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The Effects of Innovation on Employment in Developing Countries

Evidence from Enterprise Surveys

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Abstract

While existing evidence in advanced economies suggests a possible role for technological innovation in job creation, its role in developing countries remains largely undocumented. This paper sheds light on the direct impact of technological as well as organizational innovation on firm level employment growth based on the theoretical model of Harrison, Jaumandreu, Mairesse, and Peters (2014) using a sample of over 15,000 firms in Africa, South Asia, Middle East and North-Africa and Eastern Europe and Central Asia. The results suggest that new sales associated with product innovations tend to be produced with just as much or higher levels of labor intensity. The effect is largest in lower income countries and the African region, where firms are further away from the technological frontier. More importantly, process innovations that involve automation of production do not have a short-term negative impact on firm employment. However, there is some evidence of a negative effect of automation on employment that manifests in increases in efficiency that reduce the elasticity of new sales to employment. Overall, these results are qualitatively similar to previous findings in advanced economies and highlight a positive direct role of innovation on the quantity of employment but at a decreasing rate as firms' transition to the technological frontier.

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The Effects of Innovation on Employment in Developing Countries: Evidence from Enterprise Surveys

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1 Introduction

Innovation is the engine of the creative destruction process that spurs economic dynamism and transformation (Schumpeter 1942). At the macro level, theories of economic growth put innovation at the center of the growth process since the seminal work of Solow (1957), where economic growth is driven by technical change. This interest in innovation as a key source of growth was reinforced by the emergence of new growth theory, which emphasized the role of knowledge accumulation in the growth process and Schumpeterian creative destruction arising from a competitive R&D sector as the main engine of economic growth (Aghion and Howitt (1992); Romer, 1986).

At the micro or firm level, Klette and Kortum (2004) show how innovation activities create rich firm-level dynamics that translate into firm growth, when the theoretical literature has traditionally emphasized the tendency for large, mature firms to stagnate in contrast to quickly growing younger firms, conditional on survival, as in Hopenhayn (1992). Unlike previous models where firm growth was largely driven by firm learning, in the model of Klette and Kortum (2004), innovation increases product quality and makes firms more competitive, which increases their revenue and size and forces existing firms producing old and obsolete versions of the product to exit the market.

The process of innovation - defined by the introduction of new or significantly improved products, processes and organizational structures - is, therefore, at the center of firm growth. Investing in innovation increases the capabilities of firms, enabling them to compete in international markets, while facilitating the adoption of new technologies that improve labor productivity. Furthermore, a related literature on firm dynamics has emphasized the contributions to employment stemming from innovating firms. Haltiwanger, Jarmin, and Miranda (2013) find that a significant contribution of both gross and net job creation stems from the launch of new business ventures in the United States. One possible explanation for this finding could be driven by innovation in young firms conditional on entry. For example, Arrighetti and Vivarelli (1999) and Vivarelli and Audretsch (1998) find that more innovative new entrant firms tend to enjoy superior post-entry performance.

While innovation has the potential to generate large productivity gains and significantly improve allocative efficiency,[1] we know very little about the nature and impact of firm-level innovation activities in the developing world. Firm-level innovation activities such as R&D, or innovation outcomes such as patenting, tend to be negligible in poorer countries, and there is little understanding regarding the impact that existing innovation efforts have on performance or the main barriers to the adoption of innovative activities. Furthermore, while the benefits of innovation for productivity and economic growth are uncontested, very little is known about the short-term direct impacts of innovation on employment, especially in countries furthest away from the technological frontier. On the one hand, introduction of new product lines can generate direct positive impacts on employment; on the other hand the introduction of new processes or products with enhanced and more modern technologies can result in more efficient use of labor. Therefore, a critical question for policy is whether innovation generates a trade-off between productivity increases and employment growth. Determining what the trade-offs might be (if any) is critical, especially in developing countries where the needs to absorb new entrants to the labor market in formal and higher productivity jobs are greatest. Understanding the dynamics of any trade-off might be helpful to better align policies towards maximizing potential gains to employment.

The objective of this paper is to empirically shed light on these issues and estimate the short-run direct impact of firm-level innovation on employment. Our contribution to the literature is fourfold. First, we expand the existing evidence to a large number of low and middle income countries, taking advantage of a new wave of innovation modules that have been implemented in these countries by the World Bank Enterprise Surveys Unit. Second, since changes in employment can ultimately be closely related to any changes implemented in the organizational structure of the firm, we also consider the impact of organizational innovation on employment. Third, we disentangle the effects of process innovation from product innovation on employment when both are implemented simultaneously by using a two stage methodology with a random coefficients specification in the first stage. Finally, we study how the degree of novelty of innovation and the level of a country's development affect the elasticity of innovation to employment. Given the nature of the data we use, our results focus on average effects

[1] Lentz and Mortensen (2008), using Danish firm-level data, find that up to 75% of productivity growth comes from reallocation of inputs to innovating firms, of which 25% is entry and exist of firms and 50% reallocation to growing innovative firms.

at the firm-level, an important building block to arriving at aggregate or sector level effects on employment which inform welfare considerations.

This paper is structured as follows. The next section briefly summarizes the existing evidence, mainly for OECD countries, regarding the impact of innovation on employment. Section 3 describes the data, while section 4 develops the methodological framework used in the empirical section. Section 5 describes the main empirical findings. The last section concludes.

2 Innovation and Employment: A Brief Survey

Innovation is the outcome of firms' investments in knowledge capital, managerial practices and organizational decisions. The ultimate objective of these investments is to introduce innovations that positively impact firm performance by increasing productivity, sales, profits or markups. However, there is uncertainty regarding the extent to which firms are able to convert knowledge capital investments into innovation outcomes and furthermore, whether these innovation outcomes are likely to impact firm performance. Innovation is risky since it is almost impossible to determine *ex ante* whether the introduction of a new product, process or organizational change will lead to successful processes and products in the market. This is particularly the case in countries where there is a significant lack of complementary factors such as skills, managerial and organizational or technology capabilities to support innovation. Therefore, the impact of innovation on employment depends on the allocation of workers made by firms complementing innovations and the impact of these innovation efforts on firm performance, mainly sales changes and the product mix.

To date, most of the scarce evidence on the impact of innovation on employment has focused on developed countries. Some of the case study literature has emphasized the role of innovation as a mechanism to reduce employment, and also as a force for skill-biased technological change; since increases in firm efficiency can result in more efficient use of labor and changes in the relative demand for skilled labor. Few empirical studies, however, have supported a negative impact on employment; although the bulk of studies show evidence of skill-biased technological change. From a theoretical standpoint, predicting the effects of technological innovation on employment can be ambiguous. While product innovation is typically aimed at increasing a firm's demand through the introduction of a new product, process innovation by definition usually entails productivity enhancements that can be labor saving. The existence of competing mechanisms make the net effects uncertain. For instance, in the case of product innovation, even though a new product is associated with new demand and new markets, there remains the possibility that the new product may be produced more efficiently than old products. While in the short term it is possible that new product sales may cannibalize old ones, the extent to which this occurs will depend on the degree to which the new products are substitutes or complements in demand and production. Furthermore, the net effect will depend on the extent that competitors react by introducing new products themselves, resulting in dynamic competition. For process innovations, while the use of new technologies and capital may be labor saving, under competitive conditions where lower costs of production translate to lower final goods prices, increases in demand and sales may offset any initial labor displacement. Over time, process innovations can shift labor to more skilled, higher wage jobs and widespread adoption of new capital equipment would enlarge downstream sectors of the economy.

In a recent survey of the literature, Vivarelli (2012) suggests that the microeconometric literature tends to support a positive link between innovation, proxied as R&D and/or product innovation, and employment; especially when focusing on high-tech sectors. The study also finds significant evidence in favor of the skill-biased hypothesis across different OECD countries, different economic sectors, and different types of innovation. For example, in one micro-econometric study Harrison, Jaumandreu, Mairesse, and Peters (2014) study the impact of innovation on employment using a comparable data set of firms from France, Germany, Spain, and the United Kingdom. The authors find that product innovation has a positive impact on employment, but that process innovation has a displacing effect on employment. However, the positive impact of product innovation generating employment is larger than the displacement effect of process innovation, and, therefore, the net effect of innovation on employment tends to be positive. Using a similar methodology, Hall, Lotti, and Mairesse (2008) find a low but positive effect of product innovation on employment in Italy, and no displacement effect from process innovation. Similar studies are Dachs and Peters (2014) for European countries and Benavente and Lauterbach (2008) for Chile. These findings are also relevant for policy, see Castillo, Maffioli, Rojo, and Stucchi (2014), Brown, Earle, and Lup (2005). Overall, the literature finds a positive direct link between product innovation and employment, whereas the effects of process innovation tend to be negative.

