The Economic Payoff of Creating Good Job Conditions: Theory and Evidence from Latin America[*]

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Abstract: based on Akerlof and Kranton (2005), who argue that group identity and social norms influence individual preferences towards work effort, a model is developed to understand why firms create good job conditions, taking into account the cost of implementing them and their impact on wages and productivity. Then, using individual-level data from the Gallup World Poll for 18 Latin American countries, the main predictions of the model are tested using propensity score matching. We find a positive link between good job conditions, workers' labor income and productivity when there are several simultaneous signals of a good work environment. We conclude that there is a positive payoff of investing in good job conditions for both workers and firms.

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1 Introduction

Human resource management (HRM) has become a major field in labor economics (Bloom and Van Reenen, 2011b). HRM applies standard economic tools to explain management labor practices and their influence on firms' outcomes (Lazear and Shaw, 2007). Central topics in HRM are what incentives are selected by the firm to motivate its workers, and how they affect productivity and other key economic outcomes. In particular, we are interested in the role of good job conditions such as coaching and encouraging workers, adapting tasks and allocating responsibilities to fit their strengths, and other actions that foster among workers a sense of identity with their work and the firm (Akerlof and Kranton, 2005). These aspects of HRM, which are central to other academic disciplines such as organizational behavior psychology (Luthans and Youssef, 2007), are gaining ground in the economic profession (Kahneman and Krueger, 2006).

This paper aims at understanding why individual workers seem to be exposed to different job conditions depending on their personal characteristics. Extending the original model in Akerlof and Kranton (2005), we develop a model that explains how firms choose job conditions by type of worker in order to maximize their profits, taking into consideration that better job conditions raise productivity but are costly to implement and may cause wage increases, depending on the bargaining power of each type of worker. The main predictions of the model are tested empirically using individual level data of the Gallup World Poll of 2007 for Latin American countries, which included a set of questions on perceived working conditions which arguably measure the degree to which workers are identified and satisfied with their jobs.

By theoretically and empirically exploring the relation between good job conditions, wages and productivity, we attempt to contribute to two different branches of the literature. The first is positive organizational behavior (Keyes and Haidt, 2002; Luthans, 2002; Bakker and Schaufeli, 2008), which focuses on the determinants and consequences of constructive attitudes between employees and management, as opposed to the more traditional counterproductive work behavior literature (Penney and Spector, 2005). The second branch is the role of management practices and working conditions in developing countries (Robertson et al., 2009; Bloom et al., 2010a; Bruhn et al., 2010; Bloom et al., 2011a; Fields, 2012).This literature has found a large variation, both within and between developing countries, in the quality of management practices and working conditions.

Although the cross-sectional nature of our dataset and the empirical strategy implemented do not allow us to strictly claim any causal effects from the results, we deal with the selection problem in the data by deploying a battery of propensity score matching techniques, where each worker treated with a given job condition is matched with one or more workers that share similar individual characteristics and psychological traits but is not exposed to the same working conditions. The results give strong support to the hypothesis that good job conditions have a significant and economically important relation with labor income and, though in a less robust way, with an imputed measure of labor productivity.

The rest of this paper proceeds as follows. Section 2 provides a short survey of the most relevant literature on the influence on productivity of the quality of human resource management, as measured by objective indicators and as perceived by workers. Section 3 presents the theoretical model and its predictions. Section 4 is devoted to the dataset and the calculation of labor income and imputed labor productivity. The econometric techniques and the empirical findings are presented in Section 5. A final section summarizes the results and discusses their implications.

2 Literature review

There is a substantial body of evidence of persistent heterogeneity in firm productivity (and other measures of firm-level performance) in narrowly-defined sectors in many countries, both in the developed and the developing world (Bartelsman and Doms, 2000; Bloom et al., 2010a). Some of that heterogeneity is due to differences in the quality of the resources used by firms of different size or location, and some is due to misuse or misallocation of the resources as a result of inefficient scale of production or poor technology choice (Pagés, 2010). Still, much of that heterogeneity remains unexplained and may at least in part be the result of different managerial practices, especially HRM practices.

