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Innovation and Employment in Sub-Saharan Africa

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Abstract

The debate on the role of innovation in employment growth is still inconclusive with the available literature focusing largely on industrialised economies. With this concern, we examine the potential of innovations in creating permanent full-time jobs in registered manufacturing companies in Sub-Saharan Africa (SSA) by fitting the model of Van Reenen (1997) to a two-period panel of 687 manufacturing firms. Our paper is the first to examine the impact of innovation on employment with a particular focus on SSA and the first to apply a panel data approach to a larger set of developing countries. Our findings indicate that in the past, innovative firms created more jobs compared to non-innovative ones when controlling for sales, wages, time-invariant firms and country specifics. Likening the results with emerging or developing economies outside of SSA, we find that the effect is considerably larger in SSA than in other regions. As a consequence, we recommend that SSA governments strengthen their technological adaption and adoption mechanisms in their manufacturing sectors to foster innovations. Nonetheless, as a way to discourage imitations (which may not be well aligned to the production demands in SSA), governments are encouraged to invest in sector-specific research and development.

Keywords:

[Innovation, Employment, Sub Saharan Africa, Panel model, Enterprise Survey]

1. Introduction

The potential of Sub-Saharan Africa (SSA) cannot be overestimated. The region boasts rich natural resources and a young fast-growing population (Filmer and Fox, 2014). With the creation of the African Continental Free Trade Area in 2019, it is part of the largest area of free trade worldwide in terms of the numbers of countries participating. However, SSA is also the region with the highest share of extreme poverty in the world (ILO, 2020). Even in optimistic post-pandemic scenarios, projected economic growth will remain below the expected growth of the population. So despite all success in recent years, poverty reduction remains critical for the region's development (World Bank Group, 2020; IMF, 2019). This study focuses on job creation in SSA manufacturing firms, which can be considered crucial for economic development with its substantial contributions to poverty reduction, economic stability and inclusive economic growth (Meyer, 2014; Haltiwanger et al., 2013; IMF, 2019). Fostering innovation and entrepreneurship for job creation is an integral part of the policy of many governments of SSA (for example Ministry of Innovation and Technology in Ethiopia, Ministry of Environment, Science and Technology in Ghana, Ministry of Science, Technology and Innovation in Uganda) or institutions dedicated to development (for instance, initiatives of the World bank's ETIFE [firms, entrepreneurship and innovation] unit or the German GIZ innovation fund). However, empirical evidence about the impact on labour markets is scarce. Our study is intended to provide policymakers with empirical information on the impact of programmes fostering innovation, specifically concerning the creation of decent jobs (ie permanent jobs in formally registered companies) within the innovating firm. More precisely, our study will provide answers to the questions if innovative firms from the manufacturing sector in SSA were able to create more jobs in the past and in the affirmative case, how the average size of such labour expanding effect compares to other regions of the world. It should be noted that with its firm-level design, our study cannot provide results on the aggregate level, which is a well-known problem in the empirical literature on innovation and employment (see section 2 for an overview of the literature). However, as we will see, in SSA the major problem is not aggregate job creation, but the creation of decent jobs, since considerable parts of the population are engaged in family work or the informal sector. Therefore, we argue that evidence on firm-level can give valuable insights for policy-makers.

Economic theory has not given clear answers to the question if innovative firms create more jobs. The theoretical literature on innovations and employment has identified a variety of effects, some of which are labour expanding and others labour reducing, so that general statements on the overall impact are impossible (see Vivarelli, 2014, or Calvino and Virgillito, 2018, for a comprehensive discussion). For this reason, any policy dedicated to fostering innovations for development and poverty reduction is advised to consider the empirical impacts in the respective market. Despite the vast empirical literature on innovation and employment (the next section will give an overview), the empirical evidence for SSA is scarce, because most existing research is dedicated to industrial countries. Labour markets and innovations in SSA, however, are substantially different from industrial economies: In SSA, typically a large share of labour is bound in subsistence farming, family work or the informal sector (ILO, 2020). As the ILO report of 2020 further puts it, because of the “lack of social protection which forces people to take up any kind of economic activity to survive”, the transition from agriculture mostly takes place into low-skill services, and not in the manufacturing sector where the more decent, high value-added jobs are created (ILO, 2020). Besides, innovations in SSA are usually incremental and imitations (Cirera and Sabetti, 2019; Avenyo et al., 2019), as many firms lag behind the technological frontier (Okumu et al., 2019). They typically lack the technical expertise of firms in industrial countries to operate and adapt to more complicated innovation (Zanello et al., 2016). In light of these fundamental differences, the impact of innovations on job creation in SSA can hardly be assessed with studies from other regions. A policy building on empirical findings requires more pertinent research, most notably, relying on data of firms located in these countries.

In the academic literature, there is a shortage of studies dedicated to innovations and employment in SSA. Among the published articles aspiring to go beyond the single country view, none is placing a distinct focus on SSA. Cirera and Sabetti (2019) study developing countries worldwide and also include firms from SSA (DRC, Ghana, Kenya, Namibia, Nigeria, South Sudan, Sudan, Tanzania, Uganda, and Zambia), Avenyo et al. (2019) cover a restricted number of countries from SSA (DRC, Ghana, Tunisia, Zambia, Uganda) and Okumu et al. (2019) include countries from all over Africa the majority of which are from SSA. Despite their different regional focus, the results of these studies may give some insights to policymakers in SSA and we will discuss them in greater detail in the next section. At this stage, it is worth noting that the cited works all use cross-sectional data. The major contribution of our study to the literature is that – to the best of our knowledge – it is the first to use panel data from SSA. Apart from the general contribution that the exploitation of any new dataset can make to the empirical research, and besides the superior informative value of panel data for analyzing the effects of innovation on firm level’s employment, the major importance of this study is twofold. First, with our panel design, we can avoid some severe general problems inherent in any cross-sectional design and second – to the best of our knowledge – it is the first study to apply the leading approach in the field to SSA, which is Van Reenen’s panel model (Van Reenen, 1997). In the following, we will explain both of these contributions to the literature in more detail.

