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Mezid N. Keraga
Andreas Stephan

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Does innovation stimulate employment in Africa? New firm-level evidence from the Worldbank Enterprise Survey

Mezid N. Keraga[†] and Andreas Stephan[*‡]

[†]Addis Ababa University, Ethiopia, mezid-nasir.keraga@ju.se
[‡]Linnaeus University, Sweden, andreas.stephan@lnu.se

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Abstract

This paper provides novel evidence on the question of whether innovation expands or reduces employment using firm-level data from the World Bank Enterprise Survey (ES) for six African economies. The results of the difference-in-differences estimations combined with propensity score matching confirm that both product and process innovations significantly expand job opportunities in Africa. In addition, the findings show significant intra-industry innovation spillover effects on employment. In sum, this study supports the view that innovation enhances employment in the analyzed African economies.

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

JEL: O30, J20

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1 Introduction

African countries spend only a very small fraction of GDP on knowledge production in terms of R&D expenditure. The average innovation score index for Africa was 22.4 in 2020 which is below emerging economies' average (Hamid et al., October 2021).[1] Similarly, export of medium or high-tech goods from African economies is at very low levels (Hamid et al., October 2021). And yet, there is hope that advancements in information and communications technology may stimulate firm-level innovation in Africa. Already in 2003, the Ministerial Council of Africa developed a common set of indicators of science, technology, and innovations (STI) for Africa, and about 43 member states implemented these indicators in 2019 (M. Sithole, 2020). Moreover, the African Union has adopted a ten-year (2014-2024) STI strategy for Africa (STISA-2024). The African Union (AU) Assembly has encouraged Heads of State and Government to invest at least one percent of the gross domestic product (GDP) in STI.

While innovation is expected to boost exports and increase the productivity of firms, its impact on firm-level employment is less well understood. Though it is generally assumed that the income of firms when having innovative products will increase thereby increasing labor demand, innovation may influence firm-level employment negatively if increased labor productivity causes a reduction of labor demand. At the level of the entire economy, Say (1964) predict that innovation will lead to reallocating jobs from one sector to another sector. Thus, there is an expectation that job losses in one sector could be compensated by gains in other sectors. However, whether or not innovation expands employment at the firm level is an empirical question that this paper tries to address.

A few empirical studies on the nexus between innovation and employment exist, however, those are mainly for advanced economies (e.g., Petit, 1993; Pianta, 2003; Vivarelli, 2014, 2015).[2] However, it is worth noting that the findings of those studies are mixed. For example, Van Roy et al. (2018) and Stare and Damijan (2015) find that innovation enhances employment while Gagliardi (2019) find negative employment effects from external technology shocks.

Regarding the effects of innovation on employment in developing countries, the literature is almost silent on this issue (for a literature review, see Vivarelli, 2014). A common perception is that developing countries are mere recipients of new technologies. In other words, innovation in Africa has been equated to the import of machinery and capital goods from developed countries. Consequently, most attention has been given in previous literature to the spillover effects of R&D investment of developed countries on economic performance of developing countries (for example, see seminal papers Coe et al., 1997; Grossman & Helpman, 1995). A few earlier empirical studies on Africa concentrated on the relationship between innovation and trade, foreign direct investment (FDI), and productivity, also given a general

[1] Note that Rwanda and Malawi were ranked 1st and 3rd in the top three innovative countries in the low-income category in 2021 (WIPO, 2021).

[2] See also Gagliardi (2019) for Great Britain; Van Roy et al. (2018) use 22 European countries; Pantea et al. (2017) perform their analysis for seven European countries, and Stare and Damijan (2015) provide evidence for Spain regarding the impact of innovation on employment at the micro level. For an overview of earlier studies, we refer the reader to the surveys of Pianta (2003) and Calvino and Virgillito (2018) of the empirical literature on the nexus between innovation and employment.

lack of firm-level data (Coe et al., 1997; Mazorodze & Tewari, 2018).

The available evidence for Africa regarding the employment effects of innovation are the studies Avenyo et al. (2019), Cirera and Sabetti (2019), Gyeke-Dako et al. (2016), Medase and Wyrwich (2022), and Okumu et al. (2019). Okumu et al. (2019) perform an analysis for 27 selected African countries, while Gyeke-Dako et al. (2016) provide evidence for Ghana. Overwhelmingly, these studies rely on cross-sectional data, which may imply a severe limitation for studying the impact of innovation on employment, as this relationship will have an important temporal dimension.

Given the lack of previous empirical studies, our paper contributes to the existing literature in several aspects. Firstly, it adopts a quasi-experimental approach by applying difference-in-differences estimations in combination with propensity score matching using longitudinal cross-country data to identify the impact of innovation on firm-level employment. Secondly, it extends previous studies by including inter- and intra-industry spillover effects in the analysis. Thereby we are able to infer the aggregated impact of innovation on employment. Finally, the paper distinguishes innovation types and also employment forms in order to obtain a more accurate picture of the relationship between innovation and employment.

The estimation results, using firm-level data from the World Bank Enterprise Survey, 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.

