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Abstract

Based on a model proposed by Harrison, Jaumandreu, Mairesse, and Peters (2008) and an estimation of this type of model for Costa Rica by Monge-González et al. (2011), using an IV approach, this study assesses the direct impact of Internet diffusion on total labor demand, the demand for skilled labor, and the demand for female labor. Using data from a sample of manufacturing firms in Costa Rica from 2006 to 2007, the study finds that both process and product innovations are positively related to employment growth and that the use of the Internet by workers for business purposes does not impact demand for labor. The positive impact of product innovation on labor demand increases when workers use the Internet for business purposes. This relationship was not found in cases of skilled and female labor demand. These findings underscore the Internet's importance in improving the impact of product innovation on employment growth and suggest that employee use of the Internet is neither a labor displacement innovation nor a gender or skill-biased innovation. Further research is needed to understand the effects of the use of the Internet on innovation and the identification problem associated with use of Internet variables in Harrison et al.'s framework.

JEL Classification: D22, O31, O38

Keywords: innovation, employment, skills, gender, information and communication technologies, Internet, Costa Rica

1. Introduction

This research focuses on the direct effects of the use of the Internet on employment in terms of quantity and quality at the firm level. Several reasons justify this focus. First, it has been claimed that the introduction of the Internet in business processes may be skill-biased, and may have immediate effects on employment (Basant et al., 2006; Harrison, 2008). Second, we can conceive of Internet diffusion as having an indirect effect on a firm's propensity to innovate. Third, the use of the Internet is likely to influence the degree to which agents within firms resist or encourage use of these technologies and their subsequent effects on employment. Fourth, in this case, firms are the target of Internet policies. Knowing how employment in firms responds to the use of these types of technologies, which may be influenced by specific policies, can be valuable for policymakers. Creators of Internet policy should ideally take into account the impact of Internet use on employment to provide effective ways to overcome or mitigate the costs of potential displacement effects. Possible strategies might include—parallel to any initiatives to increase the use of the Internet by firms—unemployment risk mitigation policies that help the economy to reap the benefits of using this technology, protecting those who may stand to lose from those changes.

This paper aims at assessing whether the use of the Internet creates or destroys employment in Costa Rican manufacturing firms. In particular, the research focuses on the differential effects of the Internet on employment growth. We also investigate how the use of the Internet by manufacturing firms affects different characteristics of employment demand, i.e., the impact of the Internet on skilled labor and the extent to which the diffusion of the Internet is positively correlated with female labor force demand.

This paper makes three main contributions to the literature. First, we explore the differential effects of the use of the Internet for business purposes on employment growth in a small developing country. Second, we explore differential impacts across firms as to how the use of the Internet affects skilled and unskilled labor demands. Finally, we study the impact of the Internet on female labor force demand.

A better understanding of how manufacturing firms' use of the Internet relates to employment growth in Costa Rica can provide useful empirical evidence for policymakers attempting to make better use of existing resources, for example by focusing training policies, targeting Internet policies, promoting particular Internet strategies, and so forth. This is particularly important for Costa Rica, where a Presidential Council on Competitiveness and Innovation was created in 2010, whose major concern is to promote economic growth and sustainable development based on moving the country from an efficiency-driven economy toward an innovation-driven economy.[3] Promotion of Internet use by firms is one of the major concerns in this process as it provides a way to improve firms' competitiveness.

The structure of the paper is as follows: Section 2 discusses the relevant literature; Section 3 presents the econometric models; Section 4 describes the data used in the estimations; and Section 5 discusses the evidence provided by simple descriptive statistics on employment, innovation outcomes, and Internet diffusion, as well as the main econometric results using firm-level data. A final section summarizes the work presented in the preceding sections.

2. Literature Review

The positive impact of the Internet on business performance has been documented by many researchers. According to the World Bank (2006), for instance, businesses that use information and communication technologies (ICTs)—especially the Internet—grow more quickly, invest more, and are more productive and profitable than those businesses that do not.

There are few studies, however, of the effect of Internet use on the demand for various types of labor, especially at the firm level. Among those that do exist, a comparative analysis from Brazil and India by Basant et al. (2006) found that size and foreign ownership of firms tend to be associated with higher Internet adoption, and that in Brazil there is strong evidence that increasing Internet adoption has been associated with a higher proportion of educated workers. This study also shows very high returns to the use of the Internet. More recently, Harrison's (2008) study of the same countries showed that Internet use was diffusing rapidly through the manufacturing sectors of Brazil and India, and that Internet use explained up to one-third of the average increase in the share of skilled workers in Brazil and up to one-half in India.

These results are similar to those of earlier studies in developed countries. The study by Berman, Bound and Machin (1998) found shifts away from unskilled labor within industries in 12 Organisation for Economic Co-operation and Development (OECD) countries during the

[3] The Costa Rican government moved to strengthen governance through the creation and adoption of Executive Decree N° 36024-MP-PLAN, which called for the establishment and consolidation of a Presidential Council on Competitiveness and Innovation as an organ of guidance, advice, coordination, and follow-up on public policies, plans, goals and objectives, and their design.

1980s, suggesting pervasive skill-biased technological change. Other studies in developed countries suggest that the impact of Internet use depends on making complementary investments; factors such as the availability of skilled workers, type of organization, firm size, and economic activity may also influence the effects of Internet use (e.g., Pilat, 2004). The availability of skilled workers trained in areas such as problem solving, statistical process control, and administration of ICTs has also been found to influence the levels of benefits of the incorporation of the Internet in firms' operations (Spyros, 2004).

On a related note, Calza and Rovira (2011) mention that, in addition to the direct effects of the Internet on a firm's performance, there are some indirect effects on the demand for skilled labor, innovation, and organization changes that may accompany Internet adoption. Bresnahan et al. (2002) investigated the relationship between the Internet, workplace re-organization, and product and service innovation as a skill-biased technological change affecting labor demand in the United States.

When considering these topics it must be remembered that although firm demand for workers skilled in the use and administration of ICTs has almost universally increased, there is not always a sufficient supply of capable workers, which causes imbalances in the labor market, constant turnover of skilled employees, and a need to seek out and train new workers (CEPAL, 2010). A study carried out by the Costa Rican Chamber of ICT companies (CAMTIC, 2010) shows that this problem exists in Costa Rica and recommends the implementation of labor practices such as improved training, family benefits, etc., which improve employee retention.

3. Econometric Models

In a previous effort using the basic model developed by Harrison et al. (2008), Monge-González et al. (2011) studied how different types of innovations create or displace employment in Costa Rican manufacturing firms. Based on that framework, we use an extension of Harrison et al.'s basic model to explore how the use of the Internet for business purposes may impact manufacturing labor force demand as well as different characteristics of employment demand, such as skills and gender.

In what follows, we summarize the conceptual framework used in Monge-González et al. (2011) and present the principal ideas which suggest that Internet diffusion might impact employment growth in the Costa Rican manufacturing sector.

3.1 The Basic Model

The literature suggests that the effect of innovation on employment generation depends on the relative intensity of the displacement and compensation effects that it generates on labor demand. Assuming a two-goods production function and two different years, Harrison et al. (2008) derive a production function in which firm productivity levels are influenced by individual productivity, i.e., all unobservable factors which make a firm more or less productive than the average firm using the same technology,[4] and non-technological productivity shocks, i.e., all the unobservable shifts in the production function for reasons other than the development of technology.[5] The authors claim that employment and other decisions about inputs are made based on cost minimization, given these individual productivity effects and productivity shocks. From this framework, they derive a labor demand function and conclude that in trying to distinguish between the employment-creation versus displacement effect of innovation on this demand, a distinction between product and process innovation is useful.