Cross-sectional data have a severe limitation for estimations on firm-level: Many firm-specifics, such as quality of management, international openness, or incentives can be assumed to be correlated with both, the firm’s employment and innovation, so omitting them produces inconsistent and biased results. However, typically, these control factors are unobservable constructs. So, in the attempt to avoid the bias, proxies are used as covariates whose construct validity often remains obscure, especially considering that they are often calculated from datasets not designed for this purpose. Even more importantly, there are no generally accepted conceptual guidelines on the exact selection of these covariates, so researchers are bound to specify their models with some trial-and-error heuristics at the risk of impairing the comparability of the results across different studies.[1] These problems can be avoided to large extent by using panel data instead

[1] It should be noted that studies following the approach proposed by Harrison et al. (2014), like the one of Cirera & Sabetti (2019) are not subject to this critique.

of cross-sectional data. This is because most of the firm-specifics correlated with innovation and employment can be assumed to be persistent (see Van Reenen, 1997, for a discussion) which allows to treat them as fixed-effects in the econometric specification. Similarly, any (approximately) time-invariant country-specifics, like the quality of institutions, education etc., are wiped out of the model.

Besides the potential to produce consistent and unbiased results, panel data allows us to apply the prevailing approach of the empirical literature on innovations and employment to SSA which is the panel model proposed by Van Reenen (1997). As we will see, Van Reenen's specification is theory-based, parsimonious, and robust to endogeneities. It has been widely tested and successfully applied in Italy (Barbieri et al., 2019 or Piva and Vivarelli, 2005), the UK (Greenhalgh et al., 2001), Germany (Lachenmaier and Rottmann, 2011), or Europe (Van Roy et al., 2018 or Bogliacino and Vivarelli, 2012) among others. Also, the generality of the assumptions (CES production function and profit maximization, see chapter 4 for more details) allow for applications beyond industrialized economies, so, for example, Haile et al. (2019) adopt Van Reenen's model for Ethiopian firms. Overall, with its robustness and its widespread use, we rate Van Reenen's model as the best framework for understanding and measuring the employment effects of innovations in SSA to provide policymakers with sound and reliable guidelines.

The remaining part of this paper is divided into four sections. In the following section, we take a closer look at the literature in the field, before discussing the methodology and specification in light of the available data. Subsequently, we present the panel dataset used for the estimation and show some stylized facts. Afterwards, we present the results together with a robustness analysis. In the final section, conclusions and implications are drawn from the findings and potential limitations are pointed out.

2. Literature review

Innovation is grounded in various activities such as the introduction of new goods, new methods of production, opening new markets and or conquest of new sources of supply. Innovation can broadly be categorized into either product or process innovation. The Oslo-manual guidelines of 2018 define product innovation as "the introduction of new or improved good or service that differs significantly from the firm's previous goods or services and that has been introduced on the market". Likewise, process innovation is defined as "any improvement in production or delivery methods, which can range substantially in their impact on efficiency and employment" (Manual, 2018).

The impact of product and process innovation on labour remains ambiguous and often varies depending on circumstances, market mechanisms and/or institutional rigidities. On the one hand, the so-called expanding effect of product innovation is anticipated to lead to job creation through the emergency of either completely new goods or new variants of existing products (Vivarelli, 2014). In return, this opens up new markets, changes the demand function (by increasing the consumers' willingness to pay), hence raising the labour demand (Vivarelli, 2014). Indeed, the

Keynesian-Schumpeterian mechanisms postulate that the development of entirely new economic branches and products stimulates consumption, leading to higher demand and new jobs (Calvino and Virgillito, 2018). However, there is also a possibility for job destruction as a result of cannibalism when new products substitute old ones (Vivarelli, 2014).

On the other hand, theoretical literature postulates that there exists a direct labour-saving effect of process innovation on employment when output is fixed (Calvino and Virgillito). Nonetheless, there are other indirect ways in which the lost jobs could be compensated for, such as the introduction of new machinery, lower prices, new investments and declining wages. There is an assumption that technological processes that require the introduction of new machinery can lead to job destruction in the downstream industries where innovation is introduced. But, it could as well create jobs in the upstream industries that manufacture the capital goods. Another assumption is that in a perfectly competitive market, new machines are likely to reduce the average cost of production, which could translate into lower prices hence stimulating demand. Consequently, this may call for more production thus creating employment. Further, it is assumed that compensation effects due to new investments could also occur when the extra profits generated by innovative entrepreneurs are reinvested, thus creating jobs due to new productions. For a detailed discussion of these assumptions, see Vivarelli (2014), and Calvino and Virgillito (2018). Although the assumption above could hold for some situations, their applicability in the SSA setting is still questionable. We note that countries in SSA are largely importing economies, and as such may not necessarily gain from the upstream job-creation impact of new machinery. If the imported new machinery replaces obsolete machinery, there may not be any compensation at all. Also, the assumption of perfect competition could be unrealistic in the SSA setting, given the erratic inflationary tendencies, high interest rates, demand rigidities and unstable political environments. Consequently, it is doubtful that lower production costs automatically translate into falling prices or increasing demand.

The theoretical review suggests that the overall effects of innovation on employment on the firm level cannot be predicted, hence empirical analysis is required (Vivarelli, 2014 and Calvino and Virgillito, 2018). Extant empirical literature demonstrates that product innovations have a positive impact on employment growth particularly in the developed world (Van Roy et al., 2018; Harrison et al., 2014; Benavente and Lauterbach, 2008) and Latin America (Aboal et al., 2015). Interestingly, this seems to be the conclusion even among the few published African studies, like Avenyo, et al. (2019) or Okumu et al. (2019). The findings of Avenyo et al. (2019) suggest that there are expanding effects of product innovations on both permanent and temporary employment. The authors assert that this particular finding could be due to the rising middle-class citizens in SSA who often crave new products. Cirera and Sabetti (2019) who study developing countries find that in Africa, the labour expanding effect of product innovation is by far higher than in any other region of the world. They explain this result by the fact that in Africa many firms produce far from the technological frontier so that new or upgraded products typically lead to higher market shares without increasing (labour-saving) efficiency to the same extent as in other regions.

