.064	0.850
Firm size (category)	1.715	1.736	-4.300	-0.750	0.454	1.050
City (dummy)	1.340	1.444	-21.400	-3.500	0.000	0.910

Notes: *if variance ratio outside [0.84; 1.18]

Table 6: Average Treatment Effect (ATE) of innovation on employment

	Product innovations		Process innovations	
	(1)	(2)	(3)	(4)
Employment type	Permanent	Total	Permanent	Total
Treated	0.546***	0.576***	0.611***	0.667***
	(5.70)	(5.80)	(6.76)	(7.14)
cons	3.257***	3.450***	3.232***	3.412***
	(39.64)	(40.66)	(43.10)	(44.14)
N	725	741	733	750

Notes: t statistics in parentheses and * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 7: The impact of product innovations and its spillover effect on employment

	Log of permanent employment			Log of total employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Matched	Full	Pooled	Matched	Full	Pooled
Product Innovation	0.233**	0.142**	0.264***	0.266**	0.131**	0.303***
	(0.108)	(0.0599)	(0.0364)	(0.114)	(0.0630)	(0.0373)
Inter-Spillovers	-1.079**	-0.215	0.542***	-0.647	-0.262	0.562***
	(0.516)	(0.313)	(0.113)	(0.436)	(0.300)	(0.116)
Intra-Spillovers	3.913***	0.860	1.960***	3.530**	1.331**	2.275***
	(1.243)	(0.617)	(0.161)	(1.427)	(0.668)	(0.165)
2006	0.455***	0.104	0.521***	0.678***	0.506	0.370
	(0.141)	(0.282)	(0.190)	(0.251)	(0.308)	(0.232)
2007	0.486*	0.394**	-0.271*	0.150	0.643***	-0.545***
	(0.272)	(0.162)	(0.154)	(0.230)	(0.188)	(0.197)
2009	0.400	-0.180	0.205	-0.221	-0.117	-0.00242
	(0.267)	(0.155)	(0.236)	(0.409)	(0.142)	(0.267)
2013	0.00323	0.189	-0.315**	-0.156	0.401*	-0.597***
	(0.179)	(0.199)	(0.159)	(0.126)	(0.227)	(0.202)
2017	-0.169		0.315	-0.641		0.154
	(0.284)		(0.222)	(0.431)		(0.258)
2018	0.0526	0.174	-0.253	-0.0545	0.401*	-0.460**
	(0.199)	(0.202)	(0.165)	(0.151)	(0.230)	(0.207)
2005		-0.249	-0.143		0.0654	-0.0867
		(0.177)	(0.213)		(0.234)	(0.261)
2011		-1.150***	0.0773		-0.551	-0.0574
		(0.360)	(0.184)		(0.394)	(0.224)
2016		-0.00498	0.157		0.262	-0.298
		(0.239)	(0.165)		(0.257)	(0.207)
2019		0.179	0.0550		0.445*	-0.139
		(0.210)	(0.165)		(0.238)	(0.207)
Constant	1.909***	2.784***	2.313***	2.350***	2.555***	2.598***
	(0.630)	(0.304)	(0.159)	(0.735)	(0.346)	(0.202)
Observations	1,298	3,874	3,874	1,306	3,914	3,914
R-squared	0.185	0.049	0.098	0.121	0.050	0.123
Number of firms	623	3,318		627	3,352	

Notes: Cluster robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

Table 8: The impact of process innovations and its spillover effect on employment

	Log of permanent employment			Log of total employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Matched	Full	Pooled	Matched	Full	Pooled
Process innovation	0.174*	0.0770	0.306***	0.142	0.0685	0.328***
	(0.0976)	(0.0575)	(0.0394)	(0.105)	(0.0629)	(0.0408)
Inter-Spillovers	-0.849	-0.316	0.557***	-1.068**	-0.357	0.557***
	(0.519)	(0.301)	(0.117)	(0.495)	(0.289)	(0.123)
Intra-Spillovers	3.667***	1.051*	1.381***	3.878***	1.411**	1.906***
	(1.326)	(0.590)	(0.222)	(1.312)	(0.657)	(0.235)
2005		-0.241	0.0590		0.0680	0.176
		(0.184)	(0.157)		(0.239)	(0.161)
2006	0.561***	0.129	0.621***	0.408*	0.284	0.533***
	(0.181)	(0.307)	(0.149)	(0.224)	(0.356)	(0.166)
2007	0.305	0.209	0.0673	0.613**	0.203	-0.247
	(0.216)	(0.139)	(0.146)	(0.304)	(0.150)	(0.159)
2009	0.463	-0.162	0.193	0.247	-0.110	0.108
	(0.432)	(0.158)	(0.160)	(0.247)	(0.147)	(0.175)
2011		-0.189*	0.145		-0.0943	0.0251
		(0.106)	(0.129)		(0.114)	(0.141)
2013	0.0396	0.00123	-0.122	0.114	-0.0435	0.375***
	(0.180)	(0.0788)	(0.121)	(0.179)	(0.0800)	(0.134)
2016		0.0411	0.339***		0.0638	0.0167
		(0.267)	(0.106)		(0.310)	(0.120)
2018	0.148	-0.0131	0.0355	0.206	-0.0460	-0.161
	(0.196)	(0.0923)	(0.134)	(0.194)	(0.0935)	(0.148)
2017	0.212		0.191	-0.110		0.142
	(0.293)		(0.144)	(0.386)		(0.164)
2019			0.215*			0.0674
			(0.119)			(0.131)
Constant	1.982***	2.942***	2.365***	2.060***	3.004***	2.548***
	(0.667)	(0.244)	(0.105)	(0.618)	(0.280)	(0.118)
Observations	1,192	3,990	3,990	1,236	4,001	4,001
R-squared	0.097	0.023	0.083	0.164	0.024	0.103
Number of firms	601	3,398		624	3,403	

Notes: Cluster robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

B Figures

Figure 1: Propensity score distribution before matching

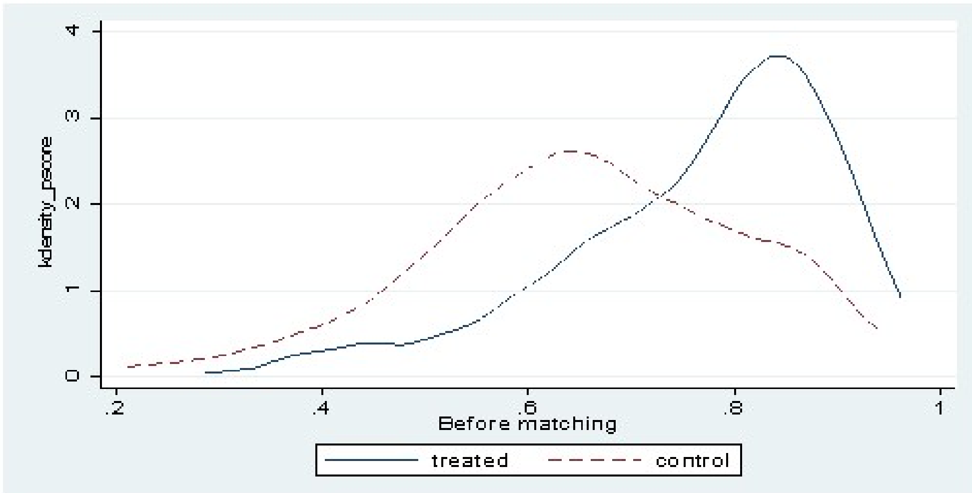

Figure 2: Propensity score distribution after matching