We begin our analysis using the Harrison et al. (2008) basic model in which two types of products are distinguished: existing products and new products. Change in employment is then decomposed into the part due to increased efficiency in production of existing products (which could be related to process and organizational innovations) and the part due to introduction of new products (product innovations). Hence, exploration of the effects of innovation on employment growth is built on the estimation of different variations of the following basic equation (see Harrison et al., 2008):

$$l_{it} = \alpha_0 + \alpha_1 d_{it} + y_{1it} + \beta y_{2it} + u_{it} \qquad (1)$$

Where **l** stands for the rate of employment growth over a specific period (t) for firm i, and $\mathbf{y_1}$ and $\mathbf{y_2}$ are the corresponding rates of output growth of old and new products (product innovations) for the same period and the same firm. The parameter $\boldsymbol{\alpha_0}$ represents the average

[4] This may include factors such as superior ability to manage innovation, higher absorptive capacity, or more efficient organization.
[5] For example, unobserved investments, bursts in capacity utilization, labor, and temporary organizational problems
[6] See Harrison et al. (2008: 10–11) for a detailed explanation of why the parameter $\boldsymbol{\alpha_0}$ captures the change in efficiency associated with production of the old products and why it should be negative.

efficiency growth in production of the old product,[6] and a binary variable **d**, equal to one if the firm has implemented a specific process innovation not associated with a product innovation, and zero otherwise, which picks up the effects of "process innovation only" through parameter $\boldsymbol{\alpha_1}$. The parameter $\boldsymbol{\beta}$ captures the relative efficiency of the production of new products. Notice that the variable $\mathbf{y_1}$ has a coefficient equal to one and can thus be subtracted from l on the left-hand side of the equation for purposes of estimation.

Equation (1) identifies two effects that are of interest for this study. By enabling the measurement of the growth of output due to the introduction of new products, it allows us to estimate the gross effect of product innovation on employment, while the observation of process innovations related to the production of old products allows us to estimate the gross productivity or "displacement" effect of process innovation. It should be noted that equation (1) has some limitations, since the variable **y1** embodies three different employment effects which cannot be separated without additional (demand) data: i) the possible "autonomous" increase in firm demand for the old products (for example, due to cyclical or industry effects); ii) the "compensation" effect induced by any price decrease for existing products following a process innovation; and iii) the cannibalization of existing product demand resulting from the introduction of new products either by the firm or by its competitors (Harrison, et al., 2008).

In what follows, we discuss in detail the problems involved in the identification and estimation of the parameters of equation (1).

3.2 Identification Issues

The identification and consistent estimation of the parameters $\boldsymbol{\alpha_0}$, $\boldsymbol{\alpha_1}$ and $\boldsymbol{\beta}$ of equation (1) depend on the lack of correlation between the variables representing product and process innovations ($\mathbf{y_2}$ and **d**) and the error term **u** or, at least, on the availability of instruments correlated with these variables and uncorrelated with **u**.

Harrison et al. (2008) claim that innovations are the result of the success of "technological investments", mainly R&D, which have to be decided upon by firms in advance and depend on their individual productivity effects. Therefore, innovations are likely to be correlated with these effects. However, as shown by these authors, they are differentiated out in

[6] See Harrison et al. (2008: 10–11) for a detailed explanation of why the parameter $\boldsymbol{\alpha_0}$ captures the change in efficiency associated with production of the old products and why it should be negative.

equation (1) and do not enter into **u**. On the other hand, the unobserved productivity shocks (ω) remain in **u**, and their correlations with the variables representing process and product innovations (**d** and $\mathbf{y_2}$) depend on the assumptions which can reasonably be made about both their characteristics and the timing of the firm's technological investments. If the firm is assumed to make its technological investment decisions in advance, and the shocks are considered unpredictable, innovations will not be correlated with ω and **u** and an OLS estimator will suffice to estimate equation (1) consistently. But if firms are assumed to make these investments within the period affected by the shocks ω, the resulting innovations will be correlated with these shocks, even if they were previously unpredictable. In this case, however, lagged values of the included variables could be considered to be uncorrelated with ω and **u** and used as valid instruments. Finally, if ω is assumed to be auto-correlated, the timing of the investment decisions becomes irrelevant because the current value of **u** depends on its past values and innovations will likely be correlated with past values of u as well as with its current value. In this case, both process and product innovations (**d** and $\mathbf{y_2}$) and their past values are endogenous and identification should rely on the use of (external) instrumental variables which can be claimed to be exogenous with respect to ω (Harrison et al*.,* 2008).

The authors make a series of general observations about the identifiability of the model. First, there are good reasons to believe that in fact productivity shocks are not predictable or very poorly predictable by firms at the moment of deciding upon and starting their technological investments; hence, consistent estimation of model (1) by OLS can be carried out. For example, it seems rather unrealistic to assume that firms can forecast their future labor or organizational problems or demand shocks when deciding upon R&D investments, which to a large extent are made well in advance of the innovations they eventually generate.[7] On the other hand, if technological investments were positively related to productivity shocks ω (e.g., if they are stimulated by an anticipated burst in firm capacity utilization and the resulting increase in labor productivity), and hence negatively with the overall error **u**, we would expect a downward bias in the coefficients of both variables, process and product innovations (**d** and $\mathbf{y_2}$). In other words, we would estimate employment displacement effects of process innovation that are too large and an impact of the introduction of new products that is too low.

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[7] This is especially true in a developing country like Costa Rica. Besides, as shown by Monge-González et al. (2011), few firms invest in R&D in this country.

Taking into account the previous discussion, we show in the next section that our estimates are free of such biases after controlling for the measurement problems and using instrumental variables.

3.3. Measurement Problems

To estimate equation (2), we have to face a difficult issue. In this equation, we must substitute the growth in nominal sales, which is what we observe, for the growth in real production. The fact that prices are unavailable at the firm level to deflate changes in nominal sales is a common problem in nearly all firm productivity data analyses. This problem is particularly relevant here, since we are attempting to estimate the relative efficiency of producing old and new products, which may be sold at different prices.