The influence of HRM practices on firm productivity (and other firm-level outcomes, such as profits or sales) has been studied from two complementary angles. One focuses on objective measures of HRM, which includes payment methods, hiring and firing practices and work organization. The other makes use of employee perceptions on job conditions, such as whether the employee feels that she has the opportunity to do what she does best, whether her supervisor, or someone at work, encourages her development, and whether or not her opinions seem to count. Although the current paper falls directly into this second strand, an overview of both strands is convenient in order to highlight their complementarities.

In the objective strand, the implicit assumption is that HRM practices are better when employees are hired, rewarded, promoted and fired, if warranted, on the basis of their ability, efforts and results. These practices are strongly correlated with firm performance indicators, such as total factor productivity and profitability (Bloom and Van Reenen, 2007).

Incentive pay is considered a central dimension of HRM. In general, incentive pay, be it individual- or group-based, has positive effects on productivity (two surveys on the topic are Prendergast, 1999; and Bloom and Van Reenen, 2011b). However, this conclusion must be qualified in various ways. First, incentives matter, and matter a lot, but not necessarily in favor of better firm outcomes. Contracts to reward employees on the basis of some measurable aspects of their work cause them to focus too much on those aspects to the detriment of those excluded (Holmstrom and Milgrom, 1991). Since most jobs are complex and hard to contract over, explicit contracts are seldom used. Subjective performance evaluations, where supervisors evaluate workers in a more holistic way, and which can be used to complement incentive pay, are a more common practice (Baker, Gibbons and Murphy, 1994). However, subjective performance evaluations are often tainted by supervisor biases (evaluations are too lenient or fail to distinguish between good and bad performers) or workers currying favor from them. Second, incentives matter in ways difficult to explain by standard economic theory. Profit sharing schemes often produce large group performance improvements, where the benefits of increased effort by each worker are shared with hundreds, or even thousands, of other workers. Why do individual workers exert effort if they gain a minuscule fraction of the benefits? The lack of proportion between effort and incentive is also apparent in the effect on sales or other outcomes of giving workers small bonuses or gifts. Third, incentive pay is generally more effective when complemented with other HRM practices (Lazear and Shaw, 2007).

In a nutshell, the main conclusion of this literature is that, while incentive pay may be useful, no organization can rely solely on monetary incentives to make workers perform well. How employees perceive their work environment and respond to it may be just as important as payment methods used by the firm. Akerlof and Kranton (2010) see identity with the organization as the key subjective dimension of the work environment. Supported by a growing body of research, they summarize their position as follows: "We argue that identity is central to what makes organizations work. Workers should be placed in jobs with which they identify, and firms should foster such attachments" (p. 41). Identity with the organization makes employees "insiders", who gain utility from putting high effort in their work. Insiders do not need a large (direct) monetary reward to work hard, but firms must invest in changing workers' identity through training, sign-on bonuses, and other benefits (pp. 41-43). Insiders do not require strict supervision to exert effort. On the contrary, they may resent the close oversight and adopt outsider identities (p. 52).

A related literature has emphasized the importance of engagement for job satisfaction and productivity (Buckingham and Coffman, 1999; Harter, Schmidt and Keyes, 2002; Ritter and Anker, 2002). According with this strand, engagement and job satisfaction can be measured with a small number of dimensions of the quality of the work environment as perceived by employees.[4] To our knowledge, no study has explored the relation between

[4] According to Buckingham and Coffman (1999), six of the 12 questions regularly used by the Gallup Organization to assess the work environment have "the *strongest* links to the *most*

perceived job conditions and productivity using samples representative at the national level for one or more developing countries. This is the gap in the empirical literature that we attempt to fill.

