## **The impact of training on wages and productivity: evidence from Argentinean SMEs.**

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## **Abstract**

*During the last decade, Argentina has experienced a strong and sustained growth, together with the increase in the level of employment, productivity and wages. However, the recent deceleration of this growth has opened up a debate about the mechanisms of transmission of those gains into higher wages. The objective of this paper it to contribute to this discussion by analyzing to what extent productivity gains derived from training activities lead to higher wages and productivity and how productive structure and labor institutions impact on the relation between wages and productivity. The empirical analysis is based on information for 1400 Argentinean SMEs for the period 2006-2008. Results show training activities are correlated to higher productivity than wage levels, which means that the benefits of better capabilities are unequally distributed between the firm and its employees and provides evidence regarding the existence of a productivity-wage gap. Results also show that this gap tends to decrease among medium- and high-tech sectors, which provides evidence regarding the impact of the process of structural change on equity. Finally, evidence is not conclusive about the impact of labor institutions which calls the attention on the need for more research on the subject.*

**Keywords:** productivity, wages, training, SMEs

## **Introduction**

Argentina has experienced a strong and sustained growth during the ten years following the economic crisis of 2002. This period of growth had some features that distinguish it from the ’90s. Particularly, i) there was a simultaneous growth of employment and manufacturing productivity, ii) the growth of formal employment was higher than informal one, and iii) there was a generalized improvement of wage levels. More recently, the deceleration of growth and the increasing of inflation opened up a debate about the productivity gains and the mechanism of transmission of those gains into higher wages.

The structural effects of economic growth and the impact on labor market were studied by the literature, mainly from aggregated and sectorial levels. From a more academic angle, these studies discussed to what extent the growth of manufacturing productivity is explained by changes in the sectorial structure of the industry (Peirano et al 2010; Lavopa, 2007, Cenda, 2010, Azpiazu and Shorr, 2010, Coatz et. al 2011, Santarcángelo et al 2011, Fernandez Burga and Porta, 2008, Basualdo et al, 2010, Roitter, et al 2013). From a more policy perspective, the changes occurred in the labor market were described on the basis of aggregated data about the dynamic and quality of employment –formality, wages- and the evolution of labor market institutions –collective bargaining agreements, minimum wage- (MTESS 2010, Palomino and Trajtemberg, 2006, Novick et al 2007, Sarabia et al 2010). Other studies used household surveys to describe the transformations of the labor market analyzing the effects of education over wages (Beccaria et al 2005, Beccaria and Maurizio, 2014, Groisman, 2014). These contributions have shown that the qualification of workers has a positive impact on wages (albeit declining, due to the lower variability of wages and higher skill levels in the workforce).

In this context, a growing number of studies on the relationship between productivity and wages have proliferated. However, less attention has been paid to this relationship at firm level and this is the intended contribution of this paper. This article is an exploratory attempt to contribute to fill this gap in the literature by studying the relationship between productivity and wages with a data-base compounded of 1400 Argentinean SMEs for the years 2006-2008. We have two main objectives. The first one is to analyze whether the firms with high productivity have systematically paid higher wages or if the productivity gains have not completely translated into wages. This analysis contributes to understand how the period of economic growth had impacted on wage improvements. The firm-level analysis allows determining if wages are a good proxy for firms’ productivity level and, if not, estimating the gap between these two variables. This approach is complementary to the literature that analyzes growth of wages and manufacturing productivity at the sectorial level, because it allows to establish a relationship between both variables without reducing the heterogeneity of productivity and wages to sectorial averages.

The second objective is to analyze the factors that mediate the relationship between productivity and wages. Thus, we consider two industry factors -R&D intensity and salary bargaining agreements- that potentially contribute to improve the relationship between wages and productivity –that is, to close the gap between them-. In the first case, we explore the idea about the positive impact of the structural change process over wages (Cepal, 2012). In the second case, we attempt to answer if the sectors that achieved higher increases in its wages throw collective bargain show a smaller gap between productivity and wage (Freeman and Medoff, 1984) than the rest.

Following Conti (2005) and Dearden et al (2006), we estimate the relationship between wages and productivity by means of studying the impact of a third variable – training- over them. According to these authors, when the impact of training is higher on productivity than on wages, then there is a gap between them, usually referred as the productivity-wage gap, which implies that the productivity benefits of training are not totally translated into wages. We use two econometric methods -propensity score matching and doubly-robust estimators- to analyze the effects of training activities during 2006-2008 over firms’ productivity levels and wages for 2008.

The remainder of this paper is as follows. The following section discusses the literature about productivity and wages and the hypotheses. Section 2 describes the data. In Section 3 we explain the methodology and the estimation procedures. Section 4 presents the discussion of the results. Finally, concluding remarks are present in Section 5.