A related employment literature has analyzed the impact of technology adoption on employment focusing on the general equilibrium effects in the labor market. Brynjolfsson and McAfee (2012) suggests that new digital technologies are having a structural impact on employment and are to blame for jobless growth. Frey and Osborne (2013) using data on occupations for the US labor market predict that about 47% of US jobs could be at risk due to computerization. Autor and Dorn (2013) suggest that the falling cost of automating routines and codifiable job tasks are one of the main determinants of the polarization of employment and wages in the US labor market. A common finding of this employment literature is the fact that new technologies, especially via automating routines, are having a strong impact on labor demand and the relative returns to different labor tasks and skill intensities.

3 Theoretical and Empirical Methodology

In order to examine the impact of innovation on firm-level employment, we use an empirical approach based on the model developed in Harrison, Jaumandreu, Mairesse, and Peters (2014). This model is well suited for cross-sectional data that contain information on a firm's current activities as well as its growth in sales and employment over a recent period. The crucial component of the model is the share of current sales due to newly introduced or improved products which is reported in our data, and that captures the extent of innovation. In this section, we briefly lay out the model and methodology and then present some extensions that we apply.

Employment growth over the period can be separated into two respective components stemming from the continued production of old products and the introduction of a product innovation as follows:

$$\frac{\Delta L}{L} = \frac{L_{12} - L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}}, \tag{1}$$

where L_{it} denotes the firm's employment attributed to product i in time period t. Based on linear-homogenous production functions for old and new goods and assuming that the marginal cost of labor input with respect to wage is constant over the time period and equal for both production goods, we can approximate equation (1) by:

$$\frac{\Delta L}{L} \cong -\frac{\Theta_{12}-\Theta_{11}}{\Theta_{11}} + \frac{Y_{12}-Y_{11}}{Y_{11}} + \frac{\Theta_{11}Y_{22}}{\Theta_{22}Y_{11}}, \tag{2}$$

where Θ_{it} represents an efficiency parameter that proportionally increases the marginal productivity of all inputs driven by the firm's knowledge capital for each respective production process.[2] Intuitively, employment growth can be seen as driven by (1) improvements in the efficiency of the production process of old products - a negative effect since more efficient use of labor for the same amount of output implies less employment; (2) changes in production of old products - where an increase in production leads to more employment; and (3) output growth associated with product innovation weighted by the ratio of efficiency between the old and new products - if new products are produced more efficiently than old ones, employment growth rises less than proportionally with sales of the new product.

While the firm's decision to innovate is assumed to be determined prior to any hiring decisions, the introduction of a completely new good or a substantially improved one, could adversely affect the firm's employment attributed to the old good to the extent that the new and old goods are substitutes in production. In contrast, if product innovation is complementary, then the effect would tend to be positive. When product innovation is aimed at expanding the market, however, the increase in demand for the new product could translate into lower final goods prices for the old product if the firm's factor productivity increases. In this case, labor demand for the old product could also increase depending on the firm's demand price elasticity and on the degree of market competition.

Under this framework, the effect of product innovation on employment growth is represented by the difference in efficiency between the production processes of old and new products ($\frac{\Theta_{11}}{\Theta_{22}}$). When new products are produced more efficiently than old ones, output growth due to new products leads to smaller increases in employment compared to old products. In the analysis, we therefore distinguish between employment effects due to improvements in efficiency of the old product, as well as the relative efficiency of producing new vs. old products.

While it is typically assumed that a firm invests in knowledge capital which in turn leads

[2] Formally, the production function is $Y_{it} = \Theta_{it}F(L_{it}, K_{it}, M_{it})$. From Sheperd's Lemma, $L_{it} = c_L(\omega_{it})\frac{Y_{it}}{\Theta_{it}}$ and it is assumed that $C_L(\omega)$ is the same $\forall i, t$.

to process and product innovations, product innovations are not necessarily related to changes in the efficiency of production, whereas process innovations are typically directed towards improvements in efficiency. As a result, *a priori* it is ambiguous to ascertain the ensuing relative efficiency *ex post* the introduction of a new product. If the firm's R&D or other knowledge investments are correlated with production process improvements, then we might expect any newly introduced product to have a greater efficiency of production. In contrast, if there is little correlation or when the firm has limited knowledge inputs, the act of producing a new or upgraded product is not necessarily more efficient compared to previous products, especially when product innovation is undertaken to expand the firm's product mix and to satisfy existing demand. Therefore, the relative efficiency measure could also be capturing to what extent product innovations are geared towards being more cost effective versus improving quality.

One further step in order to reach a final reduced form equation for equation (2) is to consider the impact of other types of innovation in explaining the two relative efficiency terms. In the original Harrison et al. (2014) formulation, in the case of no product innovation the relative efficiency term between old products in both periods can be affected by firms doing only process innovation. The authors, therefore, approximate this relative or trend efficiency term with $\alpha_0 + \alpha_1 d_i$, which separates the change in average efficiency in the production of old products in an average component for non-innovators, α_0, and a component for process-only innovators, d_i, for which the latter is expected to be greater. The reduced form representation of equation 2 is as follows:

$$l_i - y_{1i} = \alpha_0 + \alpha_1 d_i + \beta y_{2i} + u_i, \tag{3}$$

where l stands for rate of employment growth over the period (i.e., between the year $t = 0$ and $t = 2$), y_1 and y_2 are corresponding rates of output growth for old and new products, and u is the unobserved random disturbance.

In this paper, we extend the model proposed by Harrison et al. (2014) and propose three important extensions to better identify the impact of different types of innovation on employment. First, firms can also introduce organizational innovations, which lead to change in the organizational structure of the firm such as departments or units within the firm and that can also affect efficiency and the level of employment. Thus, we extend the original model in (3) to include the impact of organizational innovation on employment to also affect the relative or trend efficiency term.

$$l_i - y_{1i} = \alpha_0 + \alpha_1 d_i + \alpha_2 org_i + \beta y_{2i} + u_i, \tag{4}$$

Second, the net impact of product and process innovation is not adequately identified in (4), since in β the impact of product and process innovation are confounded when both types of innovation are implemented simultaneously. In the following sections we propose an extension to Harrison et al. (2014) to further disentangle the impacts of product and process innovation on employment.

The last extension is related to the impact of process innovation. The way process innovation is defined in most innovation surveys using Oslo-manual guidelines includes any improvements on production or delivery methods, which can range substantially in their impact on efficiency and employment. Following the literature emphasizing the impact of automation on employment, we extend the model and decompose process innovation between innovations that imply some degree of automation in the production process and other types of process innovation.

3.1 Identification strategy

One problem when estimating equation (4) is the simultaneity introduced by the impact of innovation on prices. In practice we do not have firm level prices and so our estimates are based on nominal output (sales) growth, where $g_1 = y_1 + \pi_1$ and $g_2 = y_2 + \pi_2 y_2$. π_1 measures the firm's inflation rate for old products and π_2 measures the price difference between the new product and the old product in period 1. Consequently, our estimation equation becomes:

$$l_i - g_{1i} = \alpha_0 + \alpha_1 d_i + \beta g_{2i} + u_i, \tag{5}$$

where we have netted out g_{li}. The new unobserved error term is $u = -\pi_1 - \beta\pi_2 g_2 + v$.[3] As a result, the sales growth rate due to new products, g_2, is correlated with the error term and leads to a downward bias in $\widehat{\beta_{OLS}}$.

[3]An improvement could be to approximate the firm's inflation rate for old products using an industry measure, $\tilde{\pi_1}$, in which case the error component would become $E(\pi_1 - \tilde{\pi_1})$.

IV methods are used to deal with this measurement issue as in Harrison et al. (2014). Variables that explain the success of the product innovation's sales but that are uncorrelated with its price differences with the old product should serve as good instruments. We use a series of indicator variables that measure whether the product innovation was geared towards extending the market, whether the firm invests in R&D, and whether the innovation is completely new to the firm. In all estimates, we evaluate and report the strength of our instruments as suggested in Stock and Yogo (2005) and conduct Hansen-Sargen over-identification tests.