3 Conceptual Framework

A theoretical framework to understand the relation between job conditions, effort, wages and productivity can be built on the basis of the model proposed by Akerlof and Kranton (2005), who argue that group identity and social norms have a central role in the determination of individual preferences. Under this approach, the purpose of good job conditions is to configure the work environment in such way that workers are willing to put forth more effort in the workplace. Implicit in this simplified version of the Akerlof-Kranton model is the hypothesis that job conditions that foster the identity of workers with their jobs have a positive effect on both labor productivity and labor income. However, if creating good job conditions is costly for firms, they will choose the optimal work environment for each type of worker following a profit-maximization principle, depending on the marginal productivity of workers' effort and the bargaining power of each type of worker.

Consider a principal-agent environment, where the firm is the principal and the worker is the agent. Worker's output is jointly determined by individual effort and her own human capital. The worker's wage will correspond to a solution from a Nash bargaining game between both parties. The profit-maximizing firm can influence the worker's effort choice by investing in good job conditions. If the firm decides to do so, then the worker will internalize the behavior that is expected from her as a member of the firm. In line with the Akerlof-Kranton model, suppose the worker faces the following utility maximization problem,

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business outcomes" (p. 33, emphasis in the original). They are: "(1) Do I know what is expected for me at work? (2) Do I have the materials and equipment I need to do my work right? (3) Do I have the opportunity to do what I do best every day? (4) In the last seven days, have I received recognition or praise for good work? (5) Does my supervisor, or someone at work, seem to care about me as a person? (6) Is there someone at who encourages my development?" (pp. 33-34).

$$\underset{e}{Max} \quad U(w, e, t) = w - e - \frac{t}{2}\left(e^{Ref} - e\right)^2 \tag{1}$$

$$\text{s.t.} \quad w = \beta y + (1 - \beta)c \tag{2}$$

$$y = F(\theta, e) \tag{3}$$

Note: the objective function is based on Akerlof and Kranton (2005), pp. 14, first equation. The wage equation (equation 2) is based on equation 1.20 in Pissarides (2000, pp. 17).

where w is the wage, e is worker's effort, e^{Ref} is the reference level of effort which is considered a social norm within the firm, and t measures the quality of job conditions. Therefore the worker dislikes providing effort in general, but if the firm creates good working conditions ($t > 0$), then the worker will suffer additional psychological costs if her effort is below the reference level for the firm.

We assume the wage Nash bargaining process occurs at the same time as the principal-agent model unfolds. Therefore, it becomes a constraint for both the worker and the firm. Equation 2 is the solution to this bargaining problem, where the wage offered will be a weighted average between labor productivity (y) and the worker's opportunity cost (c), which is a typical result from the labor search literature (Pissarides, 2000). β, which is strictly between 0 and 1, measures the worker's bargaining power (Osborne and Rubinstein, 1994), so the worker's wage will be below but close to her productivity, as long as her bargaining power is close enough to 1.

Finally, equation 3 describes the technology. We assume that labor productivity is a function of worker's human capital (θ) and effort (e). As usual, it is assumed that labor productivity is an increasing function of both variables ($F_\theta > 0, F_e > 0$).[5] Additionally,

[5] For notation, we will use $F_x = \frac{\partial F}{\partial x}$ to denote the first order derivative of F with respect to x. Also, $F_{x,y} = \frac{\partial^2 F}{\partial x \, \partial y}$ will be used to denote second order derivatives.

human capital is assumed to have a positive effect on the marginal productivity of effort ($F_{e,\theta} > 0$), and returns to effort are assumed to be concave ($F_{e,e} < 0$).

The first order condition from the worker's problem that characterizes optimal effort (e^*) is the following,

$$\beta F_e(\theta, e^*) + t\left(e^{Ref} - e^*\right) = 1 \tag{4}$$

There are two forces that motivate the worker to provide effort. The first one is the incentive provided by additional labor income, in particular for workers with strong bargaining power (βF_e). The second one is the lower psychological cost of deviating from the firm's effort norm, which the worker will take into account to the extent that the firm invests in good job conditions ($t\left(e^{Ref} - e^*\right)$).