These results have important policy implications for African economies. Policymakers may consider policies of promoting and enhancing firm-level innovation as a priority given its positive impact on employment. Similarly, the African Union, specifically the Economic Commission for Africa (ECA) should consider developing strategies to encourage firm-level innovation in Africa as one instrument to ease the pressure of unemployment, in particular of young persons.

The paper proceeds as follows. Section 2 presents a literature review. Section 3 describes the innovation indicators and extent of job opportunities in the continent and, specifically, for the countries included in this study followed by the presentation of the methodology in Section 4. Section 5 gives results and discussion. Finally, the conclusion and policy implications are presented in Section 6.

2 Literature Review on Innovation and its Employment Effects

The nexus between employment and innovation[3] is a classical controversy. Broadly speaking, there are two channels through which innovation can influence employment. The first channel is via labor productivity, and the second is through a price mechanism (Peters et al., 2014). In

[3] While we sometimes use the term technological progress instead of innovation, following the Oslo manual (OECD/Eurostat, 2018) innovation is not the same as technological change. There are many types of innovations that would not be described as technological change, like marketing and organizational innovations. In this study, the major types of innovation we are referring to are product and process innovations.

the latter case, innovation reduces the per unit cost of production and consequently reduces the price of products, which causes employment to rise to meet higher demand (Pigou, 1920).

In pre-industrial times, the assumption was there is a complimentary relationship between employment and technical progress (Petit, 1993). In the industrial period, the substitution of capital for labor became a new reality, and the question was raised about the impact of technology on employment. As a result, in the early 19th century workers in England were protesting against the introduction of machines in textile factories because they were scared advanced machines might displace them from their workplaces. Since then, the issue has been widely discussed in the academic literature. Theoretically, however, the linkage between innovations and employment goes back to the classical theories of economic growth (Gray, 1952; Say, 1964) and was then rigorously discussed by neoclassical economists like Solow (1956) and Swan (1956) in relation to productivity improvement. Moreover, innovation is the core of endogenous growth theories (Romer, 1990; Sala-i-Martin, 1990). On the other hand, Griliches (1957), Aghion and Howitt (1992) and Grossman and Helpman (1991), which are extensions of the Schumpeterian school of thought, discussed the sources of technical change via diffusion of technology. Their conceptualization of innovation is in line with endogenous growth theory. There are opposing axioms between neoclassical and endogenous growth theories about the mechanisms through which innovations can be affected. The former theory argues that innovations take place due to external shocks to the economic system while the latter assumes that innovations are entirely determined by factors within the system. Nevertheless, empirical evidence regarding the relationship between innovations and employment[4] at the macro level has been well documented since the 1980s while micro-level studies started later (Vivarelli, 2014).

While the innovation-employment relationship has been a classical issue, it recently has gained the attention of some scholars due to advancements in information and communication technology (ICT) and automation technologies in the 21st century. For instance, Acemoglu (2022) in the International Monetary Fund (IMF) spring issue suggested that innovations, like for example automation, have a negative impact not only on employment but also on firms' productivity. He further pointed out that now, after the Covid-19 pandemic, employers are seeking labor-saving technology and showing a tendency to displace workers. The pandemic enhanced innovation but also created involuntary unemployment. On the other hand, Fox and Oviedo (2013) highlighted that employment growth in SSA countries is associated with technology. Consequently, it is interesting to know how innovation and employment interplay in the context of Africa.

To investigate this interplay, Okumu et al. (2019) use labor productivity as an outcome variable. However, labor productivity can be improved due to forward effects, i.e., a firm that engages in innovation activities is more likely to invest in its human capital, and in turn, human capital enhances firm-level innovations. Another limitation of Okumu et al., 2019 study is the measurement of innovations in the African context. They use R&D as a binary innovation indicator for both product and process innovation. Given the information con-

[4]This refers to general employment without making a distinction between different types of employment. First, in the dataset, the data for individual countries are not organized by the types of employment except for categorizing firms' total employees as production and administrative workers. Second, the magnitude of the impact of innovations on blue-collar and white-collar jobs might vary, one could even expect a contradictory effect. Thus, it is the net effect that is important for policymakers.

tained in the dataset it is impossible to differentiate between whether the R&D expenditure is allocated for product or process innovations. Second, few firms are investing in in-house R&D activities in Africa, and there are firms that are engaged in innovative activities without formal spending on R&D. Moreover, R&D fails to capture imitator and adopter firms (Pianta, 2003), which mostly explains firms' innovation behavior in developing countries.

Another related study is Cirera and Sabetti (2019) which investigates the relationship between innovation and employment using a cross-country sample of firms from Africa. Cirera and Sabetti, 2019 study is also designed as a cross-sectional and, as a result, they cannot disentangle the impact of innovations on employment over time. Furthermore, Cirera and Sabetti (2019) do not investigate the spillover effect of innovations on employment.