## **1. Background and hypotheses**

Economic theory has extensively researched the issues of productivity and it growth. They were studied both theoretically -by the theory of economic growth and human capital- and empirically, through longitudinal studies referring to the measuring of growth, and cross-sectional works, related to gaps and structural change.

However, the recent expansion of micro- databases has increased the interest of researchers in studying productivity at the firm level. This new longitudinal databases have led to study productivity at the firm level and analyze the impact of the idiosyncratic characteristics of firms on its performance levels. Moreover, the availability of firm-level data have challenged a set of basic assumptions of the mainstream economics and this has led to rethink much of the theory of the firm, markets and even the form of aggregated macroeconomic variables are constructed.

The most conclusive and irrefutable evidence refers to the existence of large heterogeneity in the productivity levels of firms (Nelson, 1981; Bartelsman and Doms, 2000; Syverson 2011; Haltiwanger et al, 2007, Dosi et al, 2010 ; Bottazzi et al 2010). This heterogeneity is present among firms from different sectors and geographical locations but also within them. In this respect, numerous studies have documented a high variability in the productivity of firms within sectors with a high degree of disaggregation –four - digit standard classifications. The literature has also explored the existence of heterogeneity in wage levels, not only among sectors but also between firms from the same sector (Haltiwanger et al., 2000). In this context, the ideas of "representative firm" from a theoretical perspective, and "average firm" from a policy perspective, are in conflict with the new evidence provided by the micro-data and demand new conceptual approaches.

Within this context of heterogeneity, the relationship between productivity and wages has been extensively studied reaching a broad consensus on the positive and significant relationship between this two variables. However, how much of that higher productivity level is appropriated by workers through their wages differ between firms and, to a lesser degree, between workers within the same firm. For instance, using a panel data on UK firms over the 1984-2001 period, Faggio et al. (2007) find that wage dispersion -the variance- is explained by approximately 60 % for the differences between firms, which in turn is largely explained by inter- firms differences within sectors. Thus, the idea of traditional economic theory that wages are equal to the product marginal value in a perfectly competitive market is unsustainable. Consequently, wages cannot be considered as a direct measure of productivity.

Assuming that productivity and wages diverge, literature that study this relationship has been focused on the quantification of the gap between them and the explanation about how this gap varies according to the characteristics of workers and the environment, including the labor institutions. Methodologies used in the literature are diverse and depend on the availability of information. Thus, studies that have longitudinal employer-employee databases estimate, on the one hand, wage equations (as Mincer, 1974) and, on the other, productivity equations through production functions. These papers find a positive relationship between productivity and wages, but also that this relationship is mediated by worker attributes that have differential impacts on individual wages and firm productivity.

Similarly, another set of studies show differences between wages and productivity from the differential impact of a third variable, which is usually training. They test the impact of training on wages and productivity firms. When the impact is greater on productivity than on wages, it becomes clear that firms appropriate the benefits of training without transfer them completely to wages. Dearden et al (2006) provide evidence that support this hypothesis for a panel of British industries between 1983 and 1996. They build a database combining information about workers (training) and firms (productivity and investment). Using General Method of Moments estimators, they show that raising the proportion of workers trained in an industry by one percentage point is associated with an increase in productivity of about 0.6% and an increase in wages of about 0.3%. This highlight that using wages as a proxy for productivity is inappropriate because the impact of training is underestimated. Thus, articles using wages as the only measure to estimate productivity ignore the additional benefits that firms capture.

Conti (2005) also analyzes the impact of training on productivity and wage covering all sectors of the Italian economy for the period 1996–1999. The empirical evidence is based on a dataset which combines individual-level data on training with firm-level data on productivity and wages. The empirical evidence shows that training significantly increases firm productivity. However, no such effect is found for wages. This gap between productivity and wage reveals the existence of labor market imperfections. In particular, the author points out that Italy has highly regulated the labor market, with a strong role of unions in wage bargaining and high hiring and firing costs. Thus, an increase in the stock of skilled workers on about 1% leads to an increase of 0.4% in productivity and 0.1% in wages[[1]](#footnote-1).

In this paper we propose to estimate the impact of training on productivity and wages following the methodology proposed by Dearden et al (2006) and Conti (2005), with the objective of measuring the existence of the identified gap between the productivity and wages. Additionally, we explore two dimensions that can influence the magnitude of that wage- productivity gap. Firstly we analyzed whether in high- tech sectors (OECD, 1997) this gap is lower or not, which would be in line with the hypothesis of structural change for equality (CEPAL, 2012). Secondly, we analyze if the sectors in which unions reached above-average wage increases managed to reduce this gap. That is, if the strength in wage bargaining is a way to narrow the gap.