However, estimating equation 5 entails another potential endogeneity issue when there exists correlation between d andy_2 and the error term u. For instance, productivity shocks might be (positively) correlated with contemporaneous or past decisions to make innovation investments (to the extent that they are predictable), such as R&D, which could lead to the successful development of product or process innovations. On the other hand, selection could be at work where the innovation decision is driven by employment cost savings motivations. Consequently, again the estimated displacement effects on employment would be larger than estimates obtained from a causal interpretation.[4] Dealing with this source of endogeneity is more challenging, as one would need good predictors of the firm's innovation decision that are predetermined or uncorrelated with any shocks to productivity. It is possible that lagged values of the variables could serve as valid instruments; however, we do not have these in our data. This caveat needs to be considered when interpreting our results.[5]

3.2 Accounting for heterogeneity of impact

In our benchmark analysis, we pool the data and estimate equation 4 with controls for each country and industry. However, the model could be misspecified since the coefficients are assumed not to vary across clusters of firms. There are strong reasons to believe that unobserved heterogeneity plays a role at the country and sector level and furthermore, that the effects of innovation on employment growth may vary as well. As a result, in order to account for these differentiated effects, we use an extension of the model that incorporates random intercepts and coefficients by country and sector; see Rabe-Hesketh and Skrondal (2012) for more de-

[4]Assuming positive correlation with productivity shocks and y_2, the productivity shock would be negatively correlated with u, leading to a downward bias for β.

[5]While past authors have raised this endogeneity issue, they typically assume that the effects are muted.

tails. Rewriting equation 5 as:

$$l_{ij} - g_{1ij} = \alpha_0 + \alpha_1 d_{ij} + \beta g_{2ij} + u_{ij}, \tag{6}$$

where i indexes over the firm and j represents a distinct industry within a particular country. For any two firms from the same country and sector, it might be unrealistic to assume that the residuals u_{ij} and $u_{i'j}$ are uncorrelated. We decompose the total residual or error into a shared component between firms in the same country and sector, ξ_{1j}, and a firm specific component, ϵ_{ij}. Similarly, we can specify a country and sector specific random slope, ξ_{2j}, that affects g_2 in addition to the fixed component, β. The model becomes,

$$l_{ij} - g_{1ij} = (\alpha_0 + \xi_{1j}) + \alpha_1 d_{ij} + (\beta + \xi_{2j}) g_{2ij} + \epsilon_{ij}, \tag{7}$$

where it is assumed that the random effects have zero means conditional on observables and the level-1 error term has zero mean given the covariates and random effects:

$$E(\epsilon_{ij} | \mathbf{X_j}, \xi_{\mathbf{1j}}, \xi_{\mathbf{2j}}) = \mathbf{0} \tag{8}$$

Furthermore, given $\mathbf{X_j}$ the random intercept and random slope follow a bivariate distribution assumed to have zero mean and covariance matrix $\mathbf{\Psi}$.[6] The model is estimated via maximum likelihood using **xtmixed** in STATA with bootstrapped standard errors after obtaining predicted values in a first-stage equation as in the IV approach outlined in the previous section.[7]

The country and industry specific components, ξ_{ij}, represent the combined effects of omitted variables or unobserved heterogeneity at the country and industry level. Because of the shared components, the model accounts for within-country and sector dependence among the total residuals. The random intercepts and slopes can be interpreted as latent variables whose variance terms are estimated along with the other parameters and the variance term of the level-1 residual ϵ_{ij}. However, after estimating the model's parameters, including $\widehat{\psi_{11}}, \widehat{\psi_{22}}, \widehat{\psi_{21}}$ and $\widehat{\theta}$, we can obtain maximum likelihood estimates of the random intercepts and slopes by an auxiliary regression that relates the predicted total residuals on x_{ij} by OLS or empirical Bayesian

[6]The total residual is $\xi_{ij} \equiv \xi_{1j} + \xi_{2j} x_{ij} + \epsilon_{ij}$ and its conditional variance is $Var(\xi_{ij} | \mathbf{x_{ij}}) = \psi_{11} + 2\psi_{21} x_{ij} + \psi_{22} x_{ij}^2 + \theta$, where the level-1 residual is assumed homoskedastic and with conditional variance $Var(\epsilon_{ij} | \mathbf{x_{ij}}, \psi_{ij}) = \theta$.

[7]The default case sets ψ_{21} and the corresponding correlation coefficient to zero but this assumption can be relaxed using the option covariance(unstructured).

methods.

One added advantage of exploiting within country and sector variation is that it allows us to try to disentangle the impact of different types of innovation measured by β in equation (4). As suggested above, a limitation of the framework in (3) is that it does not only include the impact of product innovation of employment, since the relative efficiency between new and old products is also affected by whether firms also complement product innovations with other types of innovation, such as process or organizational innovations. Therefore, while the estimate of β is unbiased, to disentangle the true impact of product from process innovation on employment we need to decompose this coefficient. The main challenge in doing so is the lack of longitudinal data. However, the variance across country-sectors captured by the random coefficients model provides an opportunity to estimate the effects of different types of innovation.

After obtaining the predicted coefficients $\widehat{\beta}$ from the random-coefficient model, in a second stage regression we investigate how the elasticities obtained vary by country and sector according to the intensity of product, process and organizational innovation in the following equation:

$$\beta_j = \alpha + \gamma \mathbf{w_j} + u_{1j},$$

where j denotes the country and sector, α is a constant term and $\mathbf{w_j}$ is a vector of innovation intensity measures. Although imperfect estimates of each of the types of innovation elasticities given the aggregation of the data to the country-sector level, this two stage estimation allows us to explore whether combining different types of innovation matters in the impact of product innovation on employment.

4 The Data

In order to examine the innovative behavior of firms in developing countries, we use the World Bank 2013-2015 Enterprise Survey and its linked innovation modules. This is the most comprehensive set of cross-country surveys on innovation carried out to date. The survey used a stratified sampling strategy, where firms are stratified by industry, size, and location. Firm size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large-sized firms). Since in most economies, the majority of firms are micro, small and medium-sized, Enterprise Surveys tend to oversample large firms and, therefore, the results should be primarily interpreted in relation to firms of larger size. An additional advantage of the survey is that it collects substantial balance sheet and other information regarding the investment climate, which enables the linkage of innovation efforts to performance and potential obstacles.[8]

The standard Enterprise Survey covers topics such as firm characteristics, gender participation, access to finance, annual sales, costs of inputs/labor, workforce composition, bribery, licensing, infrastructure, trade, crime, competition, capacity utilization, land and permits, taxation, informality, business-government relations, innovation and technology, and performance measures. A number of the survey questions objectively ascertain characteristics of a country's business environment and assess the respondents opinions on what are the obstacles to firm growth and performance. The mode of data collection is face-to-face interviews.

The innovation survey differentiates between product and process innovation, and two non-technological innovations, marketing and organization. However, there is significant confusion when identifying the different types of innovation outcomes by firms in the survey. For example, new marketing processes such as discounts, new packaging or new client segments are sometimes identified with process or product innovations. The fact that interviewees provide a recorded description of the product and process innovations allows us to verify the identified product and process innovation and clean the wrongly attributed cases, or the cases that do not constitute an innovation at all (the detailed methodology to clean the data is described in the appendix). Overall the cleaning exercise results in a decrease in both product and process innovation rates due to cases of either not an innovation or a misclassification.[9] The appendix also contains a description of how we inferred whether process innovations could also be categorized as automation.

Our final data set consists of random samples of firms from 53 countries in broad sectors including manufacturing and services. In total our estimation sample is based on over 15,000

[8]Sector breakdown is usually manufacturing, retail, and other services. For larger economies, specific manufacturing sub-sectors are selected as additional strata on the basis of employment, value-added, and total number of establishments' figures. Geographic regions within a country are selected based on which cities/regions collectively contain the majority of economic activity. Enterprise Surveys implemented in Eastern Europe and Central Asian countries are also known as Business Environment and Enterprise Performance Surveys (BEEPS) and are jointly conducted by the World Bank and the European Bank for Reconstruction and Development. For more details see Enterprise Surveys (http://www.enterprisesurveys.org).

[9]Overall both product and process innovation rates fall from 37% to 31%.

firms where sufficient information on innovation and employment is available.[10] Firms report both their sales and employment in the year the survey was conducted, which for most firms surveyed was in 2013 or 2014, as well as three years prior. In addition, firms report information about their innovation activities, such as product and process innovations but also including organization innovations which forms a key contribution of our paper. Because firms also report the share of sales attributed to new innovations, we are able to decompose employment growth into its respective components driven by old products and new products growth.

Table 1 reports the number of firms in our sample across regions and by type of firm measured in terms of size, age and sector. Overall, we observe that the firms in our sample tend to be small, with fewer than 20 employees, and at the same time tend to be older, with the majority of firms operating for more than 10 years.