There are many mechanisms through which information or knowledge about new technology could be leaked and create potential spillovers. Some of the channels, through which information is leaked, are: in the process of licensing technology, patent disclosure, technical meetings, conversations with and hiring of employees of innovative firms (i.e., learning by hiring), and reverse engineering (see Harabi, 1997; Mansfield, 1985). A firm might, however, be engaged with its rival firms in cooperation in R&D, marketing, production of components, or information systems, which leads to symmetric spillover effects (De Bondt, 1997). R&D is an input to generate innovation outputs (see Crépon et al., 1998; Griliches, 1979). However, small firms do have a resource constraint to engage in knowledge production and instead get involved in innovative activities through knowledge spillovers. Most often, knowledge spillovers from large firms' and universities' R&D expenditures are critical elements for the innovation activities of small firms (Acs et al., 1994; Audretsch & Vivarelli, 1996). Notably, the learning-by-hiring effect is much more important for small firms than for large firms (Braunerhjelm et al., 2018). In any case, innovations have spillover effects, and hence, the benefits of innovations are not limited to the innovative firm (Nadiri, 1993). In this study, therefore, we investigate the impact of innovations' spillover effect, in other words, the knowledge/information effect on the employment of rival firms. We consider both intra- and inter-industry spillover effects of innovations and their impact on employment.

According to De Bondt (1997), spillover effects can be described as side effects of a business strategy. It can be involuntary leakage or voluntary transmission of important technological information from one firm/industry to others. On the one hand, important information is transmitted from innovator firms to competing firms. On the other hand, it may also inflict negative externalities on rival firms, like reducing the profit margin and market share (De Bondt & Veugelers, 1991). Thus, the impact of innovations on employment is not limited to the firms that are involved in the innovation activities. Rather, it may have policy relevance to look at the spillover effects of innovations on the employment of rival firms. However, previous studies on the spillover effect of innovations in advanced countries are focused on the mechanisms and magnitudes of it (Acs et al., 1994; Braunerhjelm et al., 2018; Griliches, 1991; Harabi, 1997; Mansfield, 1985; Nadiri, 1993). Knowing the side effects of innovation with respect to job effects in rival firms would enable policymakers to assess the potential impact of innovations on the competitiveness of rival firms. However, so far, the literature provides little, if not nothing, evidence about spillover effects of innovations on employment in the context of Africa.

Empirical literature on the relationship between innovations and employment in Africa is scant. To mention the available studies, Naidoo et al. (2023) investigate the impact of product and process innovations on employment using the South African National Innovation Survey (NIS) data-set of the period 2005-2016. They find that process innovations enhance employment more than product innovations. Medase and Wyrwich (2022) examine the effect of innovation on the employment growth of Nigerian firms using the Nigerian Innovation Survey (NIS) dataset over the 2005-2020 period. They find both product and process innovations to promote employment growth. Avenyo et al. (2019) study the impact of product innovations on employment in five Central African countries, namely; the Democratic Republic of Congo, Ghana, Tanzania, Uganda, and Zambia. Their findings show that there is a positive correlation between employment and product innovations. They combine Innovation Survey (IS) data with Enterprise Survey (ES) data and apply dose-response model to check the intensity of the impact of innovations on employment. Their study, however, has some limitations. First, the study uses a cross-sectional dataset, which makes it difficult to disentangle the impact of innovations with associated variables and to establish causal impact, despite that they generate statistical twins for the treated firms. Second, their study provides evidence for product innovations only, and it is less debatable in its impact on employment (see Pianta, 2003). Moreover, there is less evidence for African firms to engage in product innovations due to limited in-house development and firms' investment in R&D (Oberdabernig, 2016; Vivarelli, 2014, 2015).

Furthermore, Okumu et al. (2019) find that both product and process innovations are positively associated with employment using the WB Enterprise Survey data-set for 27 African countries. Yet, their analyses are confined to firms in the manufacturing sector only. The authors pointed out there is complementarity between product and process innovations in their effect on the increase of employment, and employment is conditioned by the size of a firm. Similarly, Gyeke-Dako et al. (2016) find that product innovations have a positive impact on employment but process innovations are employment neutral using cross-sectional data of Ghanaian firms. Moreover, M. M. Sithole and Buchana (2021) find that product innovations have a positive effect on employment growth of manufacturing firms while process innovations have a negative impact on manufacturing and service sector employment growth. In sum, empirical literature from Africa shows that product innovation is positively associated with employment, but the impact of process innovations on employment is not conclusive. Thus, it is worthwhile to add more evidence to existing empirical literature and figure out the net effect of both types of innovations on employment.

Moreover, one of the most important studies on this topic is Cirera and Sabetti, 2019 work. The authors find that product innovations have a positive impact on employment but not process innovations. However, Cirera and Sabetti, 2019 study also has some weaknesses. First, their study does not check the possibility of simultaneity between output growth and the price of products because the value of output is not deflated. Nevertheless, they use R&D as an instrumental variable (IV) for output growth. And yet, this IV has little relevance, and probably most African countries dropped out from the regression given limited firm-level investment in R&D. Second, employment growth can be confounded with the time trend. As a result, the coefficient of the estimate may not be well identified due to the cross-sectional design of their research. Hence, their result might not be robust for other types of specifications and modelings.