Denoting $\mathbf{g_1}$ as the nominal growth rate of sales due to old products, we can approximately write $\mathbf{g_1 = y_1 + \pi_1}$, where $\boldsymbol{\pi_1}$ is the rate of increase of the prices of old products. Similarly we can define $\mathbf{g_2}$ as the nominal growth in sales that is due to new products and write $\mathbf{g_2 = y_2(1 + \pi_2) = y_2 + \pi_2 y_2}$, where $\boldsymbol{\pi_2}$ is the proportional difference of the prices of new products with respect to the prices of the old products. Substituting $\mathbf{g_1}$ and $\mathbf{g_2}$ for $\mathbf{y_1}$ and $\mathbf{y_2}$ in equation (1), and moving $\mathbf{g_1}$ to the left-hand side of the equation, we obtain:

$$l_{it} - g_{1it} = \alpha_0 + \alpha_1 d_{it} + \beta g_{2it} + v_{it} \qquad (2)$$

where the new unobserved disturbance is now $\mathbf{v = -\pi_1 - \beta\pi_2 y_2 + u}$. In the case of a non-zero mean of the rate of increase of the price of old products ($\boldsymbol{\pi_1}$), the model will include $-\mathrm{E}(\boldsymbol{\pi_1})$ in the intercept and $-(\boldsymbol{\pi_1} - \mathbf{E}(\boldsymbol{\pi_1}))$ in the disturbance. To estimate the parameters of (2) consistently, we thus have to take into account two additional problems. First, the nominal growth in sales that is due to new product, $\mathbf{g_2}$ (i.e., $\mathbf{y_2 + \pi_2 y_2}$), will be correlated with the composite error term $\mathbf{v}$ (i.e., $\mathbf{-\pi 1 - \beta\pi 2y2 + u}$). According to Harrison et al. (2008), one can hope that this only happens because $\boldsymbol{\pi_2}\mathbf{y_2}$ is obviously correlated with $\boldsymbol{\beta\pi_2}\mathbf{y_2}$, and that the term $\mathbf{y_2}$ is uncorrelated with both $\boldsymbol{\pi_1}$ and $\boldsymbol{\beta\pi_2}\mathbf{y_2}$. If this condition is met, the problem amounts to finding an instrumental variable for the sales growth due to new products ($\mathbf{g_2}$) that is correlated with the real ratio $\mathbf{y_2}$ and uncorrelated with $\boldsymbol{\pi_2}\mathbf{y_2}$. We accordingly tested several possible instruments (see next section) in the estimation of equation (2) to solve this problem. As pointed out by Harrison et al. (2008), the likely bias in $\boldsymbol{\beta}$ in the absence of instrumentation is an “attenuation” bias.

Second, the composite error term $\mathbf{v}$ includes the rate of increase of the prices of old products ($\boldsymbol{\pi_1}$) as long as we cannot control for the change in the prices of the old products. This creates a problem for isolating one of the structural effects of interest. We know that any increase in efficiency decreases marginal cost by the same proportion. Therefore, if firms are pricing their products competitively by setting a markup on marginal cost, price variations are likely to be proportional to the efficiency increase (with an opposite sign). If we suppose, for example, that the price change $\boldsymbol{\pi_1}$ depends on the marginal cost change c according to the rule $\boldsymbol{\pi_1 = \pi_0 + \gamma c}$, where $\boldsymbol{\pi_0}$ is a constant and $\boldsymbol{\gamma}$ is the pass-through parameter (with $\mathbf{0 < \gamma < 1}$), and that marginal cost changes themselves are related to process innovation efficiency gains according to $\mathbf{c = \alpha_1 d}$, we can write that $\boldsymbol{\pi_1 = \pi_0 + \gamma\alpha_1 d}$. Thus, in equation (2), we will only be able to estimate an attenuated effect $\mathbf{(1 - \gamma)\alpha_1}$. In other words, in the absence of firm price information, we can only identify an effect of process innovation on employment net of (direct) compensating price variations. As such compensating movements can be important (with $\boldsymbol{\gamma}$ close to 1), we might even find that process innovation has no effect on employment (Harrison et al., 2008). To deal as best we can with this problem in our econometric analysis, and following Harrison et al. (2008), we take the corresponding industry price indexes $\boldsymbol{\pi}$ as a rough proxy for the price change of old products $\boldsymbol{\pi_1}$, available at a 2 digit-level of the Standard Industrial Classification (SIC) for Costa Rica and assigned to firms according to their main activities (the main products they produce).[8] Therefore, in practice we use $\mathbf{l - (g_1 - \pi)}$ as the dependent variable, which will leave the term $\mathbf{-(\pi_1 - \pi)}$ in the error term. We may hope that, to the extent the firm prices do not deviate much from industry prices, especially in a small, open economy, this adjustment at least partly corrects the attenuation bias in the estimated $\boldsymbol{\alpha_1}$. Given the foregoing discussion, equation (2) can be rewritten as follows:

$$l_{it} - (g_{1it} - \pi) = \alpha_0 + \alpha_1 d_{it} + \beta g_{2it} + \tau_{it} \qquad (3)$$

In short, to consistently estimate the parameters of interest in our model, we have to address the endogeneity problem created by the possible correlation of the product innovations ($\mathbf{y_2}$) with productivity shocks and by its necessary replacement by $\mathbf{g_2}$ for lack of firm-level price information and we have to consider that the variable process innovations (**d**) could also be

[8] Even in those cases where Costa Rican firms export most of their production, especially when they operate under the free zone regime, it is valid to used domestic price indices since Costa Rica is a small open economy and tariffs are very low and have not changed during the last decade.

correlated with productivity shocks. Our strategy thus relies on a choice of instrumental variables that can be considered to be correlated with the sales growth due to new products and process innovations (**g2** and **d)**, and uncorrelated with productivity shocks

3.4 Internet Diffusion, Skilled Labor, and Female Labor Force Demand

Based on Harrison et al.'s model specification, we analyze the impact of the Internet on employment growth through its effects on innovation. Since we are controlling for output growth (both existing and new products), the direct inclusion of Internet use in the regression is equivalent to the inclusion of "d" for process innovation. In other words, what the inclusion of Internet use as explanatory variable is capturing is the effect of the Internet on employment growth through the productivity increase of old products. In so doing, we must define the Internet variable as Internet-only. That is, Internet users which are not product innovators (see definitions in the Appendix A).

The inclusion of Internet in Harrison et al.'s framework is justified because given that the quality of the information on process innovation is very weak and requires a subjective answer, we use direct information on the Internet, which could be a better proxy for process innovation. Accepting that the focus of the analysis is based on the Harrison model extended to the Internet means that the emphasis is on how product and process innovation affect employment and whether these effects are different depending on the degree of Internet adoption by the firm.

In the national innovation survey, we have data on diffusion of the Internet in firms, specifically, if workers regularly use the Internet in their jobs. We do not include workers using computers as an additional ICT variable because of its high correlation with Internet use by workers and the resulting risk of multicolinearity.[9] We can therefore estimate the impact of Internet diffusion on the demand for labor including as explanatory variable a dummy for workers that regularly use the Internet in firms that are not product innovators (int*er_only*).

Given that the focus of the analysis is based on the Harrison model extended to the Internet, we claim that the emphasis is on how product and process innovation affect employment and whether these effects are different depending on the degree of adoption of the Internet by the firm. So on top of including the int*er_only* variable for the impact of the Internet

[9] In fact, the Pearson correlation coefficient between these two variables is 0.775 and is statistically significant at the 1 percent level.

on the process innovation of old products, we also test whether the effect of product innovation on employment growth is higher (or lower) depending on the adoption of the Internet by the firm. This can be done through the interaction between a dummy variable for Internet users (inter) and the sales growth due to new products g2 (i.e. interxg2). In doing so, and following Harrison et al. (2008), equation (3) can be rewritten as follows:

$$l_{it} - (g_{1it} - \pi) = \alpha_0 + \alpha_1 d_{it} + \beta g_{2it} + \lambda_1 \text{int}er\_only + \lambda_2 \text{int}erxg_{2it} + \mu_{it} \quad (4)$$