Quantification of the productivity-wage relationship is central to understand the dynamics of rent appropriation. Such analysis allows us determining the simultaneous impact of activities such as training on the competitiveness of firms and workers welfare. The literature on innovation and technological change has long warned about the impact of improved processes, products and organizational practices on productivity and employment (Jensen et al., 2007). This evidence leads to argue that innovation is the way to reconcile private benefits with welfare improvements. However, little is known about those wage improvements, which are the mechanism through which innovation “spills over” the rest of the society. More precisely, is it true that R&D intensive activities lead to improvements in the relationship productivity-wage? If the environment impacts it, which one is the role of labor institutions? Do unions that managed to reach higher wage increases contribute to close the gap? Or, conversely, do they prevent salaries to follow the evolution of productivity? These are the questions that have motivated the hypotheses of this research:

***H1. The impact of training on productivity and wages.*** *Firms with trained workers show, on average, higher levels of wage and productivity. However, the impact of training on productivity is higher than the impact on salaries.*

The verification of this hypothesis would imply that the impact of training on productivity is not completely translated into higher wages but unequally distributed between the firm and its employees.

***H2. The effect of R&D intensity on productivity-wages relationship.*** *The gap between productivity and wages tends to decrease when one moves from low to medium and high tech sectors. The verification of this hypothesis would provide evidence on the fact that, in certain sectors, workers manage to appropriate a higher share of the training gains.*

This hypothesis is based on the idea that technologically complex sectors have higher absorptive capacities, defined as the proportion of highly qualified workers. Then, in these sectors, knowledge is a key asset firms try to retain, most of the times, by means of higher wages.

***H3. The effect of labor institutions on productivity-wages relationship.*** *The gap between salaries and productivity tends to decrease when one moves from activities where collective bargaining (union-led negotiations) led to wage increases below the mean to activities where the negotiations led to over-the-mean increases.*

It is worth to mention that this hypothesis is proposed in the opposite direction of Conti’s (2005) one since it is based on the assumption that labor unions, by means of their role of negotiators, can get a higher appropriation of the productivity gains, by means of increasing the average level of the salaries.

## **2. Data and methodology**

In this paper we follow Dearden’s et al (2000 and 2006) and Conti’s (2005) proposals to analyze the effect of training on productivity and wages. These authors use panel-data information on training, wages and productivity for different periods. This allows them to apply different econometric techniques (Fixed Effects models and General Method of Moments) in order to control for unobserved heterogeneity and poten**t**ial endogeneity of training. In our case, the available database has only one observation for the main variables; therefore we cannot apply panel econometrics.

We use a micro-database made up of 1416 Argentinean SMEs from different manufacturing and service sectors, based on information collected by the Secretariat of Industry, Trade, and Small and Medium Enterprises (SMEs) of the Argentinean Ministry of Production. The database provides information about economic performance, innovation and training for the period 2006-2008. Firm productivity level and firm average wage both in 2008 are the outcome variables considered. Labor productivity was estimated as value added per employee. The firm’s value added was calculated from the available information on firms’ sales, labor costs, and intermediate consumption**s**. Wage corresponds to the firm average wage, estimated as the ratio between total amounts paid in concept of wages and other labor costs (non-remunerative payments) and total number of employees. Productivity and wages are taken in logs. Training is a binary variable which takes value one if the firm conducted training activities in the period 2006-2008.

**Figure 1. Directed acyclic graph**

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Source: Own elaboration.

Figure 1 presents the main relations among variables. We claim that training has a causal effect on both labor productivity and wages. However we cannot identify this relationship directly because there is a set of variables (observable confounders) that simultaneously affect training and outcomes variables (labor productivity and wages), and this causes a selection bias. To overcome this limitation we apply two strategies: a) non- parametric estimation based on the balance of the database following the propensity score of carry out training activities, and b) a parametric technique named doubly-robust estimators (Lunceford and Davidian, 2004).

In the first place, we use a propensity score matching technique to calculate the average treatment (training) effect. In order to balance the sample between firms that did training and did not we use the following set of confounders: innovation activities, average annual rate of growth of employment in the period 2003-2007, average annual rate of growth of wage in the period 2003-2007 firm age, and sector**i**al dummies (ISIC 2-digits).