As to other related literature, Anakpo and Kollamparambil, 2022 identify that automation is positively associated with unemployment using a panel dataset of a sample of ten countries in southern Africa countries over the period 2004-2017. Seemingly contrary to Anakpo and Kollamparambil, 2022 finding, Metu et al. (2020) report that ICTs reduce youth unemployment for SSA countries. Their study covers 48 SSA countries from 1991 to 2018. Furthermore, Ebaidalla (2014) investigate the effects of ICTs–measured by mobile subscription and Internet penetration–on youth unemployment using a panel dataset of 30 SSA countries over the 1995-2010 year series. The results indicate that ICTs have a positive impact on youth employment in Africa. Hence, the effect of innovations on (un)employment is contested and needs further in-depth investigation.

3 Innovation Outlook for Africa

The third African Innovation Outlook (AIO-3) report provides information for 23 countries based on innovation indicators developed by the ministerial council. It is worthy, therefore, to present a summary of the main point of this report to understand the status of innovation activities in the continent.

One of the biggest challenges in Africa is not only knowing the actual amount of investments in R&D in each country but also where that investment took place. For convenience, sectors are divided into four categories. These are government, business, higher education, and private non-profitable institutions that are engaged in innovation activities, whereas information about R&D expenditure is limited for Africa (AIO-3, 2019). Out of 23 countries, where data were collected for STI indicators, reliable information has been found for only 11 countries. Almost all African countries spend less than one percent of GDP on R&D. Three countries, namely, South Africa, Ethiopia, and Botswana, do invest a little more than 0.5 percent of GDP on R&D. The source of finance for R&D activities in Africa mainly originates from the governments. It ranges from the lowest government contribution of 35 percent in Eswatini to 97 percent in Ethiopia. In Uganda (53%) and Mozambique (42.7%), R&D investment is financed mainly by external sources. An overwhelmingly large amount of R&D resources are allocated to public research institutions except South Africa where 46 percent of R&D expenditure is allocated to the business sector. On the other hand, the business sector itself does not spend economically meaningful resources on R&D activities. For instance, in Eswatini and Ethiopia, the business sector spends only 0.002 and 0.003 percent of GDP on R&D, respectively, while the South African business sector allocated more than 0.3 percent of GDP on R&D. In the African context, the business sector does not invest adequately in knowledge production, though the business sector is an incubator and epicenter of innovation activities in advanced economies. Looking at the type of R&D engagement, out of the seven countries included in the survey, four countries spend more than 20 percent of R&D investment on basic research. On the other hand, except Ethiopia, which spends more than 74 percent on experimental research, the remaining countries spend less than 30 percent of the total R&D expenditure on experimental research.

In terms of personnel working in the R&D department, R&D personnel is concentrated in higher education and in the government sector except Seychelles (38 percent) and South Africa (26 percent), where R&D personnel is also found in the business sector. Moreover, the ratio of researchers per million persons in Africa ranges from 27 in Uganda to 715 in Egypt, and, on average, is comparable to some Latin American countries, like Mexico (244) and

Chile (533). The report further sheds light on the innovative performance of firms, which are found in 10 African countries. Accordingly, low-level innovation activities were reported for Cape Verde (3.9) and the highest was registered for Uganda (91.7) percent. Categorized by type of innovations, process innovation (33.4) takes the lead followed by product innovations in goods (21.6) and services (17) percent. However, close to 64 percent of Kenyan firms were engaged in organizational innovations related to workplace responsibility. Remarkably, R&D expenditure is ranked as the second option for a firm to be innovative while the first mechanism is through embedded technology transfer through importing. Moreover, the report provides evidence that innovative firms hire more employees with higher education than non-innovative firms.

On top of the above, we used the World Bank (WB) dataset to observe the intensity of engagement in innovation activities of each country considered in this study. Most often, be it for macro- or micro-level analysis, innovations can be measured in terms of the amount of resources spent on R&D–measuring the input side (knowledge production)– or in terms of the number of applications submitted to get patent rights or the number of granted patent rights–measuring the innovation output. Accordingly, data for R&D expenditure as a percentage of GDP and patent applications differentiated by residency are available in the WB dataset.

Nevertheless, information on patent applications is available for only three countries: Kenya, Rwanda, and Zambia. In addition, the size of observations for each country varies. We found a data series from 2002 to 2020 for Kenya and Zambia, and a five-year data series for Rwanda, i.e., 2014-2019. Over 19 years (2002-2020), Kenya and Zambia submitted a total of 3613 and 508 patent applications, respectively. On average, annually, Kenya has applied for 190 innovative products for the past 19 years while Zambia has submitted applications for close to 27 products. Moreover, Rwanda has submitted 37 patent rights applications within five years, which is about 7.4 applications per year. However, information is not available for the rest countries: Cameroon, Mali, and Niger with regard to patent rights applications.

Similarly, expenditure on R&D for Cameroon, Kenya, Niger, and Zambia is not available at all while observations for a few years are available for Mali and Zambia. For the years between 2007 and 2019 for five-point observations, the average expenditure on R&D as a ratio of GDP for Mali was 0.313 percent, which is below the target set by the AU. The figure for Zambia was even much lower than in Mali, i.e., 0.051 percent for seven years of observation over the period 1996-2008.