The empirical literature on the relationship between process innovation and employment growth remains mixed and unsettled. Scholars like Harrison et al. (2014) and Lachenmaier and Rottmann, (2011) show a positive association between employment growth and process innovation. Lachenmaier and Rottmann (2011) using a panel dataset of German manufacturing firms found that process innovation has a higher impact on employment growth than product innovation. Likewise, Meriküll (2010), who studied the impact of innovation on employment in Estonia, find a positive and statistically significant association between a process innovation and employment growth at the firm level, but this association becomes weaker at the industry level. However, Evangelista and Vezzani (2012) study the impact of technological and organizational innovations on employment among European firms and provide a separate argument of an inverse relationship between a process innovation and employment. The authors show that employment growth is only positively associated with innovation among firms that combine process, organizational and product innovations. Relatedly, Aboal et al. (2015) argue that employment growth is negatively associated with process innovation among unskilled labour workers while the relationship among skilled workers remains neutral. Further still, a few studies in the African context (Cirera and Sabetti, 2019; Okumu et al., 2019; Gyeke-Dako et al., 2016 for Ghana) show blurry conclusions on process innovation and employment. Cirera and Sabetti (2019) cannot detect any significant effect of process innovation in developing countries, like Gyeke-Dako et al. (2016) in Ghana. The latter authors deduce that process innovation increases the employment probability only among non-skilled labour force whereas it causes a dampening effect for skilled labour force. Okumu et al. (2019), on the other hand, conclude that process innovation is positively associated with employment growth.

The comparison of the results between different studies is hindered by the variety of approaches that authors use. Notwithstanding there are two homogenous strands in the empirical literature: The first are studies that using panel data focus on the overall effect of (product and/or process) innovation on employment, for example, Barbieri et al. (2019), Van Roy et al. (2018), Bogliacino and Vivarelli (2012), Lachenmaier and Rottmann (2011), Meriküll (2010), Piva and Vivarelli (2005), or Greenhalgh et al., (2001). These works apply the model proposed by Van Reenen (1997). The other strand is mainly dedicated to the decomposition of the effects of product and process innovation in a cross-sectional setting building on the approach proposed by Harrison et al. (2014), examples are Crespi et al. (2019), Aboal et al. (2015) or Benavente and Lauterbach (2008). Albeit being recognized as particularly suited for its purpose to disentangle product and process innovation impacts, the method requires data on sales attributed to newly introduced products which are not available for most countries in SSA[2]. For the subsample of countries in SSA for which this kind of data is available, the empirical strategy of Harrison et al. (2014) has been used in the paper of Cirera and Sabetti (2019) together with other developing countries. Van Reenen's approach, on the other hand, so far has not yet been applied to SSA. It is this gap in the literature that the present study is filling.

[2] One source are the World bank's follow-up surveys on innovation to the enterprise survey.

3. Methodology and specification

Data availability is one of the challenges when studying the firm-level effect of innovation on employment, especially for SSA as a region, because single-country studies or regional studies covering industrialized countries generally can access richer databases with more observations. The only data source for firm-level data including standardized data on innovation and employment for a substantial number of SSA countries is the World Bank's Enterprise Survey.

The Enterprise Survey covers 144 countries worldwide with a focus on emerging and developing economies. The first surveys published by the World Bank date back to the year 2002, but it was only since 2005/06 that its methodology has been harmonized. The surveys are designed to support policymakers in reforming their institutions and provide data for research on topics, such as firm performance, finance, infrastructure, job creation, or potential obstacles for firms' development like crime, corruption or gender gap. Although job creation and innovation are not the major focus of the questionnaire, key information is available for most years, particularly the firm's number of employees and indicator variables for process and product innovation activities. In many countries, surveys are repeated after some years and attempts are made to re-interview the firms from the prior surveys. Combining the repeated observations on the same firm, panel datasets are created, most of which cover two or three years, but for some countries four, five or even six years are available. As a matter of fact, due to a generally high level of attrition (increasing with the number of years included), the panel datasets contain much less firms than the individual surveys. Also, in 2009/2010 questionnaires did not include information on innovation, so that for most SSA countries the panel data only cover two years. Besides this, as there is no unique time frame for repeating surveys, the spaces between the years in the panel datasets differ across countries ranging from 3 up to 9 years with an average of 5.8 years in SSA.

Apart from the panel data, the World Bank provides a harmonized cross-sectional dataset from the Enterprise Survey which is pooled over years and countries containing by far more firms than the panel data sets. These data are used by Okumu et al. (2019) for analysing innovation and employment in SSA. As discussed in the introduction, the problem with cross-sectional data, however, is the omitted variable bias resulting from firm-specific unobservable, like management quality, degree of interconnectedness or reputation. Some authors try to incorporate such factors, mostly through proxies. For example, Okumu et al. (2019) include variables like labour productivity, size categories, the manager's years of experience and ownership dummies, as covariates in their estimation equation whereas Avenyo et al. (2019) opt for the firm's age (in levels as well as squared) or a city dummy beside the years of experience and size categories. These examples shall illustrate that the selection of the factors and/or the proxy is arbitrary so that it remains obscure whether the estimation results are unbiased. As we argue, this problem cannot be resolved with cross-sectional data, but only with panel data where the fixed-effects estimator is capable of ruling out all (approximately) time-invariant firm-specifics. It is for this reason that in our study, we focus on the panel datasets offered by the World Bank albeit the loss of observations compared to the pooled cross-section.

Van Reenen's (1997) leading approach for analysing innovation and employment with the panel can be explained as follows: Assuming profit maximization and a CES production function

$$Y = T\left((AL)^{\frac{\sigma-1}{\sigma}} + (BK)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma-1}{\sigma}}$$

with Y as output, L and K as the input factors labour and capital, T, A and B as technology parameters (T = Hicks-neutral, A = Harrod-neutral and B = Solow-neutral, i.e. changes in T will not change the capital-labour ratio, changes in A will not change the capital-output ratio and changes in B will leave the labour-output ratio unchanged) and σ as the (constant) elasticity of substitution, the marginal product of labour

$$\frac{\partial Y}{\partial L} = A^{\frac{\sigma-1}{\sigma}} Y^{\frac{1}{\sigma}} L^{-\frac{1}{\sigma}}$$

can be set equal to the real wage W/P. After solving for L and taking the logarithm, the labour demand function is

$$\ln(L) = -\sigma \ln\left(\frac{W}{P}\right) + (\sigma - 1)\ln(A) + \ln(Y) \tag{1}$$

which is the basic equation of the approach proposed by Van Reenen (1997). Additionally, Van Reenen discusses two alternative versions of equation (1): Output (or $\ln(Y)$) can either be substituted by (the log of) capital and capital costs, or – since in the long run capital can be adjusted – by input and output prices.