Equation 4 implies the following optimal effort function,

$$e^* = e\left(\beta, \theta, t, e^{Ref}\right) \tag{5}$$

In the appendix we show that (i) optimal effort is an increasing function of the worker's bargaining power ($\frac{\partial e^*}{\partial \beta} > 0$); (ii) human capital also has a positive effect on the optimal level of effort ($\frac{\partial e^*}{\partial \theta} > 0$); and (iii) optimal effort will increase with the quality of job conditions, as long as the effort norm within the firm is large enough. In particular,

$$\frac{\partial e^*}{\partial t} = \frac{\left[e^{Ref} - e^*\right]}{\left[t - \beta F_{e,e}(\theta, e^*)\right]} > 0 \tag{6}$$

Now consider the profit maximization problem of the firm. The firm chooses how much to invest in good job conditions directed toward a specific type of worker. When doing so, it has to take into account how the worker is going to react to its decisions (the incentive compatibility constraint) and the relation between the wage offer and labor productivity (the Nash bargaining solution as a participation constraint). Thus, the firm faces the following problem,

$$\underset{t}{Max} \quad \Pi(y, w, t) = y - w - H(\theta, t)$$

s.t. $e = e^*(\beta, \theta, t, e^{Ref})$ (Incentive compatibility constraint)

$w = \beta y + (1 - \beta)c$ (Participation constraint)

$y = F(\theta, e)$

where $H(\theta, t)$ measures the cost of creating job conditions of quality t for a worker that has θ of human capital.

The first order condition for the firm, which will characterize the optimal investment in job conditions (t^*), is given by equation 7:

$$[1 - \beta]F_e(\theta, e^*)\frac{\partial e^*}{\partial t} = H_t(\theta, t^*) \qquad (7)$$

The left hand side of equation 7 represents the marginal output that is captured by the firm due to additional effort exerted by the worker, in response to better working conditions, whereas the right hand side is the firm's marginal cost of increasing the quality of job conditions.

We now have all the necessary elements to analyze the equilibrium response of labor income and labor productivity to changes in the quality of job conditions. From the constraints in the worker's problem (equations 2 and 3) and the analysis of optimal effort (equation 6), the following relations should hold,

$$\frac{\partial w}{\partial t} = \beta \frac{\partial y}{\partial t} = \beta F_e \frac{\partial e^*}{\partial t} > 0 \qquad (8)$$

As a consequence, a positive relation between job conditions, wages and labor productivity should be observed in the data. This will be the main hypothesis tested in the empirical section. The magnitude of this link will depend on the worker's bargaining power, the marginal productivity of effort and the effect of job conditions on effort.

These additional hypotheses will not be tested, as our dataset has no information on the latter two variables.

4 Data and computation of wages and imputed labor productivity

The data source is the 2007 wave of the Gallup World Poll, which provides the most extensive coverage of both objective and perceived conditions of quality of life for 134 countries. The samples are representative of the population aged 15 or over in each country. The polls were taken by telephone in countries with fixed telephone coverage of over 80% of the population, and face-to-face in other countries. Respondents were selected at random from household members, with the objective of preventing representation biases resulting from interviewing the first member of the household available. The face-to-face interviews lasted approximately one hour and telephone interviews approximately 30 minutes.

Identical questionnaires were used in all countries for a set of basic questions, but some important variables, such as education or income brackets, were either not included or defined in non-comparable ways in some countries. For this reason, we restrict the sample to 18 Latin American and Caribbean countries where the required data are available. Since our unit of observation is the individual working in a firm, the sample is further restricted to the sub-sample of 3,360 individuals in jobs with direct supervisors and non-missing labor income data (summary statistics are available in the first and second columns of Table 1). However, as explained below, the sample is further reduced to those individuals belonging to reference groups large enough to allow calculating individual-level productivity using some features of the group.