From Equation (4) it is clear that the effect of product innovation on employment growth will depend on the adoption of Internet by the firm. To see this, it is sufficient to take the conditional expectation of Equation (4) for different combinations of values of Inter and g2, so that we have

$$E(l_{it} - g_{it} - \pi)|inter = 1, g2 = 1) = \alpha_0 + \alpha_1 d_{it} + \beta + \lambda_1 \text{int}er\_only + \lambda_2$$

$$E(l_{it} - g_{it} - \pi)|inter = 1, g2 = 0) = \alpha_0 + \alpha_1 d_{it} + \lambda_1 \text{int}er\_only$$

$$E(l_{it} - g_{it} - \pi)|inter = 0, g2 = 1) = \alpha_0 + \alpha_1 d_{it} + \beta + \lambda_1 \text{int}er\_only$$

$$E(l_{it} - g_{it} - \pi)|inter = 0, g2 = 0) = \alpha_0 + \alpha_1 d_{it} + \lambda_1 \text{int}er\_only$$

The impact of Internet on the effect of product innovation on employment growth is:

$$E(l_{it} - g_{it} - \pi)|inter = 1, g2 = 1) - E(l_{it} - g_{it} - \pi)|inter = 0, g2 = 1) = \lambda_2$$

We would like also to study the extent to which the use of the Internet by workers might affect the impact of product innovation on skilled labor as well as on female labor force demand. Therefore, we explore the impact of Internet diffusion on the demand for skilled labor, redefining equation (4) as follows:

$$l_{it}^s - (g_{1it} - \pi) = \alpha_0^s + \alpha_1^s d_{it} + \beta^s g_{2it} + \varphi_1 \text{int}er\_only + \varphi_2 \text{int}erxg_{2it} + \varepsilon_{it} \quad (5)$$

In doing so, l^s can be estimated as the rate of growth of the sum of employees with technical and professional education. In short, through equation (5) we can assess the extent to which Internet adoption affects employment generation when considering employment quality in addition to total employment.

There is evidence that ICTs are positively correlated with female labor force participation (ITU, 2010). In order to explore this hypothesis in the case of Costa Rica, and to detect any shift in this direction in labor demand, we divide the labor employment demand according to gender. This is possible since in the innovation survey we have data on labor divided by gender. Thus, equations (4) and (5) can be rewritten as follows:

$$l_{it}^{w} - (g_{1it} - \pi) = \alpha_0^{us} + \alpha_1^{us} d_{it} + \beta^{us} g_{2it} + \vartheta_1 \operatorname{int}er\_only + \vartheta_2 \operatorname{int}erxg2 + \upsilon_{it} \quad (6)$$

Where: (l_i^{w}) is the female labor demand growth.

As was discussed by Harrison (2008) and by Monge-González et al. (2011) for the estimation of the Harrison et al. model for Costa Rica, there are some endogeneity problems in the estimation of equation (3) that must be taken into account, and since this is the case such problems are also present in the estimation of equations (4), (5), (6) and (7). This topic will be discussed in detail in Section 5, Estimation Strategy.

4. Data

The main source of data used in the study is the Costa Rican Innovation Survey for the years 2006-2007, which we previously used for the estimation of Harrison et al.'s model for Costa Rica. The survey was conducted by CINPE for the Ministry of Science and Technology (MICIT) using a statistically representative sample of the manufacturing, energy, and telecommunications sectors. According to the official data of the National Institute of Statistics and Census (INEC), these sectors contained a total of 2,285 firms. In the case of the 2006-2007 survey, INEC provided a sample of 566 firms distributed over all sectors. Using this sample, it was possible to obtain responses from 376 firms. After eliminating firms from the energy and telecommunications sectors, as well as any manufacturing firms with fewer than 10 employees for comparability with other international studies, we finished with a sample of 208 firms.

The data from the innovation survey include most of the variables we need to estimate equations (3) to (8), such as total sales, sales of both old and new products, number of workers (skilled and unskilled; permanent and temporary), and information on the results of innovation (product and process innovations). The data from the innovation survey were combined with official data from the Costa Rican Social Security System (CCSS) and the Central Bank of Costa Rica related to total number of workers and total production value for each industry sector (2-digit codes from the SIC), respectively. The definitions of all variables used in the estimation of equation (3) through (8) are presented in Appendix A.

Although two other innovation surveys were available for the years 2008 and 2009, we decided not to use them because of data compatibility problems with the survey for 2006-2007. In the first place, the three samples were not selected using criteria which would permit the creation of a panel; each sample was selected using a random sample of the total population of manufacturing firms in the country. Second, some key questions for this research such as sales of products or innovations which were new for the firm or new for the market were included only in the first survey (2006-2007), whose results we are analyzing in this document.

5. Econometric Results

5.1 Estimation Strategy

To consistently estimate the parameters of interest in our model, we address the endogeneity problem created by the possible correlation of the variable product innovations (y2) with productivity shocks and by its necessary replacement by the sales growth due to new products (**g2**) for lack of firm-level price information, and we must also take into consideration that the process innovations (**d**) could also be correlated with productivity shocks. Our strategy thus relies on the choice of instrumental variables that can be considered to be correlated with both process innovations and sales growth due to new products (d and g2), and uncorrelated with productivity shocks. After several trials, we finally choose two valid instruments for sales growth due to new products (**g2**) – the increased range of goods indicator (which is used by Harrison et al., 2008) and the increase in productive capacity. These two variables assess the impact of innovation on the increase in the range of goods produced by firm and on its productive capacity, respectively, as reported by the firms in the innovation survey.[10]

[10] The "increased range of goods" variable is coded as zero if innovation is not relevant for the range of goods produced by the firm, one if the impact of innovation on the range is low, two if it is medium and three if it is high. Similarly, the "increase in productive capacity" variable is coded as zero if innovation is not relevant for a positive productive capacity change, one if the impact of innovation on productive capacity is low, two if it is medium and

We assume that both process innovations (d) and Internet variables are exogenous and therefore not correlated with productivity shocks. While the first assumption is valid according to Monge-González et al.'s (2011) robustness test, the second assumption cannot be supported by similar test results due to limitations on the data from the Innovation survey. Indeed, we were unable to find an appropriate instrumental variable (IV) for both the *inter*_only and int*er* variables. Therefore, in the estimation of equations (4), (5), and (6) we assume that Internet diffusion variables are not correlated with the residual terms. It is important to mention that the identification problem is also present in almost all the previous research on Internet in developed countries, and that it has been so far very difficult to find good instruments for Internet adoption (Crespi et al., 2007).

5.2 Descriptive Statistics

In this section, we present descriptive statistics and discuss the results of the initial exploration of the data. Details on variable definitions can be found in Appendix A. Table 1 presents descriptive statistics for the manufacturing sector in Costa Rica. For each variable, the sample is split into seven sub-groups according to whether the firm reports that, during the study period 2006-2007, they had not introduced product and/or process innovations; had introduced only process innovations (non-product innovations); had introduced product innovations; had used the Internet, but do not innovate; had used the Internet, but are non product innovators (int*er*_only); had not used the Internet, but are product innovators; and had used the Internet and are product innovators.

Table 1 shows that product innovators represent about 74 percent of manufacturing firms. Firms that carry out only process innovations account for 4 percent of the sample, which indicates that in most cases product and process innovations occurs simultaneously in these firms. As was pointed out by Monge-González et al. (2011), based on results from other countries these figures seem to be high for a developing country like Costa Rica.[11] Firms that use that Internet but are not innovators account for 18 percent of the sample; firms that had used the Internet but are non product innovators (int*er*_only) represent 21 percent; firms that had not used

three if it is high. We could not find any valid instrument for *d* based on the available data from the innovation survey.