Equation (1) illustrates that two effects are at work when considering the impact of changing labour productivity, $\ln(A)$, on labour demand, $\ln(L)$: The direct effect or substitution effect which is $(\sigma - 1)$ and the indirect effect or compensation effect which is $\partial\ln(Y)/\partial\ln(A)$. The direct effect stands for the labour demand changes independent of output changes; an increase of $\ln(A)$ is expected to make labour more productive whereas capital productivity should remain constant. The effect on labour demand depends on the elasticity of substitution (given the factor prices): when firms cannot easily replace capital by labour (ie σ is low), the direct effect is negative because firms will reduce their workforce. For high values of σ, on the other hand, firms will replace capital with labour, thus demanding more workforce. The indirect effect is the increase of the workforce resulting from an expansion of production induced by innovation. If companies pass the reduction in marginal costs created by the higher labour productivity, MC, to prices, demand will increase. The size of the indirect effect depends on the price elasticity of demand $\partial\ln(Y)/\partial P$, the market form (under perfect competition prices are assumed to be aligned to marginal costs) and the impact of the innovation on marginal costs $\partial MC/\partial\ln(A)$ (see Van Reenen 1997):

$$\frac{\partial\ln(Y)}{\partial\ln(A)} = \frac{\partial\ln(Y)}{\partial P}\frac{\partial MC}{\partial\ln(A)}$$

The indirect effect is non-negative, but since the sign of the direct effect is determined by theory, the same is true for the overall effect of innovation on labour demand. The direction and the magnitude of the impact of innovation on labour, therefore, have to be assessed on empirical grounds.

For estimating the labour demand, equation (1) can be transformed into a stochastic version:

$$\ln(L_{it}) = \beta_1 \ln(A_{it}) + \beta_2 \ln(Y_{it}) + \beta_3 \ln\left(\frac{W_{it}}{P_{it}}\right) + \mu_i + \nu_{it}$$

Here *i* denotes the index for the firm, *t* is the index for the time, i for the firm, μ_i is the firm-specific fixed effect and ν_{it} the iid residual. Discriminating between some metric for product innovation, $iprod_{it}$, and process innovation, $iproc_{it}$, and replacing natural logarithm with small letters the equation can be written as

$$l_{\mathrm{it}} = \beta_1 iprod_{it} + \beta_2 iproc_{it} + \beta_3 y_{it} + \beta_4 w_{it} + \mu_i + \nu_{it} \qquad (2)$$

with l_{it} as the natural logarithm of L_{it}, y_{it} is the natural logarithm of Y_{it} and w_{it} is the natural logarithm of the real wage W_{it}/P_{it}.

To find the most appropriate measures when applying (2) to SSA, we review some studies using Van Reenen's approach. The authors of these studies – listed in table 1 - unanimously measure L_{it} as the number of permanent full-time employees of the firm, and wages W_{it} as the total expenditures for wages divided by the total number of employees. With both of these pieces of information included in the Enterprise Survey, we use the same metrics. Like the other authors, we use some standard price index – the country-specific annual CPI collected by IMF – to deflate wages, because prices on firm-level are not available. For the remaining variables of equation (2), we encounter substantial differences concerning their measurement. Particularly, there is a great variety of how innovation and output are measured and if capital and/or additional covariates are included. These differences that are highlighted by the columns of table 1 will be discussed in the following.

As can be seen from the table, innovation was either measured as innovation input (R&D expenditures, innovative expenditure) or output (patents, counts or indicator variables for innovation activities). R&D expenditures and patents are incomplete measures for innovation in developing countries because as Vivarelli (2014) points out, firms only have limited capacities to invest in R&D and most innovations are incremental and not patented. According to Vivarelli (2014), more appropriate measures in developing countries are innovative expenditures, because innovations typically are imported and come through investments in new machinery or "embodied technological change". However, such measures are more correlated to process innovation rather than product innovation (which on the other hand is highly associated with R&D, see Barbieri et al., 2019 and Vivarelli, 2014 for a discussion). So, with our goal to discriminate between these types of innovations, we will measure $iprod_{it}$ and $iproc_{it}$ as innovation output, particularly, we will include indicator variables for innovation activities. In most years, the Enterprise Survey contains information on whether the firm has introduced any product or any process innovation during the previous 3 years. Since product innovation typically involves some degree of process innovation (see Harrison et al., 2014), to disentangle the effects, we create a variable measuring product and/or process innovation and a separate dummy variable for process innovation only.

Table 1: Empirical studies using Van Reenen's (1997) approach, overview of differences in specifying equation (2)

Authors	**Database**	**Measurement of innovation**	**Measurement of output**	**Treatment of capital**	**Additional controls**
Barbieri,Piva, Vivarelli (2019)	265 Italian firms between 1998 and 2010	R&D expenditures, total innovative expenditures and embodied technological change	value-added	excluded	
Bogliacino, Vivarelli (2012)	European industries between 1996 and 2005	sector-specific R&D expenditures	sector-specific value-added	sector-specific investment or capital stock (as the sum of investments)	L_{it-1}
Bogliacino, Piva, Vivarelli (2012)	677 European firms between 1990 and 2008	R&D expenditures	sales	gross investment	L_{it-1}
Greenhalgh, Longland, Bosworth (2001)	500 firms from the UK between 1987 and 1994	R&D expenditures	sales	excluded	sector-specific factor costs (capital, materials and energy)
Haile, Srour, Vivarelli (2019)	1940 Ethiopian firms between 1996 and 2004	imported technology and globalization (share of foreign ownership in a firm, export to output ratio)	output (no further information)	share of investment out of the total output	L_{it-1} location (Addis or outside Addis)
Lachenmaier, Rottmann (2011)	690 German firms between 1982 and 2002	indicator variables (process innovation, product innovation, R&D or patents during last year), 0-2 lags	industry-level gross value added (a proxy for demand in the industry) or industry dummies	excluded	L_{it-1}, L_{it-2}
Meriküll (2010)	1122 Estonian firms between 1998/2000 and 2002/2004	indicator variable for innovation during the last 3 years	excluded	capital (tangible and intangible fixed assets minus goodwill)	L_{it-1}, L_{it-2}
Piva, Vivarelli (2005)	575 Italian firms between 1992 and 1997	gross innovative investment, 0-1 lags	sales	excluded	L_{it-1}
Van Reenen (1997)	598 firms from the UK between 1976 and 1982	number of innovations, 0-6 lags	excluded	capital (sum of costs of deflated past assets)	L_{it-1}, L_{it-2}, number of industry innovations
Van Roy, Vértesy, Vivarelli (2018)	20,000 European firms between 2003 and 2012	patents (weighted with forward-citations), 3 lags	gross value added	gross investment (growth in fixed assets)	L_{it-1}

Note: All authors deflated their variables measured in currencies using standard price indices. Most studies include dummy variables for years.