5 Results

5.1 Employment and sales growth among innovators and non-innovators

Before proceeding with the econometric analysis, we look at some descriptive statistics and check differences between innovators and non innovators, and other groups. Figure 1 displays employment growth rates annualized over the three-year period based on the most recent Enterprise Survey questionnaire by firm size groups. In general we observe that a large proportion of firms display no employment change and there is some tendency for younger firms to display higher rates of employment growth in line with predictions from the theoretical firm dynamics literature. For firms with less than 10 employees in the base year, we plot histograms of change in employees in lieu of growth rates. We observe that very few firms - less than two percent of the sample - display growth rates above the 20 % threshold (or an increase in roughly 8 employees for firms with less than 10 employees), which would classify them as high-growth firms based on the OECD definition.

Table 2 compares firm employment and sales growth rates over the three-year period from the year in which the survey was completed, according to whether firms are non-innovators, process-innovators only, product innovators, and if so, whether they are also engaged in pro-

[10] The appendix contains a list of countries.

cess innovation, by manufacturing and services sectors respectively. Innovation is larger in manufacturing than in services; and process and organizational innovation are the less prevalent forms of innovation; although process innovation is more prevalent when combined with product innovation than organizational innovation. In manufacturing, roughly 46% of firms report undertaking some form of innovation, with roughly 27% of firms reporting product innovations. Slightly over half of firms with product innovations have also introduced process innovations.

The rate of technological innovation is strikingly large in Africa and South Asia, even when the data is thoroughly cleaned as described in the Appendix. Rates for innovations defined as new to the national market are much lower, and the gap between new to the firm and new to the national market is significantly large for Africa and some low income countries. Radical innovations - innovations new to the international market - are rare in these countries, as is the use of patents. Overall, this suggests large imitation rates in these regions and the fact that many of the innovations that are new to the firm in most of the countries in our sample are likely to be marginally incremental; such as new product additions or small improvements.

On average, firms that have introduced product and/or process innovations tend to display higher growth rates both in employment and sales, but the results are mixed depending on region and sector. On average, the differences on sales and employment growth are not statistically significant. Interestingly, when decomposing sales growth for product innovators into respective shares made up of old and new products, we observe that sales growth for old products tends to be negative. As a result, much of the overall sales growth for these firms tends to be driven by new products, which might be due to cannibalizing of old products. Figure 2 plots the cumulative distribution function of employment and sales growth for innovators vs. non-innovators by size and confirms that neither distribution stochastically dominates the other. However, we observe some evidence that innovating firms exhibit higher growth rates for parts of the distribution, particularly for larger firms.

Table 2 also highlights the challenge described in section 3 when trying to disentangle the employment effect of product and process innovation. Around one half of product innovators in manufacturing and 30% in services implement both product and process innovation simultaneously. This implies that when looking at the impact of sales attributed to innovation on employment in some cases firms only introduced new or updated products, but in other cases process innovations that can also affect the productivity terms of the new products were also introduced.

5.2 The impact of innovation on employment

5.2.1 The impact of innovation on employment growth

Table 3 shows the results of estimating equation (3) by OLS for the pooled sample and by different regions and income groups, with process innovation only, sector-country, size and age dummies.[11] Starting with the coefficient of process innovation only, this is negative and statistically significant, with the exception of ECA, MENA and high income countries; suggesting that cases where firms only introduce new processes, increases in efficiency can result in a decrease in employment growth. Adding the process innovation only coefficient to the constant term allows retrieving the original intercept that reflects the trend productivity term of old products (with negative sign).[12] The trend productivity parameter is negative for Africa, MENA and low income countries sample, which suggests that labor productivity for all products in these regions have gone backwards. For the entire sample, the trend productivity parameter is positive for process innovators only, and also positive for all firms in South Asia, ECA and high income countries.

Regarding the main coefficient of interest, the elasticity of sales attributed to product innovation on employment growth, is statistically significant and positive in all specifications, and 0.6 on average for the whole sample. Interestingly, the coefficient is below unity in all OLS specifications, which implies that new products are produced more efficiently than old products as in equation (2) and suggests a positive but less than proportional employment elasticity to innovative sales that results in some labor displacement. This elasticity is also larger in the MENA and South Asia region and middle income countries in general.

As discussed in section 3, however, OLS estimates are likely to be biased due to the endogeneity of the sales growth of new products when the true real change in growth of sales

[11] An alternative to splitting the sample by region and income groups would be to estimate the full sample and include interaction terms. However, the potential endogeneity of the innovation sales to employment changes described in previous sections makes it very difficult to find suitable instruments for the interactive terms.

[12] The size and country-sector dummies are restricted to add up to zero

is unobserved due to the lack of appropriate price deflators. Table 4 shows the IV estimation result, where sales growth from new products is instrumented using indicators for whether the product is completely new to the firm and whether the firm invests in R&D. The Hansen-Sargen Overid test p-value confirms the validity of the instruments used. The new IV estimates suggest that the previous OLS estimates on the innovation elasticities were biased downwards. The new estimates are also statistically significant but much larger, especially in Africa and to a lesser extent in low and middle income countries. This suggests that the employment growth associated to product innovations is larger in these regions, likely as a result of having lower efficiency gains on innovation in new products from being further away from the technological frontier, which makes the elasticity of employment changes to innovative sales changes larger in these countries. The elasticity is farther from and below unity only in the ECA region and high-income countries, suggesting that innovation in countries closer to the technological frontier increases employment less than proportionally given the larger impact of innovation on efficiency.

In contrast, the impact of process innovation only in the instrumented specifications on employment growth is never statistically significant. In addition, regarding the trend productivity parameter of all products, in the instrumented specifications the parameters are not statisticaly significant, with the exception of the ECA region where it is positive and marginally significantly negative for South Asia, MENA and low income countries. This result for the last three regions is slightly puzzling since we would expect to find a positive or not statitiscally significant trend in labor productivity.

Since these results could be explained by the different sector composition in these regions, we examine how these elasticities vary across aggregate sectors, technological intensity levels and skill intensity. Table 5 examines the employment effects of product innovation according to whether the firm operates in the manufacturing or services sector. We find that β is on average higher in manufacturing than in services, but in both cases we cannot reject that the elasticity is equal to one, suggesting that product innovations are not labor displacing in both sectors. When we disaggregate manufacturing into its degree of technological intensity, measured according to a sector's intensity of R&D expenditures, we find that contrary to intuition the effect increases when comparing low-tech firms to medium-high tech firms, from 0.917 to

1.002; although again we cannot reject that the elasticities are equal to unity. Columns 5 and 6 of Table 5 display results from splitting the sample of manufacturing firms into those with high intensity of skilled employees and low intensity firms defined as having a share above or below the sector average, respectively. As expected, the elasticity coefficient is larger in low skill intensity firms than in high skill intensity firms, suggesting larger employment effects for firms with less skilled employees, potentially due to lower efficiency gains from innovation given the lack of complementary factors.

5.2.2 Employment effects of more novel innovations

Typically, product innovation reported by the firm can include radical innovations that are new to national or international markets, but mostly it includes cases of marginal product upgrading or introductions of new product lines. It is possible, therefore, that the additional impact on employment from introducing innovations largely depends on their degree of novelty. On the one hand, more radical innovations may have a larger impact on efficiency and as a result on labor displacement. On the other hand, less novel innovations can have a marginal impact on quality attributes and product differentiation and less so on efficiency, so additional demand and sales dominate efficiency and employment is expanded more than proportionally.

Table 6 displays the results when considering innovation for differing degrees of novelty. First, we consider separately when innovation is a product upgrade versus a completely new product. This is important when we look at equation (2) since β is the ratio between the efficiency parameter of the old product and the new product, and we should expect that in the case of product upgrade the impact of innovation on efficiency between the old and the new product could be larger than when they are two separate products. As suggested, the estimates show a negative coefficient on product upgrade reducing the elasticity coefficient; however both for manufacturing and services, the coefficient is not statistically significant. Therefore, we do not find differentiated significant effects when comparing quality upgrade vs product diversification.

We then extend the analysis to the extent of "radicalness" on innovation and compare innovation defined as new to the firm vs innovations that are new to the national or international market in columns (3) and (4). The results suggest that in manufacturing there is no additional effect in terms of employment of more radical innovations as compared to new to the firm innovation - imitation. On the other hand, the results for services suggest a positive employment elasticity premium of more radical innovation. One potential explanation of this is the fact that knowledge transmission in service firms often relies on human and organizational factors more intensively than in manufacturing and where management plays a central coordinating role. This more intensive use of labor, especially skilled labor, can be exacerbated in more radical innovations and, therefore, more than offsetting any labor productivity changes; see Tether (2003).