The list of "yes or no" questions on personal job conditions available in the database are as follows (in their order of appearance in the questionnaire):

- Do you currently have a job or work (either paid or unpaid work)? ("work" from here onward);

- Are you satisfied or dissatisfied with your job or the work you do? ("job satisfaction");
- In your work, do you have an opportunity to do your best every day, or not? ("do your best");
- Is there someone at work who encourages your development, or not? ("encouragement");
- Do you have a supervisor, someone at work who you report to? ("has supervisor");
- At work, do your opinions seem to count, or not? ("opinions count");
- Do you think you could lose your job in the next six months? ("fear to lose job").

For more information on how the Gallup organization has designed and used these questions, see Buckingham and Coffman (1999).[6] Although the survey does not have a specific question on the degree of identification of workers with their jobs, we presume that identification is stronger when job conditions as perceived by the worker are better. Specifically, we posit that workers who do their best, feel encouraged, think their opinions count, and do not fear to lose their jobs are workers who have good job conditions and fully identify themselves with their jobs.

For Latin American countries, the Gallup data has information on monthly labor income in national currency, using country-specific income brackets. It has been transformed (by Gasparini et al., 2008) into a continuous variable using uniform probability distributions, so that each individual is assigned a random income level inside the income bracket he selected as an answer. In order to have comparable units, income levels are transformed

[6] Except for the last question, which was included at the request of the Inter-American Development Bank in the Latin American countries questionnaires for the 2007 wave.

from national currencies into international US$ at purchasing power parity values (US$ PPP)[7].

To compute individual-level productivity, which is not directly observable, we use the assumption from the conceptual framework of a Nash bargaining process which relates wages, labor productivity and bargaining power (Equation 2 from the worker's problem),

$$w = \beta y + (1 - \beta)c \qquad (2)$$

Recall that *w* is wage, *y* is labor productivity, β is the bargaining power of the worker in the Nash bargaining game between the worker and the firm, and *c* is the reservation wage of the worker. Wages are close to labor productivity only for those workers that have a strong bargaining position. If a worker has weak bargaining power, the firm will offer her a low wage, just enough to make her accept the offer. This would be a wage barely above the opportunity cost of working or the second-best option faced by the worker. An implicit assumption is that $c \leq w \leq y$.

To calculate the implicit value of labor productivity in equation 2, in addition to labor income, information on bargaining power and reservation wage for every worker is needed. We compute these two variables assuming that individuals who share similar socio-economic characteristics within a country (i.e. their reference group) face similar labor market conditions. Essentially, this implies that individuals belonging to the same reference group will have the same bargaining power, and that, given that bargaining power, the differences in their wages must reflect differences in productivity.

A reference group consists of workers with similar socio-demographic characteristics. Workers with the same age and similar education levels compete in related labor markets and usually face similar wage bargaining conditions. For example, middle-age workers with low levels of education in rural areas have little bargaining power and a very low reservation wage, whereas young workers with higher education in urban areas have a

[7] See Gasparini, et al. (2008) for a detailed explanation of this procedure.

stronger position to bargain wages and, at the same time, have a higher opportunity cost of working. This means that a good measure of bargaining power is the variation in wages inside each reference group within a given country. As another example to illustrate this point, if all individuals inside a reference group earn the minimum wage, then their bargaining power is close to zero and the firm is just paying a wage mandated by law. But in groups where workers have a strong bargaining power, there should be evidence of variation in wages, reflecting their differences in labor productivity.

In the labor search model by Pissarides (2000), the reservation wage *c* is the outside option that the worker would obtain if the job match is destroyed. We need an approximate measure of this reservation wage and we posit that reference groups also carry some useful information for this matter. Recall that we assumed that workers inside the same reference group face similar labor markets. Therefore, the lower tail of the income distribution inside each reference group is a good measure of a worker's income under adverse economic conditions, such as being fired or not being able to find a job quickly. We use the 25th percentile of labor income as a measure of reservation wages at the reference group level.