From table 1 it can be noted that Y_{it} is typically proxied by sales or value-added. As pointed out above, output in equation (1) can be replaced by the capital stock, but from the studies presented in table 1, only Van Reenen (1997) and Meriküll (2010) follow this approach, probably, because the capital stock is difficult to obtain from most datasets. The Enterprise Survey does not contain enough information to proxy capital, so in our specification, we will focus on output instead. Also, from table 1, some authors (e.g., Bogliacino et al 2012) include investments, which are easier to observe than the capital stock, together with output. We will not follow this line, mainly for the reason that it is not justified from Van Reenen's conceptual model (equation 1), but also because, as we have seen earlier, in developing countries process innovations typically come through investments, so controlling for investments is not desirable when interpreting the coefficient of (process) innovation dummies. Our proxy for output is the companies' total sales during the last fiscal year because unlike value-added, this figure is given in the Enterprise Survey. Particularly, our measure for y_{it} is the natural logarithm of sales deflated with the country's CPI. Unfortunately, replacing output by sales introduces a measurement error in (2), because changes in sales can be due to changes in prices rather than in output. However, we do not expect prices to be considerably correlated with the other explanatory variables (innovation and the real wage), so the measurement error is not assumed to introduce a high degree of endogeneity in (2).

Finally, table 1 demonstrates that many authors use lagged employment as an additional covariate. Market regulations and other rigidities lead to high costs of adjustment in labour markets (Van Reenen 1997) so the current labour demand is expected to be correlated with the previous year's demand. The panel dataset used in this study, however, only contains two waves with a period of around 6 years between them on average, in contrast to the annual frequency and multiple periods of the dynamic models reported in table 1. It can be expected that for such a long lag, correlations are small and thus neglectable. For this reason, it is not necessary to include dynamics in our estimation.

With all these considerations, our model given in (2) equals the specification used by Barbieri et al. (2019) with the only difference that we use dummy variables for innovation instead of R&D expenditures, total innovative expenditures or embodied technological change. Table 2 summarizes how the variables of equation (2) are measured in this paper.

Table 2: Definition and measurement of variables of equation (2)

l_{it}	ln(employment)	employment = number of permanent full-time employees of the firm at the end of the last fiscal year
$iprod_{it}$	product innovation	1 if any product innovation during the previous 3 years, 0 otherwise
$iproc_{it}$	process innovation	1 if any process innovation (but no product innovation) during the previous 3 years, 0 otherwise
y_{it}	ln(real sales)	real sales =companies' total sales during the last fiscal year deflated with country-specific annual CPI
rw_{it}	ln(real wage)	real wage = total expenditures for wages divided by the total number of employees deflated with country-specific annual CPI

Like Barbieri et al. (2019), we assume μ_i in equation (2) as deterministic and apply the fixed effects estimator including time dummies. Since our dataset contains two periods only, the fixed effects estimator is equivalent to the OLS estimator applied to (2) in differences:

$$\Delta l_{\mathrm{it}} = \beta_1 \Delta iprod_{it} + \beta_2 \Delta iproc_{it} + \beta_3 \Delta y_{it} + \beta_4 \Delta w_{it} + \Delta v_{it} \qquad (3)$$

Note that by taking differences the fixed effect μ_i is wiped out, so (3) is not subject to endogeneities arising from the omission of time-invariant characteristics firm, country or industry effects. This powerful advantage of the fixed effects estimator justifies the parsimony of (2), but it comes at the cost of a loss of efficiency, particularly for the coefficients of variables with small temporal variation. If firms, for example, either innovate persistently or do not innovate persistently, the impact of innovation on employment cannot be determined (3). Since in (3) the levels of the variables are eliminated, the focus is on the impulses that any change of innovative behaviour has on the employment growth.

There are several reasons why innovations in (2) or (3) can be assumed to be predetermined. First, the innovation dummies in equation (2) refer to the past 3 years (ie they take the value of 1 if the company innovated during any of the 3 years before the survey), whereas l_{it} is the labour in the previous year only, so by construction, our innovation dummies are longer termed than the labour demand. Besides this, it can be assumed that innovation decisions are taken long before the innovation activities (see Lachenmeier and Rottmann, 2001) and not simultaneous to labour decisions. Decisions to employ labour to innovate in the future (for example to build up R&D) are assumed to be of minor importance in SSA.

4. Data and Descriptive Statistics

The data were taken from the website of the Enterprise Survey (www.enterprisesurveys.org). Most of the panel data especially from SSA include two years only, so in the cases where more years were available (Benin, Cameroon, Democratic Republic of Congo, Kenya, Mali, Niger, Rwanda, Zimbabwe) we created subsets of panel data covering the two subsequent periods. Table 3 gives an overview of the countries from SSA where panel data is available, as well as the years of both surveys and the number of firms (N) included.

As can be seen from table 3, for 2,294 firms from SSA panel data are available and 1,798 of these firms come with the entire information required to estimate equation (2) in one of the years t =1, 2. However, when estimating 2, information has to be complete in both surveys, and the number of firms meeting this requirement further reduces to 687. The major reason for this extensive loss is that in the years 2009 and 2010, the Enterprise Surveys did not include questions on innovation, so whenever a survey took place in one of these years, there is no data available for calculating the differences of the innovation dummies and the complete country drops out. As a consequence, many countries of SSA are no longer included when estimating equation (3). We will run some robustness checks to evaluate if the results for the remaining countries are representative of the countries that dropped out.