5.2.3 Process innovation and automation

Frey and Osborne (2013) discuss how automation and computerization of tasks may eventually render many labor tasks obsolete. One problem of the previous estimates is the fact that when considering process innovation one mixes firms that introduce any new process or delivery method with the introduction of an automated process (see Appendix A). As a result, the process innovation dummy is likely to be capturing very different efficiency generating process innovations that on average do not have an impact on employment.

Table 7 reports estimates of the baseline instrumented model where we decompose process innovation into two components: innovations that involve automation of any process and non-automation innovations. To isolate which process innovations fell under the category of automation, we relied upon the actual descriptions of the innovation as opposed to whether a process innovation was self reported as automation as a robustness check. We first scanned for keywords in the process innovation description such as “automate”, “robots”, “manual” and then inspected each description individually for an indication that new machinery or equipment was introduced to facilitate or reduce human labor in the production process.

The estimates suggest that the effects of automation only on employment growth in general are not statistically significant for most sector disaggregation. This suggest that while automation is likely to have significant effects on the skill and task composition of firms, at least in the short-run and when automation only is implemented as an innovation, it does not appear to have a direct impact on firm employment. An exception to this appears to be services where we find a marginal statistical negative effect.

5.2.4 Impact of organizational innovation

As suggested above, one important type of non-technological innovation that can have an impact on employment growth is organizational innovation. Changes in firms departments and organizational structure, outsourcing of tasks or management structure changes (see Appendix A for the definition) are likely to have an impact on employment growth. Table 8 shows the baseline estimates of including an organizational innovation only dummy. Organizational change was only reported in the survey for large and medium size firms, so there is a significant loss of observations when analyzing this type of innovation.

The estimates show that as it was the case for process innovation only, organizational innovation only does not seem to impact employment growth in the instrumented regression. Improvements in the organizational structure or outsourcing of tasks do not appear to affect the level of short term employment of the firm when implemented in isolation from other types of innovation.

5.2.5 Disentangling the effects from different types of innovations

One problem with the estimates in the previous section lies in the fact that a large share of firms conduct both product and process innovation simultaneously. As a result, the elasticity coefficient on growth in sales due to new products is to some extent also capturing the impact of process innovation when implemented along with a product innovation. Therefore, the total effect of process innovation on employment is the sum of the coefficient on process innovation only and the extent to which the effect on employment growth from sales of new products is affected by complementarities between product and process innovation. Similarly, the estimated effect β may not be entirely attributable to product innovation.

Given the nature of our data and the lack of within firm variation, it is difficult to isolate the true effects of each individual type of innovation. As suggested above and given the large heterogeneity of impact across sectors and countries, one option is to estimate the model allowing the elasticities to vary by country and sector, and then in a second stage, determine how these β are correlated with the intensity of different combinations of types of innovation. In a similar approach, we also examine the joint effects when the firm also engages in organizational innovation or automation.

Table 9 shows the results from the random coefficients specification, including the estimated standard deviations of the random intercept and random slope and the level-1 residual standard deviation. Column one reports the model with random intercept and slope, where we test whether the random slope is needed in addition to the random intercept. The likelihood ratio test where the null hypothesis $\xi_j = 0$ is strongly rejected in favor of the random intercept model. The average elasticity estimate of growth in sales of newly introduced or improved products is similar to the results of the fixed effects model in Table 4 where we obtained an estimate of 0.938. Based on the estimated variance, roughly 95 % of random slopes fall in the interval $0.962 \pm 1.96 \times .243$; Figure 3 plots the density of predicted random slopes. Column two implements the same model but includes the effect of organizational innovation only. Column three decomposes process innovation into automation and process innovation excluding automation.

Table 10 shows the estimates of the second stage, where we use the variation of elasticities across country-sectors and analyze their correlation with the share of product innovators and the share of product and process innovators, product and organizational innovators, and product and automation innovators. In each model, we include a column that controls for sector specific effects that may explain differences in the size elasticities, for example the degree of sector capital and labor intensity. The estimates for the share of product innovation across specifications is not statistically significant, suggesting that having more innovators in the country-sector is not a determinant of that size elasticity. The coefficient on product and process innovation is as expected negative in column 1, suggesting that country-sectors that more intensively combine product and process innovation have lower elasticities, suggesting a potential efficiency gain from process innovation that reduces the additionality on employment creation. However, when we control for sector effects in column (2) the coefficient becomes statistically not significant.Overall, our estimates find no impact of process innovation on employment, not even when combined with product innovation.

A more interesting picture emerges when using the intensity of product innovation jointly with automation. In this case we find that the employment elasticity of new sales dues to innovation is lower in sectors where product innovations are more likely to be accompanied of automation of production processes. As a result, while automation alone may not affect short-term employment, when accompanied with product innovation is likely to increase efficiency and reduce the ability of generating additional employment.

6 Conclusion

This paper has analyzed empirically the impact of firm-level innovation on employment. The main result of this paper is that product innovation, when successful and bringing additional sales to the firm, has a positive direct impact on employment in the short-run. This is a very important finding given some views that innovation efforts are often entirely labor saving for the firm. The extent to which sales cause additional employment, however, is directly related to the impact on efficiency resulting from the innovation process. The results suggest that in lower and middle income countries, and especially in Africa, where innovations are more incremental and there may be less efficiency gains due to the innovation, the employment growth associated with a dollar increase in sales from innovative products is larger than in high income countries. In fact, the model estimates predict that for most countries if all products could be replaced by new or upgraded products, the overall level of employment of the firm would be at least as high as the previous level. On the other hand, for high income countries, especially in ECA, new sales attributable to innovation generate new employment but at lower rates since the new or upgraded products are more efficient in the use of labor.

The findings point towards product innovation as the main channel of employment creation. Organizational innovation does not appear to have any impacts on employment changes, when considered alone or when implemented with product innovation. The same occurs with process innovation, which does not seem to impact employment, even when considering the introduction of automation processes. it is likely that the main effects of these types of innovation are on the quality of labor - skill biased technical change - rather than the quantity of labor. However, we find some support to the idea that automation may actually displace labor by reducing the employment elasticity of product innovation when these are introduced jointly.

Overall, the implication for policy is important. Innovation policy, when effective in generating additionality on innovation activities and successful innovations, even via imitation, can also be an important policy to increase employment in the short-run. This is especially the case for those countries farthest away from the technological frontier, where the effect on employment from generating new sales due to innovation is largest. On the other hand, for higher income countries, the additionality impact on employment mirrors that of lower income countries with low additionally given their greater ability to generate productivity gains in new products.

More work is, however, needed to better understand the short-run impact of innovation on the skill composition of the firm and the effect of the different types of innovation combined. While innovation is likely to be skill biased, we know very little about the extent of potential skill displacement within the firm, on the job learning and more generally what is the impact on unskilled workers inside innovative firms.