4 Empirical approach

4.1 Identification strategy

To identify the impact of innovations on employment, we adopt the standard neoclassical model of profit maximization. The demand for labor is a derived demand from 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 parameters, 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 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 innovations and specified a stochastic labor demand function.

On the other hand, we follow a similar method of 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 total population of firms in two-digit industry of (m), and sIN_{mt}^{k} is the share of innovative firms in total population of firms in the two-digit industry of (m). α_{mjt} is a weight measurement which is the share of output of industry (m) purchased by firms in 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. Thus, our empirical identification strategy that examines the impact of innovations and its spillover effect on employment in Africa is described below.

To identify the impact of innovations on employment, we apply the Fixed Effect (FE) estimator after matching. As we know, the standard fixed effect estimator has clear limitations in disentangling the impact of some interventions. The crucial parallel trend assumption is likely to be violated in the FE estimation method. Therefore, there is a need to reduce the model dependency of the estimate (Ho et al., 2007) by reducing the link between the treatment and covariate variables. Thus, the result of estimates is likely to be independent of different model specifications. However, the combination of the FE with a matching estimation method can solve the model dependency problem by finding statistical twins for the treated firms.

FE estimation with matching is executed in a two-step estimation 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 wage, log of capital, proportion of skilled labor, firm size, share of export and foreign ownership, and location dummy. We applied a nearest-neighbor matching algorithm to match between treated and control firms. Second, based on the matched sample, FE estimation is applied. We have added indicators of spillover effect variables in the second regression. Once again, we re-estimated the empirical model by applying the FE estimator without matching and pooled OLS: ignoring the time dimension of the dataset as a mechanism to check the sensitivity and robustness of our findings. The variables included in our empirical model specification are based on the empirical literature that we reviewed.

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

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 the (j) industry, 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 the associated vector of coefficients. Finally, firm, industry, and country-specific unobserved heterogeneity are captured by γ, η, and δ, respectively, and ϑ is the macroeconomic shocks indicator. Finally, μ is the random error term.

Eq (6) is estimated using the FE estimator after matching. However, initially we estimated the model using a flexible double difference model, but we could not retrieve a coefficient of DID estimate of the innovation impact. As a result, we switched to FE with matching to fit the dataset available for African countries. Since innovation, the treatment variable starts at different times in each country, and the time gap between two survey periods is also not constant across all countries included in this study, a FE estimator with matching was a better fit. Otherwise, it is more appropriate to estimate the impact using flexible DID. For details on flexible double difference and associated STATA commands, one can see (Dettmann et al., 2020).

4.2 Sample and variable description

We use the Enterprise Survey (ES) dataset. It is secondary 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 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 was followed to select enterprises in the ES sample. Strata are made based on firm size, 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. Sectoral strata 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.

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

The other important issue that we addressed in this paper is the spillover effect of innovations on employment.

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 left for innovation-related issues. However, the ES uses two instruments that are designed for manufacturing and key service sectors separately. In this survey about 146 countries are covered but it is not conducted in the same years across countries. Some countries have rich datasets while others were included in fewer rounds. For this study, we considered countries that have at least three rounds in the survey dataset. We found 7 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 African 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 $Winsor$ outlier fixation technique. Details of the variables we used for this study are presented in Table 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 sub-systems 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 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

5 Results

5.1 Descriptive statistics

In this subsection, we present the descriptive statistics of the data-set comparing innovative with non-innovative firms in different firm-specific characteristics.

A summary of the sample size in each country and the survey year is presented in Table 2 below. As can be seen, a total of 7736 firm-level observations are being considered for this study. A relatively large sample size comes from Kenya, which is 2439 with the latest round of survey data for the year 2018, while the smallest sub-sample of firms comes from Niger 439. In 2006, we have survey data for two countries: Cameron and Niger. Similarly, Kenya, Mali and Zambia were surveyed in the year 2007. Furthermore, in the year 2009 we have survey data for Cameron and Niger, and in 2013 for Zambia and Mali. Finally, we have the latest survey data from 2019 for Rwanda and Zambia.

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

Survey	Selected Countries						
Year	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

In Table 3 below, we present employment growth of firms over three years. In the WB ES data-set, we have two periods of information. Firms are asked to declare the number of permanent employees three years ago and the number of permanent employees in the survey period. We followed Fisman and Svensson, 2007 firm-level employment growth calculation, i.e., the logarithm difference between the two periods gives us the growth (percentage change) of employment over three years. To know the annual average, we can divide it by three. Accordingly, employment growth ranges from -253 percent to 340 percentage points. Thus, some firms have cut employment by more than 253 percent while others have increased permanent employment more than threefold within three years. However, on average there is a positive employment growth rate in all countries. Within three years, on average, employment growth is registered to range from 11 percent in Zambia to close to 21 percent in Rwanda. Overall, on average, employment has grown by 12.2 percent over three years. Hence, annually, firms' employment size is expanded by seven percent in Rwanda and close to 3.67 percent in Zambia while the overall annual growth is close to 4.1 percent. This descriptive statistic is somehow close to the ILO (2020) report where the average employment growth ranges between 2.5 and 3.0 percent for Africa. Of course, the ILO (2020) report refers to total employment for all sectors while we used permanent employment for industry and service sectors only. As a result some marginal deviation on average employment is observed.