Table 3: Countries in SSA, years of surveys and number of firms included in the panel data of the Enterprise Survey

Country	Year of survey 1	Year of survey 2	N total*	N eq. (2)**	N eq. (3)***
Angola	2006	2010	121	82	0
Benin	2004	2009	62	22	0
Benin	2009	2016	39	36	0
Botswana	2006	2010	52	49	0
Cameroon	2006	2009	42	41	0
Cameroon	2009	2016	40	32	0
Chad	2009	2018	35	33	0
Côte d'Ivoire	2009	2016	48	28	0
Dem. Rep. Congo	2006	2010	58	54	0
Dem. Rep. Congo	2010	2013	34	27	0
Ethiopia	2011	2015	171	167	123
Ghana	2007	2013	21	11	0
Kenya	2007	2013	95	93	66
Kenya	2013	2018	136	132	91
Lesotho	2009	2016	31	25	0
Liberia	2009	2017	48	48	0
Malawi	2009	2014	44	29	0
Mali	2003	2007	69	40	0
Mali	2010	2016	53	39	0
Niger	2005	2009	39	0	0
Niger	2009	2017	19	11	0
Nigeria	2007	2014	321	166	91
Rwanda	2006	2011	33	24	0
Rwanda	2011	2019	31	31	25
Senegal	2007	2014	133	86	0
Sierra Leone	2009	2017	35	35	0
Tanzania	2006	2013	83	82	74
Togo	2009	2016	18	15	0
Uganda	2006	2013	125	123	56
Zimbabwe	2007	2013	91	70	0
Zimbabwe	2011	2016	167	167	161
		sum	2294	1798	687

* N total=Number of firms included in both surveys, ** N eq. (2) = number of firms included in both surveys containing all information for estimating equation (2), *** N eq. (3) = number of firms included in both surveys containing all information for estimating equation (3)

When comparing year 1 and year 2 from the surveys in table 3, the irregularities of the panel structure mentioned in the last section becomes evident. These irregularities can induce two problems for the estimation of (2): First, surveys are from different years, so unobserved time-effects like trends or macroeconomic shocks can bias results. To address this problem, dummy variables for each year of the survey will be included in the estimation. Second, due to the varying spaces between the years of both surveys, the period for calculating differences in equation (3) is not constant, leading to heteroskedastic residuals. As a remedy, we divide all variables in equation (2) by the period (ie number of years) between the surveys. Note that the difference of the weighted variable (in logarithm, as in equation (3)) can be taken as proxies for the relative average annual change.

To compare our results with other regions of the world, our dataset also contains the (two-years) panel data for countries outside of SSA which are available on the World bank's webpage. The number of firms for each of these countries are listed in table 8 of the appendix.

In table 4, firms are classified according to whether they were innovative in the first survey and/ or in the second survey. Interestingly, with around 80%, the majority of the firms located in SSA report some product innovation at least in one of both periods. This value is remarkably high when compared to the other countries included in the sample ("out of SSA": 68%) or to process innovation unaccompanied by product innovation (21% both in SSA or out of SSA). Around 36% of the firms from SSA introduced product innovations in both periods, whereas for only 1% the same is true for process innovation. As discussed in the previous section, the fixed effects estimation places its focus on firms changing their innovative behaviour. However, from table 4, we can see that the majority of firms were either innovators or non-innovators in both periods (for product innovation 56% in SSA and 64% out of SSA; for process innovation around 80%). Therefore, with the elimination of the levels, the fixed effects estimator might suffer from a substantial loss of information in addition to the above-mentioned attrition.

Table 4: Frequency distribution of innovative activities

		% of firms		% of firms	
Survey 1*	Survey 2*	in SSA	out of SSA	in SSA	out of SSA
		Product innovation		Process innovation only	
Innovation	no innovation	25.04%	19.83%	10.19%	10.98%
no innovation	no innovation	20.09%	32.38%	79.18%	78.94%
Innovation	innovation	36.39%	32.01%	1.31%	2.32%
no innovation	innovation	18.49%	15.78%	9.32%	7.76%
	Sum	100.00% (687 firms)	100.00% (2668 firms)	100.00% (687 firms)	100.00% (2668 firms)

*Innovation during the last 3 years before survey 1 or survey 2

Finally, table 5 reports how much on average employment as well as the covariates real sales and real wage have changed for the different categories of innovative activities. From the first column of table 5, it becomes evident that product innovations are associated with positive impacts on employment: Average growth rates of employment are found to be negative for non-innovators and positive for innovators. At the same time, the minimum average growth rate is for firms that changed their status from innovators to non-innovators, whereas the maximum is for firms that were innovators in period 2, but not in period 1. Notably, these differences in growth rates are more pronounced for firms in SSA and this result might be taken as evidence that in these countries product innovations have higher employment effects than in other developing or emerging economies. Albeit for process innovation (column 4 of table 5), we do not find similarly clear patterns, average growth rates are still lower for firms that switched their status from innovators to non-innovators than for firms that became innovators in period 2, indicating that process innovation also might have positive impacts on employment.

Table 5: Growth rates of employment*, real sales and real wage; averages for different innovative activities

		Average annual change of					
		Product innovation			Process innovation only		
Survey 1	Survey 2	ln(employ-ment)	ln(real sales)	ln(real wage)	ln(employ-ment)	ln(real sales)	ln(real wage)
		Firm in SSA					
Innovation	no innovation	-0.0411	-0.1032	0.0109	-0.0460	-0.0869	0.0111
no innovation	no innovation	-0.0286	-0.0592	0.0390	0.0028	-0.0573	0.0205
Innovation	innovation	0.0181	-0.0626	0.0250	-0.0656	-0.1346	0.0492
no innovation	innovation	0.0302	0.0041	0.0132	-0.0054	-0.0402	0.0442
		Firm out of SSA					
Innovation	no innovation	-0.0141	-0.0359	0.0761	0.0049	-0.0305	0.0578
no innovation	no innovation	-0.0002	0.0190	0.0721	0.0020	0.0008	0.0518
Innovation	innovation	0.0145	0.0123	0.0398	0.0928	0.0818	0.1454
no innovation	innovation	0.0209	-0.0213	0.0285	0.0104	0.0055	0.0650

* Growth rates are proxied by the average differences of the natural log of the variable divided by the number of years between surveys.

The remaining columns of table 5 report the average growth rates of the covariates of equation (2). For almost all innovation profiles, the growth of (real) sales and wage in SSA is much lower than out of SSA. Particularly the pattern found for sales in SSA illustrates the difficulty of interpreting table 5 in terms of causalities: Higher growth rates of sales are associated with higher growth rates of employment and at the same time, as a tendency, both growth rates were higher when the impulse from innovation was higher. The results from the multivariate estimation of equation (2) presented in the next section are expected to disentangle these effects.