[11] For example, Harrison, et al. (2008) found that innovators represent between about 40 percent (the UK) and 60 percent (Germany) of manufacturing firms in four countries (France, Germany, Spain and UK), and that about more than three-fourths of them have introduced product innovations (half of them together with process innovations).

the Internet but are product innovators account for 10 percent; and firms that had used the Internet and are product innovators represent 64 percent.

Employment growth for all firms was 3.3 percent. Only a few firms are non-innovators (no process or product innovations) and show an employment growth rate equal to 3.5 percent, with employment growth for product innovators being less than half that of process innovators only (3.3 percent versus 7.4 percent). On the other hand, firms that use the Internet but are non-product innovators, show a growth rate of 2.9 percent very similar to that for firms that use Internet but are not innovators at all (2.8 percent). This result may suggest that the use of the Internet as a specific type of innovation does not have an impact, as an average, on employment growth.

Table 1. Manufacturing Firms: Process and Product Innovators, Growth of Employment, Use of the Internet, and Other Variables[1]

Descriptive Statistics		Period 2006-2007				
		Mean	Median	Standard deviation	Minimun	Maximun
Number of Observations		208				
Distribution of Firms (%)		100%				
	Non-innovators (non process or product innovators)	22				
	Process only innovators (non product innovators)	4				
	Product Innovators	74				
Distribution of firms according to the use of Internet (%)						
	Firms that use Internet, but do not innovate	18				
	Firms that use Internet, but are non product innovators (int	21				
	Firms that do not use Internet, but are product innovators	10				
	Firms that use Internet and are product innovators (inter)	64				
Employment growth (%) (yearly rate)						
	All firms	3.3	0.0	10.9	-36.4	63.6
	Non-innovators (non process or product innovations)	3.5	0.0	12.9	-36.4	57.1
	Process only innovators (non product innovators)	7.4	4.3	9.9	0.0	28.2
	Product Innovators	3.3	0.0	10.9	-36.4	63.6
Employment growth (%) according to the use of Internet (yearly rate)						
	Firms that use Internet, but do not innovate	2.8	0.0	13.7	-36.4	57.1
	Firms that use Internet, but are non product innovators (int	2.9	0.0	12.8	-36.4	57.1
	Firms that do not use Internet, but are product innovators	0.6	0.0	6.8	-13.9	20.5
	Firms that use Internet and are product innovators	3.3	0.0	10.8	-36.0	63.6
Number of employees at the beginning of (each) survey 2006		177	43	397	10	3575
	2007	182	44	405	10	3575
Foreign Ownership (10% or more)		15	0.0	36	0.0	100
Located in the capital of the country		58	100	50	0.0	100
Sales growth (%) (nominal growth) (yearly rate)						
	All firms	23.7	19.1	25.9	-41.4	134.7
	Noninnovators (no process or product innovations)	27.3	22.6	25.9	-10.0	106.7
	Process only innovators (non product innovators)	11.7	10.8	16.4	-8.4	46.2
	Product innovators	23.4	18.8	26.2	-41.4	134.7
	of which:					
	Old products	-54.9	-100	55.9	-100	106.7
	New products	78.6	99.5	58.5	0.0	234.7
Prices growth (%)						
	All firms	14.3	16	7.1	-4.0	23.1
	Noninnovators (no process or product innovations)	14.1	16	7.8	-4.0	23.1
	Process only innovators (non products innovators)	11.8	10.8	6.8	3.2	19.3
	Products innovators	14.6	16	7	-0.5	23.1

1/Sales growth for each type of firm is the average of variable g and averages for old and new products are the averages of variables g1 and g2, respectively

2/Prices computed for a set of industries and assigned to firms according to their activity

Source: Costa Rica Innovation Survey for 2006–2007.

Finally, firms that are product innovators show different employment growth rates depending on whether they use the Internet or not. Indeed, those firms that are product innovators and use the Internet show a must higher employment growth than those that do not use this technology (3.3 versus 0.6). However, it is worth mentioning that the variance in the first group is higher than in the second.

To summarize, the data show that employment grows more in innovative firms, but not more intensively in firms with product innovations than in firms with process innovations. Besides, firms that are product innovators and use the Internet for business purposes show a higher employment rate of growth than product innovator firms whose employees do not use the Internet.

It is also important to explore the relative importance of skilled labor in different types of firms depending on their involvement in innovative activities and access by the employees of these firms to the Internet. Table 2 shows that one-third of the labor force in all Costa Rican manufacturing firms are skilled workers; as an unexpected result we found that this share is smaller in the case of process innovators (25 percent). These figures do not change markedly if we divide firms into groups according to their employees' access to the Internet, except for the case of product innovators that do not use the Internet (42 percent)—another unexpected result.

As it was pointed out before, process innovators have the highest growth rate among different types of firms. However, the results show important differences when we split the labor force according to labor capabilities (skilled and unskilled). In fact, in the case of process innovators the proportion of unskilled labor grows faster than that of skilled workers (13 percent versus 3.5 percent). Finally, in the case of product innovators the proportion of unskilled workers grow slightly more quickly than that of skilled workers from 2006 to 2007, but both rates are relatively high (4.5 percent and 4.1 percent, respectively).

Differences in labor growth between skilled and unskilled workers were also found when we divide different type of firms according to the use of the Internet. Firms that use the Internet for business purposes but do not innovate show a higher rate of growth of skilled than unskilled labor (5.2 percent versus 1.1 percent). A similar result was found in the cases of non product innovators that use the Internet (int*er*_only) and product innovators that do not use the Internet (4.7 percent versus 1.3 percent, and 2.4 percent versus 0.1 percent). An unexpected result was found in the case of product innovators that use Internet for business purposes, where unskilled labor shows a slightly higher rate of growth than skilled labor (5.0 percent versus 4.2).

Table 2. Descriptive Statistics for Employment Composition

	Mean	Median	Standard deviation	Minimun	Maximun
Share of skilled labor 2006					
All firms	32	26	26	0	100
Non-innovators (non process or product innovations)	33	25	27	3	100
Process only innovators (non product innovators)	25	17	28	0	85
Product Innovators	33	26	25	0	100
Share of skilled labor 2006 according to firms´use of Internet					
Firms that use Internet, but do not innovate	33	24	27	3	100
Firms that use Internet, but are non product innovators (inter_only)	31	23	26	3	100
Firms that do not use Internet, but are product innovators	42	29	34	4	100
Firms that use Internet and are product innovators (inter)	33	26	23	1	100
Skilled labor growth (%)					
All firms	4.5	0.0	17.7	-50.0	133.3
Non-innovators (non process or product innovations)	6.1	0.0	18.5	-25.0	100
Process only innovators (non product innovators)	3.5	0.0	6.9	0.0	18.3
Product Innovators	4.1	0.0	17.9	-50.0	133.3
Unskilled labor growth (%)					
All firms	4.4	0.0	20.5	-40.0	185.7
Non-innovators (non process or product innovations)	2.2	0.0	11.9	-37.5	45.5
Process only innovators (non product innovators)	13.0	0.0	26.6	0.0	81.8
Product Innovators	4.5	0.0	21.9	-40.0	185.7
Skilled labor growth (%) according to firms´use of Internet (yearly rate)					
Firms that use Internet, but do not innovate	5.2	0.0	18.8	-25.0	100
Firms that use Internet, but are non product innovators (inter_only)	4.7	0.0	17.5	-25.0	100
Firms that do not use Internet, but are product innovators	2.4	0.0	17.1	-50.0	50
Firms that use Internet and are product innovators	4.2	0.0	17.8	-36.8	133.3
Unskilled labor growth (%) according to firms´use of Internet (yearly rate)					
Firms that use Internet, but do not innovate	1.1	0.0	12.0	-37.5	45.5
Firms that use Internet, but are non product innovators (inter_only)	1.3	0.0	11.3	-37.5	45.5
Firms that do not use Internet, but are product innovators	0.1	0.0	7.0	-21.7	18.8
Firms that use Internet and are product innovators	5.0	0.0	22.9	-40.0	185.7

Source: Authors' calculations based on Costa Rica Innovation Survey for 2006-2007.