We started assuming there is an outcome variable of the firm *i*, Yi, the value ofwhich will depend on having or not having conducted training activities[[2]](#footnote-2). Additionally we defined a binary variable, Di, which takes value 1 if the firm has conducted training activities and 0 if it has not –treatment variable-. According to that, the outcome variable is defined by the following expression:

$Y\_{i} \left\{ \begin{array}{c} Y\_{i0} if D\_{i}=0\\ Y\_{i1} if D\_{i}=1\end{array}\right.$ (1)

Then, we can define the average treatment effects of the training activities in the following way:

$$ E\left(α\_{TT}\right)=E\left[{\left(Y\_{i1}-Y\_{i0}\right)}/{D\_{i}=1}\right]=E\left({Y\_{i1}}/{D\_{i}=1}\right)-E\left({Y\_{i0}}/{D\_{i}=1}\right) (2) $$

$$ $$

Evaluating the impact of training means to answer the following questions: What would have happened if training had not been conducted? What would have happened with the productivity and wage level**s** of firm i in absence of those activities? To know the effect of training we must compare the observed outcome with the outcome that would have resulted if the firm had not trained their workers. However**,** we have the problem of missing data because the potential outcome of the control group, $E(Y\_{i0}/D\_{i}=1)$, cannot be measured. This potential outcome is called *counterfactual* and must be estimated as the average outcome of those firms that did not conduct training activities, $\hat{Y\_{i0}}$. According to that, the equation of average treatment effect on the treated group is defined as follows:

$E(α\_{TT})=E\left[\left(Y\_{i1}-\hat{Y\_{i0}}\right)/D\_{i}=1\right]$ (3)

As firms having conducted training activities are not randomly determined, we cannot rule out the possibility of selection bias when we estimate the impact of Di on Yi. Neither can we measure the counterfactual outcome using the average of firms that do not receive matching treatment, $E(Y\_{i0}/D\_{i}=1)\ne E(Y\_{i0}/D\_{i}=0)$. To overcome this selection problem we use the *conditional independence assumption* (Rubin, 1977) which states that both the participation and potential outcome are statistically independent for firms with the same set of exogenous characteristics, X. Following this assumption it is possible to say that $E(Y\_{i0}/D\_{i}=1,X)=E(Y\_{i0}/D\_{i}=0, X) $and the difference between both groups can only be assigned to training. If the *conditional independence assumption* holds, the $α\_{TT}$ can be written as:

$E\left(α\_{TT}\right)= E(Y\_{i1}/D\_{i}=1,X=x)-E(Y\_{i0}/D\_{i}=0, X=x)$ (4)

Some key points are worth mentioning. One of them is the fact that overlapping between the control and treatment groups (control support) is necessary for the success of the matching estimator. The control group should contain at least one firm sufficiently similar for each firm in the treatment group. In practice, this requirement is satisfied by restricting the sample to a common support. To do this, the minimum and maximum thresholds are calculated, and then the observations which get a higher or lower propensity score than this threshold are eliminated. If the overlapping between samples is too small, the matching estimator is not applicable.

The matching technique must face another challenge named “the course of dimensionality”. The number of exogenous factors which affect both the treatment and the outcome variable could be excessively large to find a perfect match for each firm in the control group. On the other hand, a too small set of covariates makes the matching not possible. Rosenbaum and Rubin (1983) suggested the use of a propensity score as a single index to reduce the number of variables included in the matching function to just one. Thus, the matching procedure conceived as a multi-dimensional problem is reduced to a one-dimensional problem. Therefore a Probit model is estimated on the dummy indicating training activities. The estimated propensity scores are subsequently used as a matching argument.

However, having an estimation of propensity score is not enough to solve the problem of the counterfactual outcome. Finding two firms with the exact propensity score is unlikely. The econometric literature about impact evaluation develops a number of matching procedures to overcome this problem such as Nearest Neighbor and Kernel, among others. We use Kernel matching because it is more appropriate to study small samples. In this procedure each firm of the control group is paired with a weighted average of all firms in the control group and the weights that they receive are inversely proportional to the distance it holds with the untreated firm.

In summary, the objective of the procedure is building a control group employing matching techniques. This allows to control the observable difference between firms which have conducted training activities and those which have not, looking for pairs of firms from the treated and the control group. The idea is to balance the sample between the two of them. Remaining differences in the outcome variable between both groups are then attributed to the treatment. The main assumption underlying these steps is the proposition that conducting training activities is only determined by observable factors. If it is not the case, the impact evaluation will be biased. The source of this bias resides in the potential correlation between the unobservable variables that affect both having conducting training activities and their potential outcome on productivity and wages. However, given the availability of information and the fact that counterfactual information is never available, this technique has been proved to be robust in providing evidence about the impact of these types of variables. It is also the technique commonly used in impact studies, which improves the comparability of this research.