We define 18 reference groups for each country, considering three criteria to construct them: age, education level and living zone.[8] Every individual working under supervision is assigned to one of these groups.[9] This allows us to calculate a bargaining power index and a reservation wage for each reference group. Finally, we combine both measures with individual labor income data to obtain an imputed productivity measure for each worker.

[8] Three age groups: between 15 and 35 year of age, between 35 and 50 years, and between 50 and 65 years. Also three education groups: incomplete primary schooling, complete primary or some secondary schooling, some college education. And two living zone groups: rural or urban area.

[9] According to a basic Mincer estimation for the correlates of labor income, gender should also be taken into account as one of the variables for creating reference groups. We did not include gender to avoid losing a significant amount of data, but we overcome this problem by making an adjustment to labor income. The Mincer equation points out that prime-age (between 35 to 50 years old) male workers earn 9% more than prime-age female workers. All reference group averages and standard deviations take into account this basic gender gap.

Formally, if worker i belongs to reference group j, of size N_j and average labor income $\overline{w}_j$, then imputed individual labor productivity y_{ij} is defined by equation 9, after solving for y in equation 2:

$$y_{ij} = \frac{[w_{ij} - (1 - \beta_j)c_j]}{\beta_j} \tag{9}$$

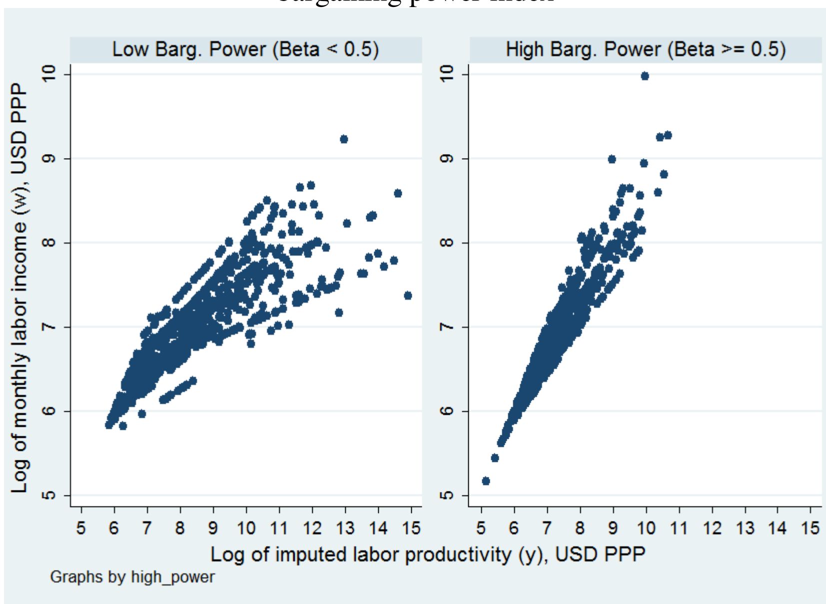
where c_j is the 25$^{\text{th}}$ percentile of labor income within reference group j and β_j is the bargaining power index for reference group j based on labor income standard deviation, σ_j, as defined by equations 10 and 11. Notice that σ^{Min} and σ^{Max} refer to the smallest and the largest standard deviation across all 18 reference groups within each country:

$$\beta_j = \frac{\sigma_j - \sigma^{Min}}{\sigma^{Max} - \sigma^{Min}} \tag{10}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{N_j} (w_{ij} - \overline{w}_j)^2}{N_j - 1}} \tag{11}$$

We only use reference groups with sample size of at least 20 individuals. Under this condition, we were able to impute individual labor productivity for 1,967 workers from 18 Latin-American countries. Summary statistics for this group of workers are available in the third column of Table 1. In conclusion, Figure 1 presents monthly labor income and imputed labor productivity for worker's with high ($\beta_j > 0.5$) and low ($\beta_j < 0.5$) bargaining power. As expected, labor income is closer to labor productivity for those workers with a high level of bargaining power.