5.3 Econometric Results

5.3.1 Labor Demand and Internet Diffusion

Table 3 presents the results of estimating equations (3) and (4) by OLS. The dependent variable is employment growth minus the growth of sales due to unchanged or previously existing products. As discussed above, we control for changes in the prices of older products by subtracting an industry price growth index from the nominal sales growth of unchanged products (i.e., the dependent variable is $\mathbf{l - (g_1 - \pi)}$). The value of the constant is therefore an estimate of the (negative) average real productivity growth in the production of old products for the two-year period 2006-2007. Following Harrison et al. (2008), we include a full set of industry dummies in all regressions, with their coefficients constrained to sum to zero to preserve the interpretation of the constant. The key explanatory variables are the "process innovation only" dummy **d** and "sales growth due to new products" $\mathbf{g_2}$ variables. We also include other explanatory variables such as the location of the firm in the capital city and the participation of foreign investors in the firm (see definitions in Appendix A).[12]

The first column of Table 3 shows the OLS results for the original equation (3), while the second and third columns show results when the Internet diffusion variables (int*er*_only and int*er*xg2) are added in equation (4). It is important to note that the constant $\boldsymbol{\alpha_0}$ is significant with positive sign only in the second specification.

As shown by Harrison et al. (2008), the estimated coefficient $\boldsymbol{\beta}$ of sales growth due to new products ($\mathbf{g_2}$) is an estimate of the relative efficiency of the production process for new products compared to that of old products. The fact that this coefficient is statistically different from zero and less than one in all the specifications may indicate that new products are produced more efficiently than old products. However, as discussed above, any endogeneity (due to unobserved price changes or correlation with non-technological productivity shocks) is likely to produce a downward bias in this coefficient, exaggerating the productivity gains associated with the production of new products. In fact, the results from Table 4, discussed later, in which we use IV estimates, confirm this claim.

From the second specification we can see that the *inter*_only variable is significant, but with negative sign. That is, the coefficient shows a negative relationship between Internet use as

[12] Since the coefficients associated with "located in the capital" and "foreign owned" variables were not significant, we estimate again equations 3 and 4 without using these two variables and reported only these last results.

a type of process innovation and employment growth (-21.54). On the other hand, in the third specification the inter_only variable is not significant, but int*er*xg2 it is. This last result might suggest that the use of the Internet by workers increases the positive impact of product innovation on employment growth in manufacturing firms. It is possible that the results for Internet variables are influenced by an endogeneity problem, in which these Internet variables are correlated with the error term. However, due to data limitations and the impossibility of identifying appropriate IV for Internet variables, we cannot overcome this problem. Nevertheless, we can improve the estimation in Table 3 using IV for sales growth due to new products **g2**.

Table 3. Dependent Variable: l – (g1-Π): OLS Estimation
Impact of Internet Diffusion on Labor Demand

VARIABLES	(1) 1-OLS	(2) 2-OLS	(3) 3-OLS
d	8.017	10.528*	14.101**
	(6.363)	(6.040)	(6.386)
g2	0.887***	0.787***	0.752***
	(0.042)	(0.059)	(0.055)
inter_only		-21.549***	-10.676
		(7.921)	(8.962)
interxg2			17.871***
			(6.346)
Constant	2.380	14.617**	3.564
	(3.955)	(6.378)	(7.742)
2-digit industry dummies	Yes	Yes	Yes
Observations	208	208	208
R-squared	0.823	0.833	0.843

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006–2007.

Table 4 reports our IV estimates taking the "sales growth due to new products" variable as endogenous, and using two instruments. As pointed out previously, any valid instrument for sales growth due to new products **g2** must be related to growth in sales of new products but not to any change in the price of new products compared to older products and productivity shocks.

From the variables we evaluated as potential instruments, we chose the "increased range of goods" and "increase in productive capacity" indicators, which assess the impact of innovation on the range of goods produced by firms and on their productive capacities, respectively, as reported in the innovation survey questionnaire for Costa Rica. As mentioned previously, the first variable is coded as zero if innovation is not relevant for the range of goods produced by the firm, one if the impact of innovation on the range is low, two if it is medium and three if it is high. We expect this instrument to be uncorrelated with changes in the price of new products compared to old products, and it also seems unlikely to be correlated with productivity shocks. The second instrumental variable is coded in a similar way—zero if innovation is not relevant for an increase in productive capacity, one if the impact of innovation is low, two if it is medium and three if it is high. Based on the accelerator theory we could argue that facing an increment in the demand for the goods produced by the firm, the firm has the option of increasing its production by means of an increase in its productive capacity, in which case the production of new goods would be related to the increase in productive capacity, but the increase in productive capacity would not necessarily be correlated with productivity shocks.

We verified that in practice both instruments are clearly positively and significantly correlated with the endogenous variable sales growth due to new products (**g2)** in the first-stage reduced form regression, and uncorrelated with residuals. We used the following procedure to determine the validity of the instruments and the necessity of incorporating them in equation (3). First, we used the F test to determine if a statistically significant relation between the instruments and the endogenous variable sales growth due to new products (**g2)** existed. Second, we used the Sargan over-identification test to verify that the residuals are not correlated with the instruments if the latter are really exogenous.[13] Third, we employed the test suggested by Stock and Yogo (2002) to evaluate the existence of a *strong* and statistically significant relationship between the instruments and the endogenous variable—that is, to determine if the instruments were weak or not. In this case, the confirmation of the null hypothesis established that the instruments were weak. The null hypothesis is rejected if the Stock and Yogo statistic is smaller than the Cragg-Donald critical value. Finally, we used the Davidson-Mackinnon test for the appropriateness of the IV estimators to determine if instruments for sales growth due to new products (**g2)** were required (see Table 4).

[13] In this case we cannot reject the null hypothesis, since the instruments are not correlated with the error term.

According to the test results shown in Table 4, we can conclude that instruments are required and appropriate for the variable sales growth due to new products (g2) only for the first three specifications (see the results from Davidson-Mackinnon test and Stock and Yogo test, respectively). The IV estimates of the constant differ noticeably from the OLS estimates, showing faster average productivity growth (and a corresponding decrease in employment) in the production of previously existing products only in the basic model of Harrison et al. It must be noted that only in the second specification the constant is significant and negative, as expected. It is important to remember that the constant $\boldsymbol{\alpha_0}$ of the regression shows detectable average productivity growth, which implies constantly decreasing employment for a given level of output of old products.

Other important results are shown in the three columns in Table 4. First, the coefficient for process innovation (d) is significant for all specifications, showing that this type of innovation activity seems to create employment. This last result is consistent with a previous finding by Monge-González et al. (2011). Second, the coefficient for g2 (product innovation) is significant but no longer different than one in all three specifications, so new products are being produced with an efficiency similar to that of older products. Third, the positive impact of product innovation on labor demand increases when workers use the Internet for business purposes inside the firm. That is, the coefficient for int*er*xg2 is significant and positive.