In the second place, we apply a parametric technique named doubly-robust estimators proposed by Robins and other colleagues (Bang and Robins 2005; Robins, Rotnitzky, and Zhao 1995; Robins 2000). This estimator require combine in the same estimator, the model for estimating the propensity score and the model for estimating the outcome variable. The advantage these estimators offer is that they give unbiased estimates of the treatment effect when either one or both of these constituent models are correctly specified, thus allowing the analyst two opportunities for obtaining accurate results. The unmeasured confounder assumption is still required. To do this, we depart from the propensity score estimated before ($\hat{p}\_{i}) $and generate the inverse probability of treatment weights. Using simple inverse weights equal to ${1}/{\hat{p}\_{i}}$ if the firm D=1 or ${1}/{(1-\hat{p}\_{i})}$ if D=0 leads to the following IPTW estimator (Lunceford and Davidian, 2004):

$$\hat{τ}=N^{-1}\sum\_{i=1}^{N}\left( \frac{D\_{i}Y\_{i}}{\hat{p}\_{i}} \right)-N^{-1}\sum\_{i=1}^{N}\left\{ \frac{(1-D\_{i})Y\_{i}}{1-\hat{p}\_{i}} \right\}$$

Emsley et. al. (2008) derives an alternative specification of IPTW estimator that averages over the sum of the weights for each group while still using the simple inverse weight, i.e.,

$$\hat{τ}\_{IPTW}=\left(\sum\_{i=1}^{N}\frac{D\_{i}}{\hat{p}\_{i}}\right)^{-1}\sum\_{i=1}^{N}\left( \frac{D\_{i}Y\_{i}}{\hat{p}\_{i}} \right)-\left(\sum\_{i=1}^{N}\frac{1-D\_{i}}{1-\hat{p}\_{i}}\right)^{-1}\sum\_{i=1}^{N}\left\{ \frac{(1-D\_{i})Y\_{i}}{1-\hat{p}\_{i}} \right\}$$

This estimator can be produced estimating the outcome variable as a function of the treatment indicator and the set of confounders. In this model the sample will be restricted to the common support and the observations will be weighted according to the inverse of the propensity score.

## **3. Results**

Before showing the main results of our estimation, descriptive statistics provide an illustrative representation of the phenomenon under study. As we have already stated, the database is made up by SMEs that belong to 14 manufacturing and 4 service sectors. The industrial classification follows the ISIC, though some sectors were excluded because the predominance of large firms (e.g. tobacco). Just a few service sectors were included and this is because training and innovation questions were asked just in the selected activities.

The average size is 57 sectors with significant differences among them. Labor productivity and wages (in logs and levels) show that firms also perform very differently among sectors. The same observation can be made in the case of training activities. There are activities that show a higher rate of firms conducing training activities than others. Services considered, automotive sector, machinery and chemicals systematically performed training activities more frequently (See Table 1),

**Table 1. Several statistics by activity**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sector | N | Number of employees 2008 | Log (labor productivity) 2008 | Labor productivity(pesos 2008) | Log (wages) 2008 | Average wage (pesos 2008) | Training activities % (2006-2008) |
| Food and beverages | 226 | 59 | 10.4807 | 51,462 | 10.02897 | 33,742 | 62% |
| Textiles | 45 | 69 | 10.60322 | 52,510 | 10.112 | 31,970 | 47% |
| Garment | 55 | 68 | 10.2353 | 43,053 | 9.830907 | 22,576 | 33% |
| Leather and its products | 32 | 60 | 10.59262 | 61,423 | 10.09019 | 37,405 | 47% |
| Wood and furniture | 60 | 46 | 10.02906 | 35,557 | 9.913654 | 23,218 | 35% |
| Paper and its products | 42 | 75 | 10.62018 | 49,621 | 10.2037 | 30,458 | 55% |
| Editorial industry | 75 | 55 | 10.73808 | 61,611 | 10.2077 | 32,955 | 57% |
| Chemicals | 65 | 64 | 11.15643 | 108,498 | 10.52449 | 50,569 | 77% |
| Rubber and plastic | 117 | 58 | 10.73421 | 58,269 | 10.23897 | 34,380 | 67% |
| Non-metallic minerals | 57 | 52 | 10.37354 | 43,353 | 10.09704 | 28,598 | 52% |
| Metal products | 154 | 44 | 10.61975 | 62,253 | 10.18194 | 30,689 | 62% |
| Machinery and equipment | 133 | 57 | 10.81162 | 67,750 | 10.24696 | 35,165 | 76% |
| Electrical machinery | 43 | 68 | 10.7545 | 64,562 | 10.30755 | 32,774 | 67% |
| Automotive | 104 | 60 | 10.63569 | 51,982 | 10.14228 | 31,259 | 69% |
| Mail and communication | 36 | 42 | 10.0191 | 31,829 | 10.00276 | 32,814 | 39% |
| Software and IT services | 25 | 59 | 10.77849 | 53,290 | 10.63118 | 38,138 | 88% |
| Consulting business services | 101 | 61 | 10.47837 | 57,255 | 10.1267 | 44,846 | 60% |
| Medical services | 46 | 48 | 10.59986 | 50,183 | 10.14587 | 32,761 | 71% |
| **Total** | **1416** | **57** | **10.587** | **50,553** | **10.1523** | **33,587** | **61%** |

Source: Own elaboration base on Mapa Pyme.