5. Results

The results from estimating equation (2) for SSA with the fixed effects estimator are presented in the first column of table 6. With an R^2 of 31%, all coefficients significant, and the covariates' (sales and wage) coefficients showing the expected signs, Van Reenen's approach seems an adequate framework for firms in SSA. Most interestingly, the coefficients of the dummies for product and process innovation are both positive and highly significant, so the estimation strongly confirms the labour expanding effects of both types of innovations. Furthermore, in SSA the coefficients of the innovation dummies are much higher than in the regression for the other countries (see column (2) of table 6): There the coefficient of product innovation is around 0.086 (versus 0.196 in SSA), whereas the coefficient of process innovation is insignificant (versus 0.174 in SSA). From this comparison, it seems that in SSA the firm-level labour expanding effect of innovations is particularly strong, compared to other parts of the (non-industrialized) world. Yet, when taking into account that innovations are measured as indicator variables (taking the value 1 when some innovation was introduced), the higher coefficients could also be the outcome of a higher number or a different type of innovation prevailing in SSA. Anyway, the considerable differences of the coefficients reveal that in the years under consideration, innovations in SSA played a fundamental role for job creation within the firms that innovated.

Table 6: Fixed effects panel estimation of equation (2), dependent variable: ln(employment)

Variable	SSA (1)	Out of SSA (2)
product innovation	0.1961***	0.0863***
	(0.0299)	(0.0191)
process innovation	0.1742***	0.0396
	(0.0444)	(0.0328)
ln(real sales)	0.2462***	0.1990***
	(0.0625)	(0.0138)
ln(real wage)	-0.1528*	-0.1669***
	(0.0675)	(0.0188)
R^2	0.3109	0.1890
Number of firms	687	2668
Number of obs.	2484	7485

Robust standard errors in parentheses. All regressions include time dummies and all other variables are divided by the number of years between surveys. *Coefficient is statistically significant at the 5 per cent level; ** at the 1 per cent level; *** at the 0.1 per cent level

Despite the high number of observations reported in column (1) of table 6 (N=2484), the estimation is based on 687 firms only. As explained above, with panels of two periods, the fixed effects estimation is equivalent to OLS in differences, and since between 2009 and 2010 surveys lack information on innovation, entire countries drop out of the estimation casting doubts on the representativeness of our findings for SSA. Besides, eliminating the levels of the variables might come with an additional loss of information, because as we have seen in table 5, the majority of the firms did not change the status of the innovation dummies. For these reasons, in the following, we will analyse if our conclusions are robust to this loss of information, particularly, if the fixed effects estimations suffer from a sample selection bias.

For this purpose, we estimate equation (2) with a random-effects model augmented by country dummies and a proxy for the firm size. The random-effects estimator is not subject to the suspected sample selection bias, because it also makes use of the information contained in the levels of the variables without the requirement of complete information in both periods. However, unlike the fixed effects estimator, it might be affected by a bias resulting from omitting firm-specific time-invariant variables. To get more insights into the presence of such biases, we estimate the random effects model with the sample used for the fixed effects estimation and with the full sample. Since we are interested in the overall effect of innovation on employment, in these estimations product and process innovations are combined.[3]

[3] For this reason and because the random effects model contains the firm size, the exact number of firms slightly differs from table 6. The dummy variable for the combined measure for innovation takes the value 1, if the firm has reported either product or process innovation. The combination is justified by (i) the intention to get a clearer view on the types of bias in light of the fact that a comparatively low number of firms reported process innovations alone (see table 4) and by (ii) the similarity of the magnitude of both single coefficients for SSA (see table 6). Robustness tests for separate measures of product and process innovation would not alter the conclusions of this paper.

The first three columns of table 7 are dedicated to SSA. Since the samples for the estimation of the random effects of column (2) and the fixed effects estimation of column (1) are the same, any structural difference between the coefficients is due to an omitted variable bias of the random-effects model. Overall, with a p-value of 1.55%, for a 1% level, the Hausman test cannot reject the null hypothesis of a structural difference between the models, but when comparing individual coefficients, strikingly, the largest difference is for the coefficient of innovation, which is considerably lower in the random-effects model (0.202 vs 0.147). In case this difference was not random, the coefficient of innovation would be biased downwardly in the random-effects model. On the other hand, non-random differences between column (2) and column (3) (random-effects model estimated in the full sample), can be attributed to a sample selection bias. Here, for innovation, however, the difference is in the same direction, but only of moderate size (0.147 vs 0.121). If this difference was due to a sample selection bias, this bias can be assumed to be smaller than the potential omitted variable bias arising from switching from the fixed effects model to a random-effects model. Estimating the impact of innovation on employment with the fixed effects model therefore seems to be the most appropriate framework. Finally, all coefficients of innovation are by far much larger in SSA (0.202, 0146, 0.121) than out of SSA (0.057, 0.070, 0.064, see columns (4), (5) and (6) of table 7). So, our main finding of a particularly high labour expanding impact of innovation in SSA as compared to other developing or emerging countries in the world remains unaffected by the sample selection.

Table 7: Robustness analysis, dependent variable: ln(employment)

	SSA			Out of SSA		
	Fixed effects	Random eff., sample as in (1)	Random eff., full sample	Fixed effects	Random eff., sample as in (4)	Random eff., full sample
	(1)	(2)	(3)	(4)	(5)	(6)
innovation	0.2020***	0.1456**	0.1214***	0.0568**	0.0702**	0.0638*
	(0.0335)	(0.0473)	(0.0335)	(0.0174)	(0.0253)	(0.0265)
ln(real sales)	0.2476**	0.2680***	0.2962***	0.2077***	0.2562***	0.2920***
	(0.0659)	(0.0246)	(0.0184)	(0.0186)	(0.0180)	(0.0158)
ln(real wage)	-0.1612	-0.1279***	-0.1596***	-0.1746***	-0.1700***	-0.1844***
	(0.0711)	(0.0204)	(0.0175)	(0.0337)	(0.0174)	(0.0160)
ln(size)		0.5738***	0.5118***		0.6700***	0.6104***
		(0.0345)	(0.0261)		(0.0219)	(0.0201)
Hausman test		p-value = 0.0155	p-value = 0.0645		p-value = 0.0000	p-value = 0.0000
N. of firms	670	670	1623	2615	2615	4532
N. of observ.	1340	1340	2302	5230	5230	7138

Robust standard errors in parentheses. All regressions include time dummies and all other variables are divided by the number of years between surveys. Random effects estimations include country dummies. ln(size) is the natural logarithm of the number of employees three years before the first survey. innovation = 1 if the firm has engaged in product or process innovation, 0 otherwise. *Coefficient is statistically significant at the 5 per cent level; ** at the 1 per cent level; *** at the 0.1 per cent level

6. Conclusions and implications

This study is dedicated to the problem of how countries in SSA can create decent jobs needed for development. Particularly, we focus on the potential of innovations in creating permanent full-time jobs in registered companies within the manufacturing sector. Such potential can solely be assessed with the help of empirical studies because, from theory, size and the sign of the net impact of innovation on employment are undetermined even on the firm-level. Considering the numerous governmental and institutional activities aimed to foster innovation as the motor for employment in SSA, the empirical evidence of its effects in this region seems highly disproportional. The large body of existing empirical literature mostly focusses on industrialized countries. The evidence from industrialized countries can hardly be transferred to SSA, because, as we have seen, in this region labour markets and innovations exhibit particular features.