Figure 1. Monthly labor income and imputed labor productivity, by range of the bargaining power index



Note: Monthly labor income comes from the Gallup World Poll of 2007, as processed by Gasparini, et al. (2008). Imputed labor productivity is calculated using the same data, following the procedure described in Section 4. Total sample size: 1,967 individuals from 18 countries in Latin America. The countries are Argentina, Bolivia, Brazil, Chile, Costa Rica, Colombia, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela.

5 Estimation technique and results

The main testable hypothesis from the theoretical framework is that good job conditions lead to higher wages and productivity. We use a battery of propensity score matching techniques to test this hypothesis.

5.1 Estimation technique: propensity score matching (PSM)

As mentioned, the Gallup database has information on four job conditions that presumably enhance identification with the firm (opportunities to do your best, encouragement, opinions count, and fear to lose job). Each one of these variables could be considered as a treatment, where the two outcomes are labor income and imputed labor productivity. In order to estimate the outcome effect of such treatments, a major concern is the selection bias created by the rule of selection into treatment. For example, if only high ability workers are encouraged by the firm, and high ability workers tend to be more productive, then an OLS regression would overestimate the effect of encouragement on labor productivity. As another example, if a firm only takes into account the opinion of college graduates, and college education has a positive impact on labor productivity, then the effect of taking the worker's opinion into account would also be overestimated if we run an OLS regression between labor productivity and a treatment dummy.

The literature on impact evaluation techniques offers several methods to overcome the selection bias problem (Blundell and Costa-Dias, 2009). Given our data, we consider that the best empirical strategy is to estimate the Average Treatment effect on the Treated (ATT) using propensity score matching. We take Becker and Ichino (2002) as an empirical guide for implementing PSM with our data.

Workers in the sample are often exposed to at least one of the good job conditions indicators analyzed in this paper. As it is shown in Table 2, 86% of workers feel that they can do their best effort at work every day; 82% consider that their opinions are taken into account by their supervisor, 75% think that there is someone in their workplace that encourages their development and 25% think that they could lose their jobs in the following six months. Considering the four practices together, 48% of the sample has fully favorable opinions of their work environment: they do their best, their opinions count, they are encouraged and do *not* fear losing their job.

As a first exploration of the data, Table 2 also presents labor income summary statistics both for treated and non-treated workers, and the results of a difference-in-means t-test. In all cases, workers exposed to better job conditions have, on average, a higher labor income. All these differences are statistically significant. The gap is around 17% for workers that do their best effort every day, 22% for encouraged workers and 36% for workers whose opinions are considered. Furthermore, workers that fear to lose their jobs earn 23% less than their counterparts. There is also an income gap of approximately 21% for workers in excellent working environments, as measured jointly by all four indicators (do your best, encouragement, opinions count, and job stability). As previously discussed, these raw differences may be biased due to the selection mechanism into treatment.

Table 3 presents the same set of summary statistics for imputed labor productivity. In this case, the average gap between treated and non-treated workers is wider (as a result of our imputation method), and all differences are again statistically significant. On average, an encouraged worker produces 55% more labor output; workers that do their best effort every day achieve 70% more imputed labor productivity and the gap for workers whose opinions are taken into account is 87%. The labor productivity gap for workers that see themselves in an excellent working environment is approximately 51% (last column). Again, these gaps are biased and can't be interpreted as causal results. We will only use them as reference points for the PSM estimations.