Table 3: Firm-level employment growth over three years in sub-Saharan African countries

Country	Obs	Mean	Median	Std.Dev.	Min	Max
Cameroon	840	.123	.065	.344	-2.436	2.06
Rwanda	674	.209	.143	.385	-1.744	2.485
Zambia	1584	.11	.00	.364	-1.609	2.639
Mali	986	.16	.069	.349	-1.386	3.401
Kenya	2180	.128	.074	.406	-2.526	2.526

Moreover, it has practical and academic relevance to see which type of firms are creating more job opportunities. For this consideration, average employment growth is broken down by firm size to see whether there is variation in terms of employment growth between different firm sizes. For convenience, firms are grouped into three sizes; small (less than 20 employees), medium (20-99 employees), and large (above 99 employees). Relatively speaking, a large proportion of the sample firms are in the 'small' category followed by medium-sized firms.

Table 4: 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

As can be seen from Table 4, the relationship between employment growth and firm size is less clear. On average, large firms' employment grew by 15.2 percent over the three-year interval followed by small firms with 13.9 percent. Thus, from this descriptive result, it may be difficult to establish the relationship between firm size and growth while, unequivocally, large firms create more job opportunities compared to small firms. This contribution of large firms to high employment growth might be due to our consideration of permanent employment. The growth rate could be different if we take into account temporary employment as well.

Table 5: Overall 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							
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)

cont.

	1 Overall	2 Cameroon	3 Niger	4 Rwanda	5 Zambia	6 Mali	7 Kenya
Non-innovators	894 (2,095)	66 (213)	21 (58)	22 (50)	284 (734)	40 (123)	461 (903)

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

As can be seen from Table 5 below, the overall sample statistics presented in column (1) indicate that 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. The descriptive statistics for innovative and non-innovative firms after matching are also presented in the subsequent tables. Specifically, innovative firms create more job opportunities for permanent and temporary workers compared to non-innovative firms. However, when we look at the average industrial wage per firm, non-innovative firms are paying a significantly higher wage compared to innovative firms.

Innovative firms in Zambia and Kenya have hired more employees compared to non-innovative firms. Similarly, innovator firms are generating a large amount of revenue and are more export oriented in both countries. Moreover, large firms[5] and firms that are situated in the capital cities are more innovative compared to their counterparts, i.e., small firms that are located outside the capital cities. Firms located in the political and economic center are more innovative than ones outside the center, except in Mali. On the other hand, there is no statistically meaningful difference between innovators and non-innovators in terms of total and temporary employment, engagement in the export market, and market share in Cameroon, Niger, Rwanda, and Mali. As a result, this cross-country study gives us a better understanding of the possible impact of innovation on employment than single-country studies.

From Table 6 after matching, there is no statistically significant difference in mean distribution between treated[6] 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 met 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.

[5]In this dataset, firms are categorized into four groups. These are micro firms, which have less than five employees; small firms with five to 19 employees; medium firms having between 20 and 99 employees; and large firms, which have 100 or more employees. In this paper, we reduced these four categories of firm size to two. The first two categories are considered as small while the last two are labeled as large firms. Thus, "large firm" refers to firms that have twenty or more employees.

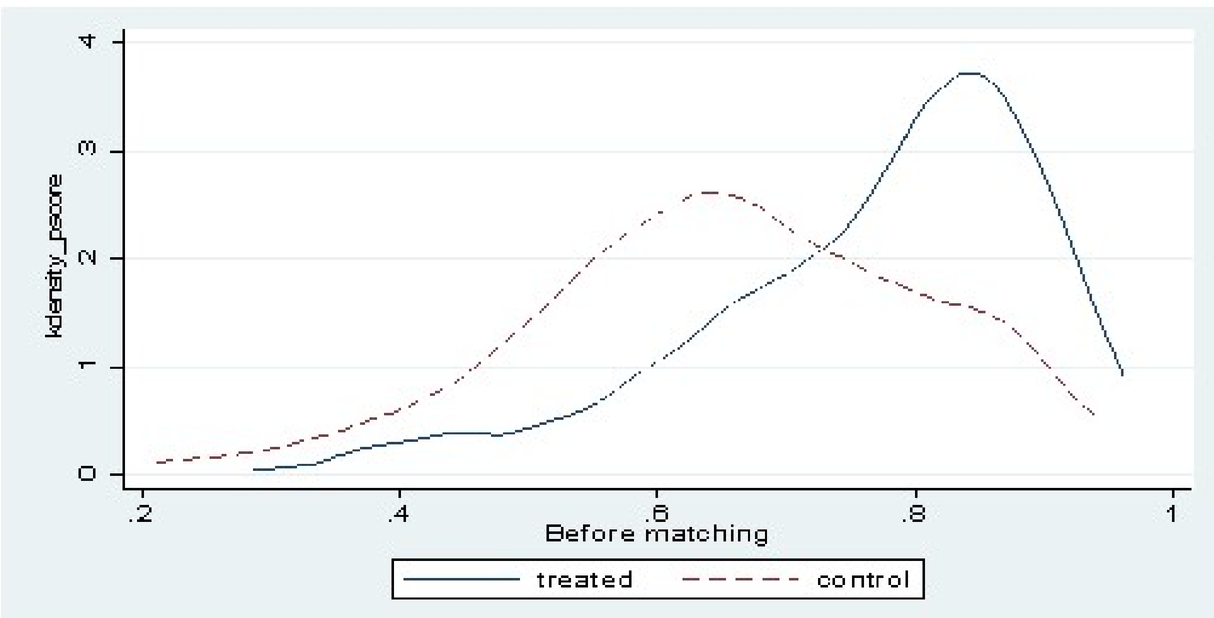
[6]Here, "treated firms" refers to firms that introduce new or significantly improved goods and services, i.e., product-innovative firms. Similarly, we have done a test for firms that are engaged in process innovations as well. The descriptive statistics are similar to what we have presented here in Table 6. Hence, to save space and avoid redundancy of information, we prefer to skip presenting the results here