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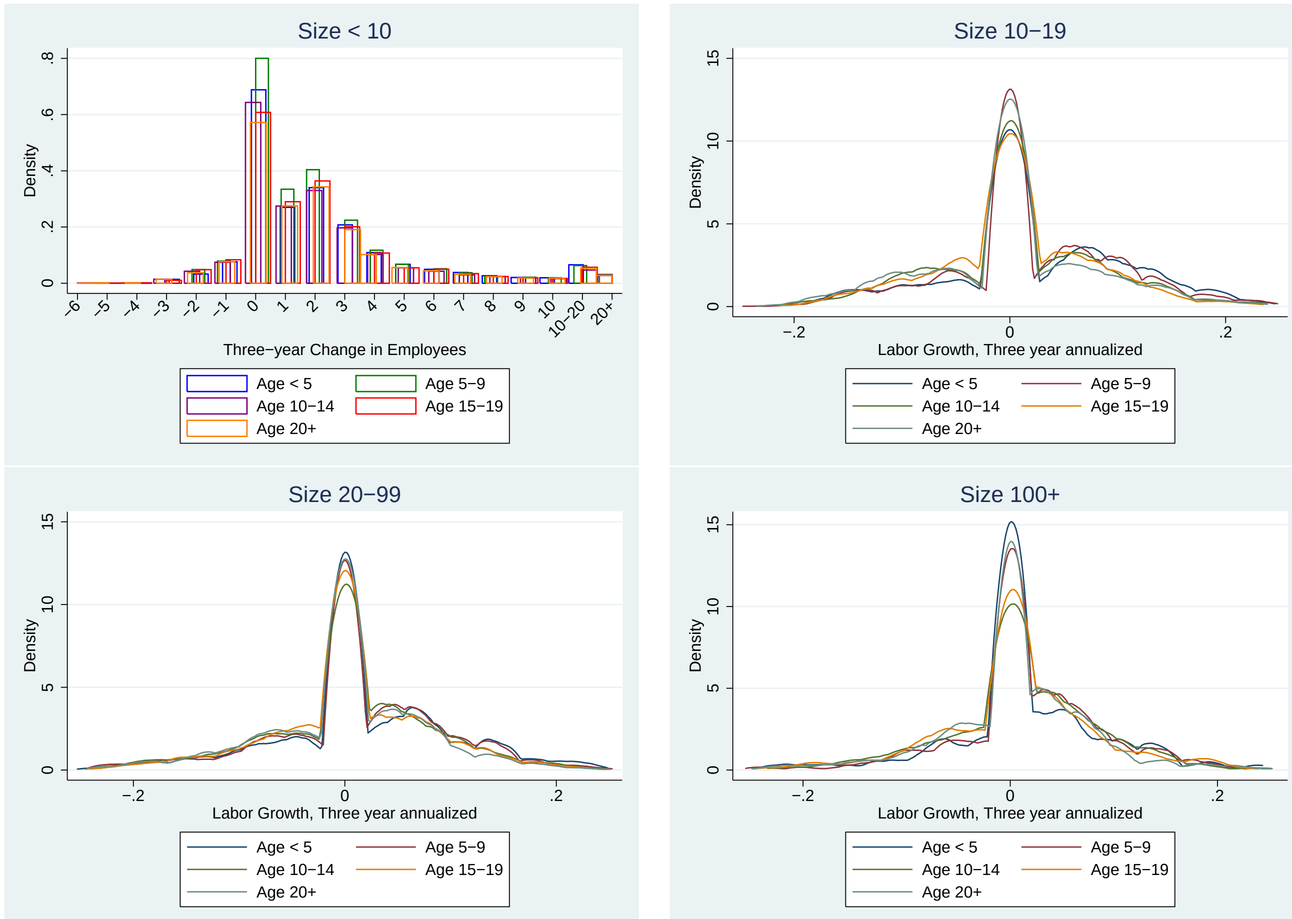
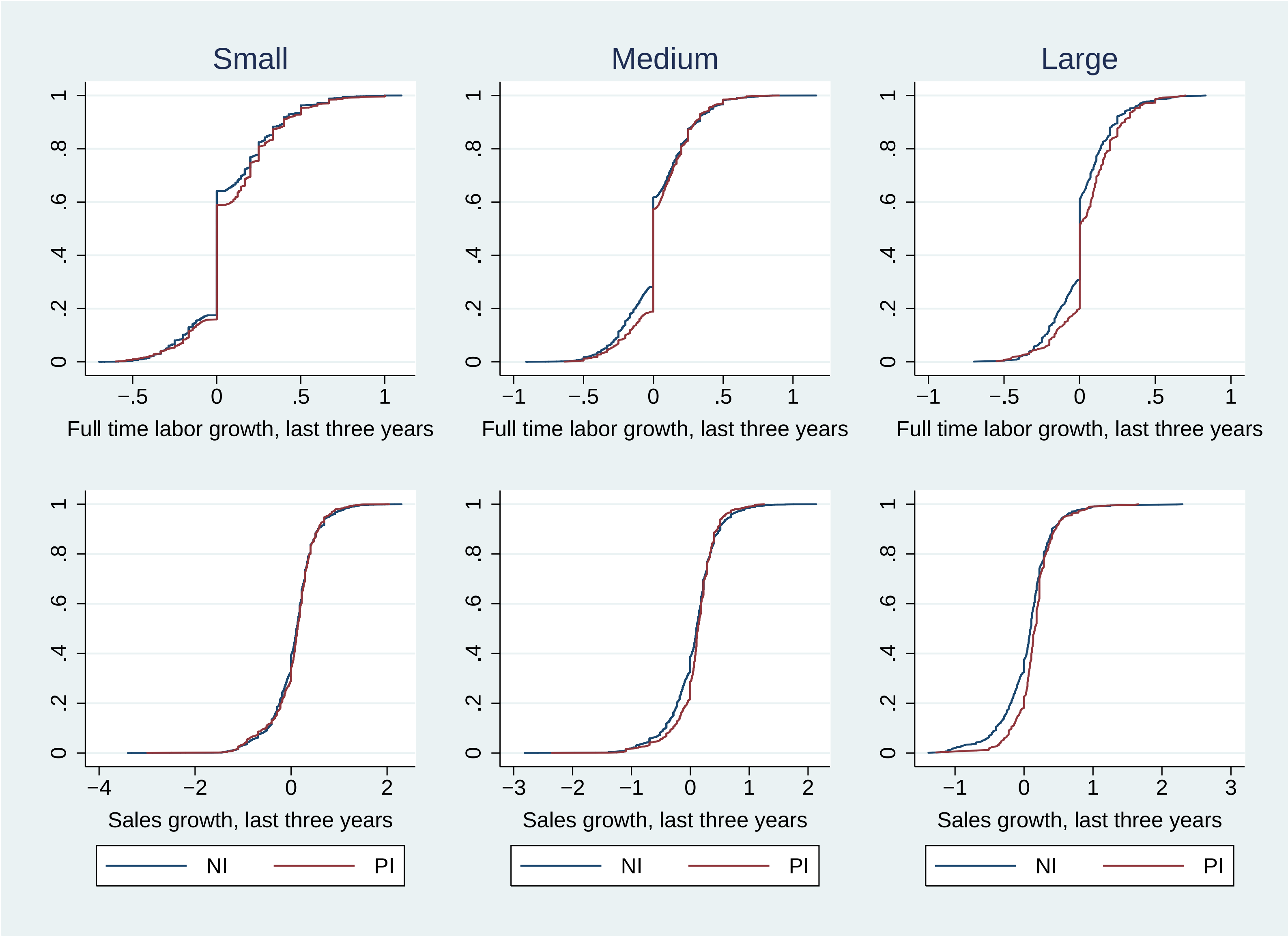
Figure 1: Employment Growth by Size and Age



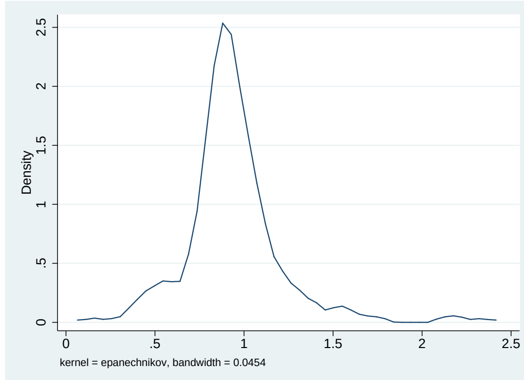
Note: Densities of firm full-time employment growth rates plotted by firm size classes measured in base year. For firms with fewer than 10 employees, change in employees displayed where increase in 8 employees corresponds roughly to 20% three year annualized growth rate for firms with 10 employees in base year. Source: Enterprise Survey 2013-2014 wave.

Figure 2



Note: Based on estimation sample of 15,033 firms.

Figure 3: Distribution of employment elasticities to innovation sales



Note: Predicted random slope coefficients based on Table 9.

Table 1: Overview

		All	Africa	South Asia	ECA	MENA
Total		15033	1652	3322	6658	3401
Size	Small ($<$ 20)	0.54	0.73	0.36	0.61	0.49
	Medium (20-99)	0.36	0.23	0.47	0.33	0.38
	Large (100+)	0.10	0.04	0.17	0.06	0.12
Age	$<$ 5	0.05	0.13	0.04	0.05	0.01
	5 to 9	0.22	0.30	0.19	0.24	0.16
	10 to 14	0.21	0.21	0.19	0.24	0.18
	15 to 19	0.19	0.12	0.17	0.23	0.18
	20 +	0.32	0.22	0.41	0.23	0.46
Industry	Food	0.08	0.09	0.09	0.06	0.12
	Textiles	0.04	0.02	0.07	0.02	0.04
	Garments	0.06	0.04	0.07	0.05	0.10
	Wood, Paper	0.03	0.03	0.04	0.03	0.02
	Publishing, Printing	0.03	0.03	0.02	0.03	0.03
	Chemicals	0.03	0.02	0.06	0.02	0.03
	Plastics	0.03	0.01	0.07	0.03	0.02
	Non metallic mineral products	0.03	0.02	0.04	0.04	0.01
	Basic metals, products	0.07	0.07	0.10	0.05	0.07
	Machinery	0.03	0.01	0.07	0.03	0.00
	Electronics	0.04	0.01	0.10	0.03	0.01
	Furniture	0.03	0.07	0.03	0.03	0.03
	Construction	0.05	0.04	0.02	0.08	0.03
	Motor vehicle services	0.03	0.05	0.02	0.03	0.02
	Transportation	0.05	0.03	0.03	0.05	0.06
	Wholesale	0.09	0.09	0.02	0.12	0.08
	Retail	0.18	0.24	0.07	0.24	0.12
	Hotels & Restaurants	0.06	0.12	0.05	0.04	0.06
	IT, Professional services	0.02	0.01	0.02	0.02	0.01

Note: Based on estimation sample covering 53 countries.