On the one hand, labor productivity is higher in low tech and in those sectors where collective bargain made little improvements. On the other hand better wages are paid in high- and medium-tech sectors and in sectors where collective bargain led to improvements above the average level. Training activities are performed more frequently in medium and high-tech sectors and in those sectors were unions have negotiated below the average levels (See Table 2).

**Table 2. Several statistics by technology intensity and by results of collective bargain**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sector | N | Number of employees 2008 | Log (labor productivity) 2008 | Labor productivity (pesos 2008) | Log (wages) 2008 | Average wage (pesos 2008) | Training activities % (2006-2008) |
| High and Medium Tech | 743 | 57 | 10.58994 | 55,865 | 10.16689 | 36,208 | 0.640541 |
| Low Tech | 673 | 57 | 10.58377 | 58,466 | 10.13618 | 36,077 | 0.578869 |
| **Total** | **1,416** | **57** | **10.58700** | **57,101** | **10.1523** | **36,146** | **0.61119** |
| Δ Wages below average | 1,185 | 56 | 10.61503 | 58,674 | 10.16867 | 36,026 | 0.624683 |
| Δ Wages above average | 196 | 62 | 10.41016 | 45,852 | 10.05948 | 33,297 | 0.556701 |
| **Total** | **1,381** | **57** | **10.58595** | **56,854** | **10.15306** | **35,639** | **0.615105** |

Note: There are less observations in distributions by results of collective bargain due to missing data for some branches in textiles and medical services.

Source: Own elaboration base on Mapa Pyme and Ministry of Labor and Social Security.

Tables 3 and 4 summarize the main results of the econometric exercise. In table 3 mean differences of training activities impact on productivity and wages are presented. The number of treated firms (firms that have conducted training activities), the number of control firms (firms that have not conducted training activities), and t-student value for establishing the statistical significance is also displayed in the referred table. Table 4 presents the regressions run on productivity and wage logs following the doubly-robust estimators. Training is our variable of interest and innovation, average annual rate of growth of employment and wage during 2003-2007 and age are control variables. Also the models include 17 sectoral dummies that are not display due to space reasons.

The first row of table 3 shows that firms that have conduced training activities have productivity levels 27% higher and paid wages 19% higher than those that have not performed any training. This means that firms that train their employees have better productive performance and pay better salaries. However, the gap between the impact of training in productivity and wages means that firms do not translate completely into wages the productivity gains derived from training. Summing up, this first row of table 3 offers statistical evidence to support hypothesis 1. At the first two columns of table 4 there is similar information coming from the OLS estimation on productivity levels and wages. In this case, although the gap is smaller, it persists.

The second and third rows of table 3 as well as columns 3 to 6 of table 4 provide information regarding hypothesis 2. The tendency of treated firms to reach higher productivity and wage levels remains. Nevertheless, the gap between impacts on productivity and wages decreases when moving from low-tech to medium and high-tech sectors. More precisely, the gap reduces form 15 to 2 percentage points. Thus, evidence supports hypothesis 2. This gap reduction can also be seen when the coefficient of training in columns 3 and 4 are compared with the same coefficients in columns 5 and 6. In this case, the gap reduction drops from 12 to 3 percentage points.

**Table 3. Mean differences**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| H1 | 1. Total Sample | Output | N (Treated) | N (Ctrol Group) | ATT (Matched) | T |
|  |
| ln(prod) | 823 | 508 | 0.273 | 5.493 |
| ln(wage) | 823 | 508 | 0.198 | 5.560 |
| **Gap** |  | **0.8** |  |
| H2 | 2. Low Tech |  |
| ln(prod) | 367 | 254 | 0.342 | 4.521 |
| ln(wage) | 367 | 254 | 0.197 | 3.471 |
| **Gap** |  | **0.15** |  |
| 3. High and Medium Tech |  |
| ln(prod) | 454 | 242 | 0.208 | 3.420 |
| ln(wage) | 454 | 242 | 0.183 | 3.460 |
| **Gap** |  | **0.2** |  |
| H3 | 4. Collective bargain has led to Δ Wages below average |  |
| ln(prod) | 510 | 337 | 0.287 | 4.102 |
| ln(wage) | 510 | 337 | 0.203 | 4.240 |
| **Gap** |  | **0.09** |  |
| 5. Collective bargain has led to Δ Wages above average |  |
| ln(prod) | 313 | 163 | 0.260 | 3.274 |
| ln(wage) | 313 | 163 | 0.185 | 3.43 |
| **Gap** |  | **0.07** |  |

Source: Own elaboration base on Mapa Pyme and Ministry of Labor and Social Security

Finally, results for hypothesis 3 are not so promising. Rows 4 and 5 of Table 3 show that the gap between impacts on productivity and wages remains the same when moving from activities where collective bargaining led to wage increases below the mean to activities where the negotiations led to over-the mean increases. Similar conclusions can be derived from columns 7 to 10 of Table 4. The productivity-wage gap in the OLS models is the same (6.7 percentage points) both for sectors that negotiate worse and for those that negotiate better. Therefore, evidence does not support hypothesis 3.