It is important to point out that Costa Rica has only recently opened its telecommunications market, and the degree to which this opening results in effective competition and a corresponding increase in Internet penetration, increased reliability of services, and affordable access costs will determine the degree to which manufacturing firms can be expected to increase the level of their use of the Internet, and the number of new jobs that might be created by those who use the Internet and are product innovators.

Table 4. Dependent Variable: l – (g1-Π): IV Estimation
Impact of Internet Diffusion on Labor Demand

VARIABLES	(1) 1-IV	(2) 2-IV	(3) 3-IV
g2	1.023***	1.049***	0.954***
	(0.051)	(0.122)	(0.139)
d	18.855*	18.942*	19.043*
	(10.126)	(10.513)	(9.871)
inter_only		4.051	4.362
		(12.963)	(12.145)
interxg2			12.052*
			(6.663)
Constant	-8.779*	-11.654	-11.902
	(4.591)	(12.447)	(11.668)
2-digit industry dummies	Yes	Yes	Yes
R-square	0.789	0.782	0.8087
Standard error	26.19	26.6	24.92
Observations	208	208	208
Number of ciiu3	16	16	16
F test, g2	75.390	16.200	11.190
p-value	0.000	0.000	0.000
Sargan test	2.178	2.206	2.618
p-value	0.140	0.137	0.106
Davidson-MacKinnon test of exogeneity	14.193	6.634	2.665
p-value	0.000	0.011	0.104
Cradd-Donald critical value	75.390	16.200	11.190
Stock and Yogos estadistic (10%)	19.930	19.930	19.930
List of instrument (s) used in g2	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006-2007.

5.3.2 Skilled Labor Demand and Internet Diffusion

Table 5 shows the results of estimating equation (5) by OLS, in which we try to analyze the possibility of skill-biased technological change due to the adoption of the Internet by manufacturing firms in Costa Rica. The first column shows the results of using the Harrison et al. (2008) basic model, while the second and third columns show the results of including the Internet variables (*inter*_only and int*er*xg2) in the model. In general, we found similar results to those for all workers in the sample (see Table 3). We found a negative and significant relationship between demand for skilled labor and Internet use by workers (second specification), as well as a positive and significant relationship between Internet use by workers in firms that are product innovators and skilled labor demand.

Table 5. Dependent Variable: l^s – (g1-Π): OLS Estimation
Impact of Internet Diffusion on Skilled Labor Demand

VARIABLES	(1) 1-OLS	(2) 2-OLS	(3) 3-OLS
d	-3.254	-0.573	3.304
	(6.602)	(7.205)	(6.919)
g2	0.849***	0.742***	0.704***
	(0.048)	(0.069)	(0.066)
inter_only		-23.010**	-11.211
		(9.303)	(9.919)
interxg2			19.391***
			(6.923)
Constant	6.972	20.038***	8.044
	(4.656)	(7.578)	(8.395)
2-digit industry dummies	Yes	Yes	Yes
Observations	208	208	208
R-squared	0.773	0.785	0.797

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006-2007.

Given the identification problems discussed in previous sections, we estimated equation (5) using instrumental variables. As in the case of equations (3) and (4) we tested for both the need for instruments and their appropriateness. The results from these tests shown in Table 6 imply that instruments for the sales growth due to new products (**g2)** are required and appropriate (strong) in all the specifications, a result similar to that found in Table 4.

We found that skilled labor demand is positively related to product innovations. However, regarding process innovation we found that the coefficient for "d" is not significant. Besides, we found that coefficients for both the Internet as a process innovation (int*er*_only) and int*er*xg2 are not significant. These last results suggest that the use of the Internet by employees is neither a labor displacement innovation nor a skill-biased innovation in the Costa Rican manufacturing sector.

Table 6. Dependent Variable: l^s – (g1-Π): IV Estimation
Impact of Internet Diffusion on Skilled Labor Demand

VARIABLES	(1) 1-IV	(2) 2-IV	(3) 3-IV
g2	1.024***	1.116***	1.039***
	(0.058)	(0.145)	(0.167)
D	10.638	11.409	11.499
	(11.562)	(12.460)	(11.850)
inter_only		13.446	13.720
		(15.362)	(14.581)
interxg2			9.743
			(8.000)
Constant	-7.332	-17.374	-17.597
	(5.243)	(14.751)	(14.008)
2-digit industry dummies	Yes	Yes	Yes
R-square	0.725	0.695	0.725
Standard error	29.91	31.52	29.91
Observations	208	208	208
Number of ciiu3	16	16	16
F test, g2	75.390	16.200	11.190
p-value	0.000	0.000	0.000
Sargan test	1.817	1.847	2.115
p-value	0.178	0.174	0.146
Davidson-MacKinnon test of exogeneity	19.704	10.721	5.783
p-value	0.000	0.001	0.017
Cradd-Donald critical value	75.386	16.202	11.192
Stock and Yogos estadistic (10%)	19.930	19.930	19.930
List of instrument (s) used in g2	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006–2007.

5.3.3. Female Labor Demand and Internet Diffusion

Costa Rica is a country with an economically active population of 3.5 million people, of which a little more than half (1.8 million) are women. On average the labor force of Costa Rica is relatively young (37 years old). From a gender point of view, the participation of women in the Costa Rican labor market is relatively small. Only 39.4 percent of the female economically active population works as opposed to 71.4 percent in the case of the economically active male population. In the manufacturing sector, female labor force participation is much lower—about 31.8 percent, according to official statistics.

The adoption of the Internet by firms might facilitate female participation to the labor market. Indeed, there is evidence that the Internet contributes positively to the demand for female labor (ITU, 2010), and we would like to study the extent to which the diffusion of the Internet is positively correlated with female labor force demand in Costa Rica.

In order to explore the last hypothesis and to detect any shift in the direction in labor demand, we separated data on labor employment by gender. Tables (7) and (8) show the results of using this segmented data for equation (6), using the OLS and IV procedures, respectively.

Table 7 shows that product innovation is positively related to female labor demand. As discussed previously, according to Harrison et al. (2008), the estimated coefficient β of sales growth due to new products (g2) is an estimate of the relative efficiency of the production process for new products compared with that for old products. The fact that this coefficient is statistically different from zero and less than one in all the specifications may suggest that new products are produced more efficiently than are older products. However, any endogeneity (due to unobserved price changes or correlation with non-technological productivity shocks) is likely to produce a downward bias in this coefficient, exaggerating the productivity gains associated with the production of new products. In fact, the results of using IV estimates, presented in Table 8, below, seem to show this effect.

Table 7. Dependent Variable: $l^w - (g1\text{-}\Pi)$: OLS Estimation
Impact of Internet Diffusion on Female Labor Demand

VARIABLES	(1) 1-OLS	(2) 2-OLS	(3) 3-OLS
D	12.532	15.232	18.653*
	(9.724)	(9.311)	(9.757)
g2	0.876***	0.768***	0.735***
	(0.049)	(0.068)	(0.064)
inter_only		-23.174**	-12.763
		(9.811)	(10.938)
interxg2			17.111**
			(6.864)
Constant	2.328	15.487**	4.904
	(4.613)	(7.248)	(9.036)
2-digit industry dummies	Yes	Yes	Yes
Observations	208	208	208
R-squared	0.758	0.770	0.778

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006-2007.