The most notable empirical research relevant for SSA is Cirera and Sabetti 's (2019) study because albeit covering developing countries all over the world, it reports some separate results for Africa. Cirera and Sabetti's work stands out among the published work on Africa (see chapter 2) by building on a well-established empirical framework, namely the approach developed by Harrison et al. (2014). However, the leading approach in the empirical literature on innovation and employment, Van Reenen's (1997) panel model, has not yet been applied to SSA. Our study is filling this gap in the literature.

Our main results are twofold: First, we find that innovative firms have created far more jobs than non-innovative firms when controlling for sales, wages as well as time-invariant firm and country specifics. Second, we find that this effect is considerably larger in SSA than in the other developing or emerging economies of our sample. Most interestingly, our results strongly confirm Cirera and Sabetti's (2019) finding that in Africa there is a positive employment effect of innovations, which is particularly high compared to other regions. The congruence of the results of both studies is noteworthy in light of their fundamental differences between conceptual approaches and samples.

The evidence of our research suggests that SSA is a region where the innovative companies' potential of creating new jobs is particularly high thus corroborating the benefits of any innovation-friendly policy. However, as already pointed out in the introduction, some caution has to be risen when drawing conclusions from firm-level data on aggregate employment: The aggregate increase of employment might be lower than the sum of jobs created by innovative firms, especially when innovative companies hire away employees from non-innovative firms. With the (firm-level) Enterprise Survey used in this study, it is impossible to estimate the extent of this mitigating effect, nonetheless, we do not assume it to be high. Considering that on the one hand, in the survey, roughly 85% of the firms from SSA declared not to face any major or severe obstacle in finding an adequately educated workforce[4] and that on the other hand, labour markets in SSA are characterized by the

[4] In the survey, companies were asked to what degree inadequately educated workforce is an obstacle to the current operations. For 39% of the firms in SSA the obstacle was non-existent, for 29% it was minor, for 18% it was moderate, whereas 11% of the firms in SSA rated it as major and 4% as very severe.

imbalance of a high number of (young and informally employed) workforce and a limited number of permanent jobs in the formal economy, it is likely that the jobs created by innovative companies significantly increase aggregate formal employment.

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APPENDIX:

Table 8: Non-SSA countries, years of surveys and number of firms included in the panel data of the Enterprise Survey

Country	Year of survey 1	Year of survey 2	N total*	N eq. (2)**	N eq. (3)***
Albania	2013	2019	41	41	37
Argentina	2006	2010	380	0	0
Argentina	2010	2017	223	0	0
Azerbaijan	2013	2019	25	20	7
Bangladesh	2011	2013	117	116	55
Belarus	2013	2018	58	55	34
Bolivia	2006	2010	96	51	20
Bolivia	2010	2017	68	56	20
Bosnia a. Herzegovina	2013	2019	52	48	31
Bulgaria	2013	2019	35	34	23
Cambodia	2013	2016	46	42	0
Chile	2006	2010	322	216	66
Colombia	2006	2010	209	202	152
Colombia	2010	2017	221	215	173
Croatia	2013	2019	29	29	23
Czech Republic	2013	2019	27	26	17
Dominican Republic	2010	2016	27	13	2
Ecuador	2003	2006	181	142	2
Ecuador	2006	2010	68	58	0
Ecuador	2010	2017	23	22	12
Egypt	2013	2016	321	0	0
Egypt	2016	2020	639	0	0
El Salvador	2006	2010	17	5	2
El Salvador	2010	2016	84	74	44
Estonia	2013	2019	21	19	16
Georgia	2013	2019	32	28	19
Guatemala	2003	2006	226	138	0
Guatemala	2006	2010	57	29	7
Guatemala	2003	2010	114	114	88
Guatemala	2010	2017	90	76	49
Honduras	2006	2010	30	9	3
Honduras	2010	2016	39	36	19
Hungary	2013	2019	28	24	10
Jordan	2013	2019	109	101	52
Kazakhstan	2013	2019	48	40	16
Kosovo	2013	2019	44	36	18
Kyrgyz Republic	2013	2019	56	52	32
Lao	2012	2016	37	37	33
Lao	2016	2018	35	35	31
Latvia	2013	2019	28	27	7
Lebanon	2013	2019	114	113	93

Table 8 (continued)

Country	Year of survey 1	Year of survey 2	N total*	N eq. (2)**	N eq. (3)***
Lithuania	2013	2019	32	29	12
Mexico	2006	2010	155	90	25
Moldova	2013	2019	49	47	35
Mongolia	2013	2019	55	55	44
Morocco	2013	2019	52	52	27
Myanmar	2014	2016	154	153	130
Nicaragua	2003	2006	239	238	213
Nicaragua	2006	2010	87	72	53
Nicaragua	2010	2016	36	35	30
North Macedonia	2013	2019	44	44	30
Panama	2006	2010	57	23	4
Paraguay	2006	2010	95	60	30
Paraguay	2010	2017	40	33	19
Peru	2006	2010	203	193	138
Peru	2010	2017	262	237	158
Poland	2013	2019	80	40	7
Romania	2013	2019	46	46	34
Russia	2012	2019	229	215	129
Serbia	2013	2019	52	49	30
Slovakia	2013	2019	14	14	6
Slovenia	2013	2019	28	25	13
Tajikistan	2013	2019	60	41	0
Turkey	2013	2019	429	354	134
Uruguay	2006	2010	189	148	78
Uruguay	2010	2017	52	46	26
Uzbekistan	2013	2019	66	0	0
Westbank and Gaza	2006	2013	49	42	0
Westbank and Gaza	2013	2019	61	60	50
			7332	4820	2668

* N total=Number of firms included in both surveys, ** N eq. (2) = number of firms included in both surveys containing all information for estimating equation (2), *** N eq. (3) = number of firms included in both surveys containing all information for estimating equation (3)