**Table 4. OLS regressions.** Doubly-robust estimators: Parametric estimation of ATT

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Hypothesis  1** | **Hypothesis 2** | **Hypothesis 3** |
| **Low Tech** | **High and Medium Tech** | **Collective bargaining leads to Δ wages below average** | **Collective bargaining leads to Δ wages above average** |
| **Output** | **1.** | **2.** | **3.** | **4.** | **5.** | **6.** | **7.** | **8.** | **9.** | **10.** |
| **Ln (prod)** | **Ln (wage)** | **Ln (prod)** | **Ln (wage)** | **Ln (prod)** | **Ln (wage)** | **Ln (prod)** | **Ln (wage)** | **Ln (prod)** | **Ln (wage)** |
| **Training** | **0.253\*\*\*** | **0.183\*\*\*** | **0.307\*\*\*** | **0.185\*\*\*** | **0.211\*\*\*** | **0.183\*\*\*** | **0.252\*\*\*** | **0.185\*\*\*** | **0.247\*\*\*** | **0.180\*\*\*** |
| Rate\_emp0307 | 0.063 | -0.270\*\*\* | -0.138 | -0.224\* | 0.156 | -0.282\*\* | -0.077 | -0.308\*\* | 0.193 | -0.210 |
| Rate\_wage0307 | -0.686\*\* | -0.367\* | -1.347\*\*\* | -0.447\* | 0.065 | -0.210 | -1.303\*\*\* | -0.772\*\*\* | 0.620 | 0.501 |
| Innovation | 0.150\*\*\* | 0.033 | 0.116\* | 0.068 | 0.179\*\* | 0.000 | 0.124\*\* | 0.037 | 0.193\*\* | 0.003 |
| Age | -0.004\*\* | -0.005\*\*\* | -0.003 | -0.006\*\*\* | -0.003 | -0.005\*\*\* | -0.003 | -0.005\*\*\* | -0.003 | -0.005\*\* |
| \_cons | 18.673\*\*\* | 20.067\*\*\* | 16.082\*\*\* | 21.397\*\*\* | 16.495\*\*\* | 19.553\*\*\* | 17.317\*\*\* | 20.037\*\*\* | 16.728\*\*\* | 18.635\*\*\* |
| chi2 p | 6.66e-23 | 2.67e-29 | 1.14e-13 | 8.07e-13 | 1.31e-09 | 4.17e-12 | 2.69e-16 | 5.37e-20 | 7.36e-10 | 1.61e-11 |
| N | 1326 | 1322 | 611 | 609 | 699 | 697 | 850 | 846 | 481 | 481 |

Source: Own elaboration base on Mapa Pyme and Ministry of Labor and Social Security

Note: 17 sectorial dummies included. Firms weighted according to their estimated propensity score and corresponding to common support.

## **4. Conclusions**

The objective of this paper was to contribute to the literature about the relationship between productivity and wages and how higher levels in the former also lead to higher levels in the later. The hypotheses were aimed to test how training activities are corresponded with higher productivity and wage levels. Given the relevance of the productive structure and the labor institutions highlighted in the literature, the impact of both dimensions on the productivity-wage gap was also tested. Based on propensity score matching techniques, the empirical analysis was based on a database made of about 1400 Argentinean SMEs for the period 2006-2008. Results confirm what predicted by innovation literature in the sense that training activities lead simultaneously to higher productivity (private) and wage (social) levels. However, they also show that the impact is unequally distributed between the firm and its employees, being the impact on productivity almost twice the impact on salaries. In this sense, this study has provided evidence regarding the productivity-wage gap and the limitations of wages to approximate productivity. Of course, they have also call the attention on the need for a better understanding of this relationship and how productivity gains are translated into higher incomes. In this sense, results coincide with the literature to the extent that even though training activities lead to higher productivity levels and higher salaries, they do it unevenly (e.g. Dearden et al, 2006 and Conti, 2005).