Table 6: Descriptive statistics after matching

Variable	mean				t-test	
	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]

Figure 1: Propensity score distribution before matching



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 7 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 signifi-

Figure 2: Propensity score distribution after matching

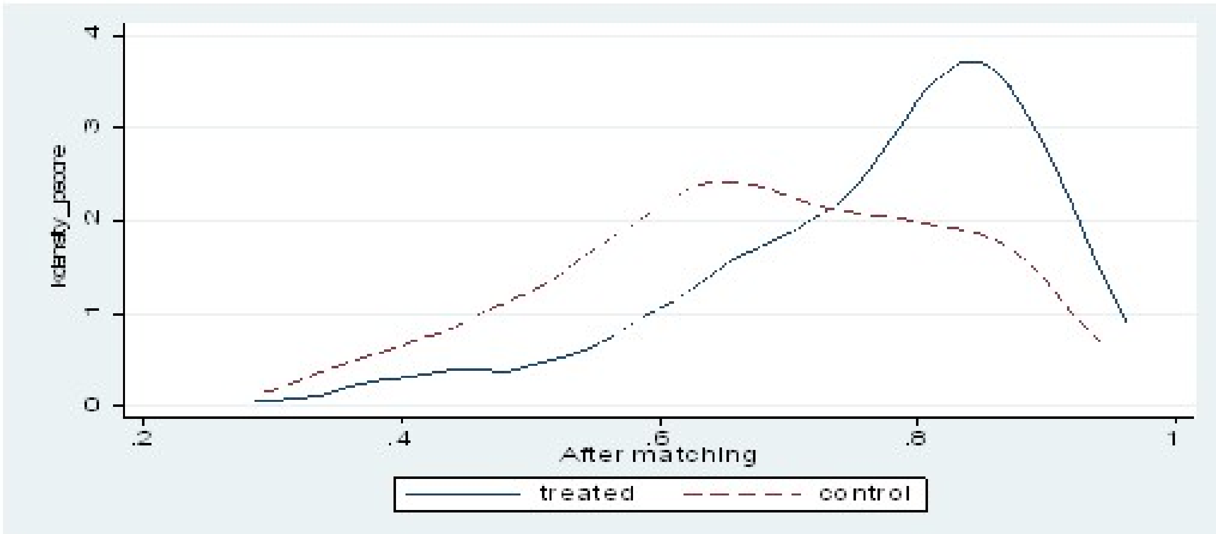


Table 7: Average Treatment Effect (ATE) of innovation on employment

	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

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

5.2 Estimation Results

We have estimated three different models to disentangle the impact of innovations (product and process) on employment (permanent and total). Column 1&4 in Table 8, attached in the annex, present fixed effect estimates on the matched sample for the impact of product innovations on permanent and total employment, respectively. Results in columns (2&5) are fixed effect estimates for the whole sample without matching. Finally, columns 3&6 present pooled OLS estimates results while ignoring the time dimension of the panel but it is clustered by the firm's unique number. Here, we present, however, fixed effect estimates without matching and pooled OLS estimates to check the strength and susceptibility of our findings for different model specifications.

Table 8: 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

As can be seen from Table 8, product innovations have a positive and significant impact on employment (permanent and total). Theoretically speaking, these results give some signal that the compensation effect of product innovations via pricing mechanism is higher than the displacement effect via demand contraction for old products. In other words, the net effect of product innovation on employment is positive.