Table 2: Growth of employment and sales, innovators and non-innovators

	Manufacturing					Services				
	All	Africa	South Asia	ECA	MENA	All	Africa	South Asia	ECA	MENA
No of Firms	7846	691	2541	2665	1949	7187	961	781	3993	1452
Non-innovators (%)	0.54	0.49	0.26	0.68	0.74	0.74	0.59	0.45	0.79	0.84
Process-innovators only (%)	0.18	0.23	0.31	0.12	0.09	0.10	0.22	0.23	0.07	0.07
Product-innovators	0.27	0.28	0.43	0.20	0.16	0.16	0.20	0.31	0.15	0.10
of which product & process innovators	0.51	0.52	0.60	0.40	0.37	0.29	0.40	0.26	0.26	0.29
Employment growth										
All firms	0.05	0.08	0.07	0.05	-0.01	0.06	0.10	0.08	0.06	0.04
Non-innovators	0.03	0.07	0.05	0.05	-0.02	0.05	0.08	0.09	0.05	0.04
Process innovators only	0.07	0.06	0.08	0.08	0.00	0.08	0.12	0.07	0.09	0.02
Product innovators	0.06	0.11	0.08	0.04	0.01	0.08	0.12	0.08	0.07	0.07
Sales growth (Nominal)										
All firms	0.09	-0.04	0.16	0.16	-0.05	0.07	-0.18	0.16	0.16	-0.07
Non-innovators	0.06	-0.06	0.14	0.15	-0.06	0.07	-0.13	0.17	0.16	-0.07
Process-innovators only	0.11	-0.05	0.15	0.18	-0.06	0.05	-0.12	0.15	0.17	-0.10
Product innovators	0.13	-0.02	0.17	0.16	-0.01	0.05	-0.37	0.16	0.15	-0.01
of which: Old products	-0.15	-0.33	-0.12	-0.05	-0.34	-0.20	-0.70	-0.13	-0.05	-0.28
New product	0.30	0.28	0.34	0.25	0.28	0.26	0.23	0.36	0.24	0.25

Note: Employment and sales growth are measured over three-year period from time survey was completed. Employment growth is measured as change in full-time employees. Sales growth is measured as change in local nominal currency.

Table 3: Effects of innovation on employment (OLS), by Region and Income Categories

	All Countries	by Region				by Income		
		Africa	South Asia	ECA	MENA	Low	Middle	High
Process innovation only	-0.037***	-0.104**	-0.051***	-0.003	0.026	-0.067**	-0.027**	0.005
	(0.01)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)
Sales growth d.t. new products	0.640***	0.373***	0.686***	0.597***	0.817***	0.583***	0.756***	0.479***
	(0.04)	(0.13)	(0.06)	(0.06)	(0.09)	(0.10)	(0.04)	(0.08)
Size 20 to 99	0.008	-0.026	0.010	0.022*	-0.011	-0.019	0.014	0.016
	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Size 100 and over	0.010	-0.036	0.031*	-0.005	-0.002	-0.012	0.015	0.017
	(0.01)	(0.09)	(0.02)	(0.02)	(0.02)	(0.04)	(0.01)	(0.02)
Constant	0.016**	0.282***	-0.038**	-0.061***	0.076***	0.113***	0.004	-0.036***
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
N	14688	1756	3322	6657	2953	3468	6024	5196

Note: Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product).

Table 4: Effects of innovation on employment (IV), by Region and Income Categories

	All Countries	by Region				by Income		
		Africa	South Asia	ECA	MENA	Low	Middle	High
Process innovation only	-0.001	-0.000	0.004	0.007	0.034	-0.024	0.022	0.022
	(0.01)	(0.06)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Sales growth d.t. new products	0.938***	1.726***	0.945***	0.803***	1.030***	1.013***	1.056***	0.797***
	(0.07)	(0.52)	(0.20)	(0.08)	(0.12)	(0.25)	(0.10)	(0.10)
Size 20 to 99	0.006	-0.043	0.007	0.021*	-0.013	-0.022	0.012	0.013
	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Size 100 and over	0.005	-0.077	0.029	-0.008	-0.008	-0.019	0.012	0.011
	(0.01)	(0.09)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)
Constant	-0.004	0.243*	0.208*	-0.133**	0.229*	0.172**	-0.039	-0.086
	(0.01)	(0.15)	(0.12)	(0.06)	(0.13)	(0.09)	(0.08)	(0.08)
N	14688	1756	3322	6657	2953	3468	6024	5196
R-Squared	0.29	0.32	0.19	0.19	0.14	0.39	0.18	0.18
First stage F-statistic	404.59	29.35	25.57	268.94	126.34	56.89	136.92	218.77
Hansen-Sargen Overid test p-value	0.87	0.93	0.44	0.58	0.84	0.64	0.86	0.49

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*.

Table 5: Effects of innovation on employment (IV), by Sector and Technological Intensity

	Manufacturing	Low Tech	Medium Tech	Medium HT	High Share of SW	Low Share of SW	Services
Process innovation only	0.008	0.022	-0.019	-0.007	-0.007	0.042	-0.007
	(0.02)	(0.02)	(0.05)	(0.06)	(0.02)	(0.04)	(0.02)
Sales growth d.t. new products	0.966***	0.917***	0.894***	1.002***	0.838***	1.189***	0.914***
	(0.11)	(0.13)	(0.24)	(0.28)	(0.14)	(0.18)	(0.09)
Size 20 to 99	0.003	-0.004	0.009	-0.004	0.017	-0.012	0.012
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Size 100 and over	0.012	0.022	-0.020	0.008	0.010	0.015	-0.013
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Constant	0.033	0.190**	-0.073	0.011	0.112*	-0.180*	-0.006
	(0.05)	(0.09)	(0.09)	(0.08)	(0.06)	(0.10)	(0.09)
N	7424	3875	1995	1554	4784	2640	7118
R-Squared	0.23	0.25	0.27	0.23	0.28	0.27	0.34
First stage F-statistic	144.34	104.88	25.20	18.26	80.13	48.14	286.28
Hansen-Sargen Overid test p-value	0.90	0.40	0.66	0.14	0.74	0.31	0.60

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*. High and Low Share of skilled workers represent firms with share of skilled workers above or below the population mean in the most recent fiscal year, respectively.

Table 6: Effects of innovation on employment (IV), by Degree of Innovation Novelty

	Product Upgrade vs. Completely New		New to Firm vs New to National or Intl	
	Manufacturing	Services	Manufacturing	Services
Process Innovation only	0.004	-0.007	0.013	-0.015
	(0.01)	(0.02)	(0.02)	(0.02)
Sales growth d.t. new products	0.963***	0.918***	1.031***	0.742***
	(0.06)	(0.08)	(0.11)	(0.11)
Product Upgrade × Sales growth d.t. new products	-0.043	0.100		
	(0.07)	(0.10)		
New to National or Intl × Sales growth d.t. new products			-0.135	0.331***
			(0.10)	(0.12)
Constant	0.039	0.059	0.036	0.063
	(0.05)	(0.09)	(0.05)	(0.09)
N	7424	7264	7424	7264
R-Squared	0.23	0.33	0.23	0.35

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*.

Table 7: Process Automation

	All Firms	Manufacturing	Low Tech	Medium Tech	HT	Services
Automation only	0.001	0.023	0.020	0.009	0.029	-0.106*
	(0.02)	(0.03)	(0.07)	(0.06)	(0.04)	(0.05)
Process only (excl. automation)	-0.001	0.003	-0.020	-0.032	0.020	-0.002
	(0.01)	(0.02)	(0.07)	(0.05)	(0.03)	(0.02)
Sales growth d.t. new products	0.941***	0.974***	1.002***	0.898***	0.922***	0.899***
	(0.07)	(0.11)	(0.27)	(0.24)	(0.13)	(0.09)
Constant	-0.002	0.037	0.012	-0.075	0.194**	0.062
	(0.01)	(0.05)	(0.08)	(0.09)	(0.09)	(0.09)
N	14688	7424	1554	1995	3875	7264

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*. High and Low Share of skilled workers represent firms with share of skilled workers above or below the population mean in the most recent fiscal year, respectively.