The second motivation of this paper was to understand how sectorial structure and labor institutions reduce or increase the gap. In this respect, results show that the gap tends to decrease among medium- and high-tech sectors, which provides evidence regarding the impact of the process of structural change and how micro-economic behaviors can impact the macro-economic aggregates. In this case, results also agree with the literature about the productivity-wage gap in the sense that it depends on certain environmental factors (Carneiro, 1998 and Zhang and Liu, 2013), but also agree with the literature about structural change and how it is a way of improving development (CEPAL, 2012).

Regarding labor institutions, evidence is not conclusive. At first sight, results show none relationship between the bargaining power of unions and the reduction in the gap. However, this contradicts most of the literature about productivity, wages and institutions and leads us to discuss the limitations of this research and the need to go deeper on the analysis of productivity and wages.

The main limitation of this analysis derives from the data availability, which in turn determines the period under analysis. In this respect, it constitutes a period of income recovery given the crisis of 2002 and the frozen of salaries during 2003-2005. In fact, collective bargains started in this later year, once the economy was recovered from the 22% unemployment rate and the 40% level of poverty. This also would explain the lack of impact of the labor unions to the extent that during that period there were high productivity gains associated more to the recovery than to genuine increases in the input-output relationship. Of course, the extension of the period under analysis could improve the research and allow more clear relationships to be analyzed.

Another limitation is given by the need to analyze and measure counterfactual relationships. Although, once again, data availability limits the possible techniques to be used, the fact that counterfactuals are analyzed reduces the number of methodological choices. However, and as it was explained in section 2, the selected methodology and the defined model are commonly used in the literature and proved to be solid for this type of analyses. In this case, the improvement in the econometric techniques and the development of new software tools will allow better estimations to be performed.

To conclude, and despite the above mentioned limitations, this research has focused on a common assumption of innovation studies and shows to what extent improvements in capabilities could simultaneously impact on productivity and wages. A deeper understanding of the productivity-wage gap could help to identify policy recommendations regarding how to maximize the impact of micro-behaviors on incomes and the innovation policy on wages. In this sense, it is worth mentioning that this research is part of a larger project aimed at constructing a database capable of accounting for this phenomenon, which is carried out by the Ministry of Labor with the collaboration of researchers from the Universidad National de General Sarmiento and the support of the Inter-American Development Bank. In this sense, this paper provides useful insights to data requirements, basic relationships and analysis levels.

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**Appendix**

As was outlined in Section 2, for each treated firm there must be a potential control observation with a similar propensity score. To do this we calculate the minimum and maximum of the propensity scores of the potential control group. It turns out that for 18 firms in the treatment group we do not have adequate equivalents firm in the control group. These observations are not considered in the matching process. Figure 1 presents the set of non-treated firms, those treated firms that belong to the common support and those that are not considered.

**Figure 1. Propensity score and common support**

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Source: Own elaboration base on Mapa Pyme and Ministry of Labor and Social Security

Other important prerequisite for matching procedure is the fulfillment of the conditional independence assumption. That is, conditional to the propensity score, the differences between treated and non-treated firms were only attributable to training activities. To check this we can see if the set of covariates are well balanced after the matching. Table 6 presents the p-value statistic of the mean difference test for all de covariates, and the percentage of standardized bias. The high score of the p-value allows us to reject the null hypothesis of zero difference between treated and non-treated firms. In addition, the percentage of standardized bias of each covariate is within the threshold of ± 10%. Considering both results, we can affirm that all covariates are well balanced. Hence we can conclude that the matching was successful, and we can measure the average treatment effect on treated (ATT).

**Table 5. Quality of balance: p-values of mean test and % of standardized bias**

|  |  |  |  |
| --- | --- | --- | --- |
| **Covariate** | **Mean** | **t-test** | **% of std. bias** |
| **Treated** | **Control** | **t** | **p>t** |
| sector | 31.755 | 32.339 | -0.60 | 0.548 | -3.1 |
| Rate\_emp0307 | .14458 | .15019 | -0.56 | 0.576 | -0.3 |
| Rate\_wage0307 | .24585 | .24236 | 0.73 | 0.468 | 3.2 |
| Innovation | .59356 | .58101 | 0.51 | 0.609 | 2.7 |
| Age | 1985.3 | 1985.2 | 0.14 | 0.890 | 0.7 |

Source: Own elaboration base on Mapa Pyme and Ministry of Labor and Social Security.

1. Of course, to extrapolate these conclusions to other regions or to generalize the results is not possible. Differences in the institutional set up and regulation of unions (by sector or by firm), in the labor legislation (tenure compensations, holidays, working hours, etc.), and in the economic context of each country make these and other results difficult to be compared. However, evidence leads to sustain that the characteristics of labor institutions affect the productivity-wage gap which implies that they have to be taken into account when analyzing it. [↑](#footnote-ref-1)
2. Productivity and mean-wage of i-firm. [↑](#footnote-ref-2)