The magnitude of its impact is higher on matched sample firms than the other optional specifications. Innovative firms created more than 23 percentage points more permanent job opportunities compared to less-innovative firms. Firms engaged in product innovations not only create more jobs for permanent workers but also for temporary workers as well. In sum, there is no trade-off between product innovation and employment, rather firm-level product innovations in Africa create more job opportunities. Accordingly, our finding is in support of the previous empirical evidence of Medase and Wyrwich (2022) for Nigeria for firms in the manufacturing sector; of Okumu et al. (2019) for 27 African countries; and of Cirera and Sabetti (2019) for developing countries. They all concluded that product innovations have a significant and positive impact on employment.

Further, as firm-level innovation has a positive impact on firms' employment, it will be interesting to examine its impact on other firms that are in the same or different cohorts of two-digit industries. According to Schumpeter (1942), innovations have also a business-stealing effect. To capture this effect, we included and intra-industry and inter-industry spillover effects of innovations in our regression. In all estimation approaches, the intra-industry spillover effect of product innovation is positive and significant for permanent employment. Thus, firm-level product innovation in Africa has a positive intra-industry spillover effect. The implication of this finding is twofold. First, this result provides evidence that product innovations do not have a business-stealing effect in the African context. This may be because less innovative firms in Africa are reluctant to respond to market share reduction in the short term due to an imperfect market structure. Another possible justification could be that a firm's innovation may incentivize other firms in the same industry to engage in innovative activities. It is well documented that knowledge spillovers from large firms are important elements in the innovative activities of small firms (see Acs et al., 1994; Audretsch & Vivarelli, 1996). On the other hand, the coefficient of the inter-industry spillover effect is negative in all model specifications and significant in matched and pooled cross-section samples for permanent employment. Our finding contrasts with Stare and Damijan, 2015 findings, though their investigation is a macro-level analysis, they found a positive impact of product innovation on the employment of vertically connected firms.

On the other hand, the impact of process innovations on employment is positive in all model specifications and significant for permanent employment for matched and cross-section design samples (see Table 9 in the annex). Like product innovation, process innovations could expand firm-level job opportunities in the context of Africa. This is a remarkable finding given the ambiguity and contentions about the relationship between process innovations and employment, theoretically and empirically.

However, our study's finding is in line with earlier studies documented by Medase and Wyrwich (2022) for Nigerian employment growth; Castillo et al. (2014) for Argentinian firm-level employment, and Zhu et al. (2021) for Chinese firms in that process innovations create more job opportunities. On the other hand, our finding does not support the findings of Álvarez et al. (2011) and Benavente and Lauterbach (2008) for Chile, Gyeke-Dako et al. (2016) for Ghana, De Elejalde et al. (2015) for Argentina stating that process innovations do not have a significant impact on employment. In general, it is clear from the results that firm-level innovations in Africa create more employment than layoffs.

Table 9: 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

Process innovations have also a positive intra-industry spillover effect on employment while the inter-industry spillover effect is negative in total employment for the matched sample. It gives a signal that, potentially, process innovations in one industry might harm employment in firms of some other two-digit industry. This result is consistent with Stare and Damijan, 2015 finding for Spain. But, in the related empirical literature, Wang et al. (2020) found that internet technology progress promotes within-industry and inter-industry employment in China.

As regards policy implications, these findings indicate the potential of innovations for employment creation in Africa. Accordingly, policymakers need to promote and provide incentives for firm-level innovations to enhance productivity and expand job opportunities. Policy interventions need to be designed to promote firm-level innovations coherently throughout the African continent while underscoring the enabling environment of each country. The African Union, specifically the Economic Commission for Africa (ECA), should develop strategies to encourage firm-level innovations in Africa as a mechanism to ease the pressure of youth unemployment in Africa.

6 Conclusions

Employment is a burning economic and political issue for most African economies. Recently, policymakers in Africa realized that innovation should become a priority to attaining stability, growth, and fair income distribution in Africa (see Asongu et al., 2016; Zanello et al., 2016). Thus, in this paper we attempt to investigate whether there is a trade-off between innovation and employment in the African context using a firm-level survey panel dataset for six African countries. We have a total of about 4,000 firms that are considered for this study while more than 725 firms are on support region are used for our estimation. We apply a two-way fixed effect estimator with matching to identify the impact of innovation on employment. The results indicate that innovation (product and process) has a strong positive impact on firm-level employment in Africa, implying there is no trade-off between innovation and employment in Africa. Firm-level innovation could have a positive intra-industry spillover effect on employment. On the other hand, firm-level innovation in Africa does not have a positive inter-industry spillover effect on employment. Thus, firm-level innovations have a positive spillover effect on firms operating within the same two-digit industry but not in another two-digit industry.

This study exploits the panel nature of the dataset, as recommended by Avenyo et al. (2019), to disentangle the impact of innovations on employment. However, further studies need to be conducted to know the potential impact of innovations on employment in Africa by merging the Innovations Survey (IS) and the ES dataset for a long panel. Moreover, the spillover effect of innovations on employment and market share considering the volume of trade within and between industries needs a thorough investigation for developing economies. Due to data constraints, we could not deal with all these issues in detail. However, this study is the first attempt to apply a quasi-experimental approach of using a fixed effect estimator with matching to identify the impact of innovations in the African context, but experimental studies on this issue will give us an additional reliable indication for economic policy.

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