Table 8: Effects of innovation on employment, accounting for Organizational Innovation

	OLS	IV
Process innovation only	-0.062***	0.021
	(0.02)	(0.03)
Organizational only	-0.068***	0.013
	(0.02)	(0.03)
Sales growth d.t. new products	0.621***	1.118***
	(0.05)	(0.12)
Size 20 to 99	-0.003	-0.006
	(0.01)	(0.02)
Size over 100	0.000	-0.004
	(.)	(0.02)
Constant	0.074***	0.070
	(0.01)	(0.08)
N	4404	4404
R-Squared	0.35	0.31
First stage F-statistic		109.43
Hansen-Sargen Overid test p-value		0.34

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. All regressions include country-industry and size dummies, constrained to sum to zero. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*.

Table 9: Effects of innovation on employment, with Random Effects

	Product, Process	Product, Process, Organizational	Product, Process, Automation
Fixed Part			
Process Innovation Only	-0.007	-0.001	0.000
	(0.01)	(0.03)	(0.02)
Organizational only		-0.004	
		(0.03)	
Automation only			-0.033*
			(0.02)
Growth new sales	0.962***	1.023***	0.961***
	(0.08)	(0.12)	(0.09)
Size 20 to 99	-0.038***	-0.080***	-0.038***
	(0.01)	(0.02)	(0.01)
Size over 100	-0.063***	-0.109***	-0.063***
	(0.01)	(0.02)	(0.01)
Constant	0.032***	0.058**	0.032***
	(0.01)	(0.03)	(0.01)
Random Part			
$\sqrt{\psi_{11}}$	0.038***	0.090***	0.048***
	(0.01)	(0.02)	(0.01)
$\sqrt{\psi_{22}}$	0.243***	0.198***	0.242***
	(0.01)	(0.02)	(0.01)
$\sqrt{\theta}$	0.432***	0.413***	0.432***
	(0.00)	(0.01)	(0.00)
N	11762	3696	11762
Pseudo log-likelihood	-7154.07	-2114.88	-7153.14
LR test	0.00	0.00	0.00

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. Standard errors computed using 5,000 bootstrapped replications. Dependent variable is net labor growth (minus growth in sales of old product). Instrumental variables are indicator whether new product is *completely new to the firm* and whether firms *invests in R&D*. Based on multilevel mixed-effects linear regression with random intercept and slope for g_2 within country and sector. Sample restricted to country sector clusters with at least 10 observations.

Table 10: Regressions of Random Effects on Innovation intensities

	Product & Process		Automation		Organizational	
	(1)	(2)	(3)	(4)	(5)	(6)
Share product innovation	0.045**	0.041*	0.043	0.036	0.018	0.023
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Share product and process innovation	-0.025	-0.007	0.078	0.101	-0.026	-0.032
	(0.03)	(0.04)	(0.07)	(0.07)	(0.02)	(0.03)
Share product and automation			-0.244**	-0.244**		
			(0.11)	(0.11)		
Share product and organizational					-0.028	-0.027
					(0.02)	(0.02)
Constant	0.955***	0.951***	0.952***	0.948***	1.026***	1.019***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
N	306	306	306	306	284	284
R-Squared	0.02	0.07	0.05	0.10	0.01	0.05
Pseudo log-likelihood	588.81	596.65	521.88	529.38	369.92	376.08

Note: Coefficients and standard errors robust to heteroskedasticity and 1, 5, and 10 percent levels of significance are denoted by ***, ** and *, respectively. Standard errors computed using 5,000 bootstrapped replications. Based on 306 country sectors with at least 10 observations.

A Definitions of Innovation

The definitions of innovation in the survey questionnaire were based on the same interpretation as in the Community Innovation Survey, outlined below.

- Product Innovation A product innovation is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics. Product innovations can utilize new knowledge or technologies, or can be based on new uses or combinations of existing knowledge or technologies.

- Process Innovation Process innovation is the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software. Process innovations can be intended to decrease unit costs of production or delivery, to increase quality, or to produce or deliver new or significantly improved products. In the questionnaire, process innovation is defined as one of the following:

  1. Automate manual processes, partially or fully
  2. Adapt a technology or method previously used by this establishment?
  3. Introduce a new technology or method
  4. Use a more efficient technology or method already used by this establishment

- Organizational Innovation

  1. Outsourcing tasks & changes in relations
  2. Changes in management structures, integrating departments/units
  3. Acquiring management systems for information & knowledge

B Re-classification of innovation

We re-classified product and process innovations based on their descriptions provided in the questionnaire in order to correct for missclassification. In some cases there was not enough information to validate an innovation, and in other cases innovations were misidentified between product and process innovations or process and marketing innovations. Below are some examples of how the re-classification was implemented.

1. Delivery
   - improved delivery process (additional, superior vehicles) = process innovation
   - introduce delivery as new offering (not core business) = product innovation
   - introduce delivery -direct sales (same core business) = marketing

- delivery method for service sector (restaurants) = process innovation
- expansion of delivery, such as additional trucks (without specifying improvements) = not innovation
- expansion of delivery to new areas or across country = marketing
- an upgrade in delivery vehicle = process innovation

2. Distinction between introducing new types of product as product innovation or marketing

   - food: new recipe but not necessarily any improvement = marketing
   - garments: new line, new design = product innovation (under assumption that there is product differentiation, quality improvements)
   - wholesaler starts to offer new product or new range of product = product innovation

3. Other

   - creation of online store = process (services)/marketing (manufacturing)
   - wholesaler opens own retailer store = product innovation
   - introduced warranty = marketing
   - product innovation same description as main line of business = not innovation
   - Process innovation leading to product innovation = classify as both product and process
   - New brand, type, design without specifying specific attribute changes = marketing
   - Training of employees, improving outcomes = process

Table A1: List of Countries

Country	Region	Income
Congo,Dem.Rep.	Africa	Low Income
Ghana	Africa	Low Income
Kenya	Africa	Low Income
Namibia	Africa	Higher Middle Income
Nigeria	Africa	Low Income
SouthSudan	Africa	Low Income
Sudan	Africa	Low Income
Tanzania	Africa	Low Income
Uganda	Africa	Low Income
Zambia	Africa	Low Income
Malawi	Africa	Low Income
Bangladesh	South Asia	Low Income
India	South Asia	Lower Middle Income
Nepal	South Asia	Low Income
Pakistan	South Asia	Low Income
Albania	Eastern Europe	Lower Middle Income
Armenia	Eastern Europe	Lower Middle Income
Azerbaijan	Eastern Europe	Lower Middle Income
Belarus	Eastern Europe	Higher Middle Income
Bosnia and Herzegovina	Eastern Europe	Lower Middle Income
Bulgaria	Eastern Europe	Higher Middle Income
Croatia	Eastern Europe	Higher Middle Income
Czech Republic	Eastern Europe	High Income
Estonia	Eastern Europe	Higher Middle Income
Georgia	Eastern Europe	Lower Middle Income
Hungary	Eastern Europe	Higher Middle Income
Kazakhstan	Eastern Europe	Higher Middle Income
Kosovo	Eastern Europe	Lower Middle Income
Kyrgyzstan	Eastern Europe	Low Income
Latvia	Eastern Europe	Higher Middle Income
Lithuania	Eastern Europe	Higher Middle Income
Macedonia	Eastern Europe	Lower Middle Income
Moldova	Eastern Europe	Low Income
Mongolia	Eastern Europe	Lower Middle Income
Montenegro	Eastern Europe	Higher Middle Income
Poland	Eastern Europe	Higher Middle Income
Romania	Eastern Europe	Higher Middle Income
Russia	Eastern Europe	Higher Middle Income
Serbia	Eastern Europe	Higher Middle Income
Slovakia	Eastern Europe	High Income
Slovenia	Eastern Europe	High Income
Tajikistan	Eastern Europe	Low Income
Turkey	Eastern Europe	Higher Middle Income
Ukraine	Eastern Europe	Lower Middle Income
Uzbekistan	Eastern Europe	Low Income
Egypt	MENA	Lower Middle Income
Israel	MENA	High Income
Jordan	MENA	Lower Middle Income
Lebanon	MENA	Higher Middle Income
Morocco	MENA	Lower Middle Income
Tunisia	MENA	Lower Middle Income
West Bank	MENA	Lower Middle Income
Yemen	MENA	Low Income

Source: World Bank Enterprise Surveys, 2013.