When considering the effect of the Internet as a process innovation (int*er*_only), we found a negative and significant relationship with female labor demand (second specification from Table 7). In general, we found similar results to those for the skilled workers in Table 5, especially a positive and significant relationship between product innovation and female labor demand. On the other hand, when considering the use of the Internet by product-innovator firms, we found a positive and significant relationship between int*er*xg2 and employment growth (17.11).

Table 8. Dependent Variable: l^w – (g1-Π): IV Estimation
Impact of Internet Diffusion on Female Labor Demand

VARIABLES	(1) 1-IV	(2) 2-IV	(3) 3-IV
g2	1.011***	1.015***	0.922***
	(0.061)	(0.144)	(0.167)
d	23.295*	23.143*	23.243**
	(12.040)	(12.328)	(11.842)
inter_only		0.898	1.203
		(15.199)	(14.571)
interxg2			11.706
			(7.994)
Constant	-8.755	-9.215	-9.460
	(5.459)	(14.595)	(13.998)
2-digit industry dummies	Yes	Yes	Yes
R-square	0.718	0.717	0.740
Standard error	31.14	31.19	29.89
Observations	208	208	208
Number of ciiu3	16	16	16
F test, g2	75.390	16.200	11.190
p-value	0.000	0.000	0.000
Sargan test	1.637	1.657	1.875
p-value	0.201	0.198	0.171
Davidson-MacKinnon test of exogeneity	98.737	3.930	1.517
p-value	0.002	0.049	0.220
Cradd-Donald critical value	75.386	16.202	11.192
Stock and Yogos estadistic (10%)	19.930	19.930	19.930
List of instrument (s) used in g2	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity	Increased range of goods; increase in productive capacity

* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level; *** at the 1 percent level; no asterisk means the coefficient is not significantly different from zero.
Source: Authors' calculations based on the Costa Rican Innovation Survey for 2006-2007.

When using IV estimators to correct for endogeneity problems, Table 8 shows that the results are more robust than those from Table 7 in all three specifications, where instruments for the variable sales growth due to new products **(g2)** are required and strong according to the Davidson-MacKinnon test and the Stock and Yogos test, respectively. The coefficient of product innovation in these three specifications shows that this variable is positively related to demand for female labor, and that new products seem to be produced with an efficiency that is similar to that for the production of old products (the coefficient is not significantly different from one). In addition, process innovation seems to be positively related to demand for female labor.

Finally, as in the case of skilled labor, we did not find any relationship between the use of the Internet as a specific type of process innovation and female labor demand, or any effect of the use of the Internet on the impact of product innovators on female labor demand. These two results contrast with those from other studies that found evidence that ICT technologies are positively correlated with female labor force participation (ITU, 2010).

6. Concluding Remarks

Our initial analysis of descriptive statistics (Section 5.2) showed that employment grew more in innovative firms. Firms which innovated by introducing new products experienced decreasing demand for their older products, which was more than counterbalanced by sales of their new products, which were responsible for an overall increase in demand for products. This finding appears to confirm that compensation effects are present, and that estimations using Harrison et al.'s (2008) model are necessary to assess the relative roles played by process and product innovations when analyzing the impact of Internet diffusion on labor.

Three sets of analyses of the impact of Internet diffusion on labor demand were carried out, focused on total labor demand, the demand for skilled labor, and the demand for female labor; in each case, results using both OLS and IV models were reported.

It was found that both process and product innovations are positively related to employment growth. Moreover, the use of the Internet by workers for business purposes, as a process innovation, does not impact any demand for labor (total, skill or female). In contrast, the positive impact of product innovation on labor demand increases when workers use the Internet for business purposes inside the firm. Such a relationship was not found in the particular cases of demand for skilled labor and female labor. These findings point to the relative importance of the Internet for improving the positive impact of product innovation on employment growth. They also suggest that the use of the Internet by employees is neither a labor displacement innovation nor a gender or skill-biased innovations.

Interestingly, neither the location of firms in the capital city of Costa Rica nor foreign ownership of firms is related significantly to the total demand for labor, the demand for skilled labor, or the demand for female labor when Internet diffusion variables are considered in the analysis.

Policies are therefore needed to increase access to and the use of the Internet, especially in those companies that are involved in product innovation activities, including steps to improve infrastructure to overcome technological barriers caused by insufficient investment. This might be achieved through institutional changes aimed at improving market efficiency and including more participants in the market, including regulation to avoid having only the most profitable segments of the market become more developed. Policies that improve access of firms (especially product innovation firms) to necessary equipment would be highly useful; the development of sources of financing for businesses should be included among the actions that these policies promote. It is also important to promote the skills necessary to make use of this equipment. Education in the use of the Internet should be included in curricula in educational institutions at all levels, as well as in on-the-job training efforts, and steps should be taken to improve the content of courses to increase the impact of this education and training.

Further research is needed in order to understand the reasons why the use of the Internet for business purposes affects only the impact of product innovation on labor demand and not the impact of process innovation. Finally, research is also needed to deal with the potential identification problem associated with the use of the Internet variables in Harrison et al.'s framework.

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Appendix A

Variable Definitions (in alphabetical order)

Employment growth **(l)*:*** Rate of change of the firm's employment for the whole period.

***Female employment growth (l^w)*:** Rate of change of the firm's female employment for the whole period.

***Foreign owned 10 percent or more*:** Dummy variable which takes the value 1 if the enterprise has more than 10 percent of foreign capital and 0 otherwise.

Increased range of goods: Variable that takes the value 0 if the firm reports that the effect of innovation has been irrelevant for the broadening of the range of goods and services, 1 if it has had a low impact, 2 if it has had a medium impact, and 3 if it has had a high impact.

Increased in productive capacity: Variable that takes the value 0 if the firm reports that the effect of innovation has been irrelevant for increasing the productive capacity, 1 if the impact of innovation is low, 2 if it has had a medium impact, and 3 if it has had a high impact.

Industry dummies: System of industry dummies at a 2-digits level of the International Standard Classification.

***Located in the capital*:** Dummy variable which takes the value 1 if the firm is located in the capital city of Costa Rica, and 0 otherwise.

***Prices indices at detailed industry levels*:** Obtained for manufacturing at a 2-digit level of the International Standard Classification from Central Bank of Costa Rica.

Process innovator only **(d):** Dummy variable which takes the value 1 if the enterprise reports doing *only* process innovations (where the "only" refers to firms that do not do product innovation), either to the firm, country or world, during the considered period, and 0 otherwise.

Real sales growth of old goods **(g1-π):** Sales growth due to old products minus the increase of prices at detailed industry level.

Sales growth due to new products **(g2):** Computed as the product of the fraction of turnover due to new or significantly improved products and one plus the rate of change of the firm´s turnover for the whole period.

Sales growth due to old products **(g1):** Sales growth minus sales growth due to new products.

***Skilled employment growth (l^s)*:** Rate of change of the firm's skilled employment for the whole period.

Workers with Internet (Inter): Dummy variable which takes the value 1 if the enterprise reports having at least one worker using the Internet for business purposes, during the considered period, and 0 otherwise.

Workers with Inter_only: Dummy variable which takes the value 1 if the enterprise reports having *only* at least one worker using the Internet for business purposes (where the "only" refers to firms that do not do product innovation), during the considered period, and 0 otherwise.