5.2 Logit models for the propensity scores

The first step to perform PSM is to estimate logit models in which the dependent variables are treatment dummies. The models are then used to estimate the propensity score of being treated, given a vector of individual characteristics. Table 4 presents the logit models for the job conditions analyzed, before saturation. All the models control for demographic and economic characteristics, household characteristics, computer skills, life satisfaction five years ago and life attitudes. All these are individual level variables from the Gallup World Poll.

The most relevant result from these models is the positive gradient for education. Note that workers who completed a college degree are more likely to have better job conditions: they feel they can do their best every day as well as encouraged, their opinions are taken into account and they have more job stability. Furthermore, recall that we are measuring the exposure to job conditions through the direct opinion of workers, and not using a direct measure from inside the workplace. Therefore, we must control somehow for personal traits that may influence attitudes and opinions. That is the role of the last control in all the logit models: life satisfaction, on a 0 to 10 scale, five years ago. This is a common control in the subjective well-being literature for personality traits and optimism, usually called *lag life satisfaction* (Diener et al., 1999).

These basic logit models have an average adjusted R^2 between 4% and 6%. In order to increase their fit, we followed a saturation process by including interaction terms between each variable and country dummies (coefficients not reported). This saturation process increases the fitness of the models, so the variation in treatment across countries is explained in a better way. After including all the interactions terms, the average adjusted R^2 goes up from 4% to 23%. Another criteria used in determining the final correlates for the logit models is the Balancing Hypothesis, according to which there should be no statistical difference between treated and non-treated individuals, with similar propensity scores, on the mean of all the correlates used in the model. If the Balancing Hypothesis is assured, then treated and control observations used in the matching process are very close to one another, at least in the set of observable characteristics used to predict the propensity score. We follow the steps described by Becker and Ichino (2002), pp. 360, to test the Balancing Hypothesis of each model.

5.3 PSM results

Each treated and non-treated worker has a propensity score predicted from the saturated logistic models. The selection bias problem is taken into account if we compare the imputed labor productivity of two workers, one treated and the other not, but with very similar propensity scores. By matching treated and non-treated workers in this way, we can state that any gap in income or productivity between both workers is due to job conditions, and not to the difference in other correlates such as education or age.

Since there are many ways to match treated and non-treated observations using PSM, we follow the suggestion by Becker and Ichino (2002) of performing more than one matching technique and comparing the consistency of results across all techniques. Recall that we have four possible treatments (do your best, encouragement, opinions count and fear of losing job) and two possible outcomes (labor income and imputed labor productivity). For analyzing the effect of each treatment on any outcome, we built four PSM estimations. The first one is the *nearest - neighbor matching*, where each treated worker is matched with the non-treated worker with the closest propensity score. Then, we perform *radius matching*, where each treated observation is compared with the average outcome of all the non-treated observations with a propensity score within a predetermined circumference. The larger the radius, the more observations are included in each average. In this case, the radius is 0.001. The third PSM estimation is a *kernell matching*, where the counterfactual for each treated worker is a weighted average of the outcome for all non-treated workers in the sample. In this case, the weights are inversely proportional to the propensity score distance. The fourth and final PSM is a *local lineal regression matching* (Heckman et al., 1998), which is similar to *kernell matching*, but is stricter in choosing the non-treated individuals used to calculate each counterfactual. Tables 5 through 8 present all the PSM results. For more information on the details of these techniques, see Leuven and Sianesi (2003) and Becker and Ichino (2002).

Table 5 presents the PSM results for the effect of each treatment on labor income. Table 6 has the same structure, but refers to imputed labor productivity. For each PSM technique, we report the number of workers treated and non-treated included in the sample, the estimated ATT effect, its standard error and corresponding t-statistic. We first analyze the effects of the four job conditions taken separately. According to the *local* *linear regression matching*, of the four job conditions, two have a significant effect: a worker that is able to do his best effort every day earns 18% more than a similar worker that is not offered such opportunity (panel 5.a); and the gap between workers who fear losing their job in the next six months and those who don't is close to 17% (panel 5.d). In every case, the effect measured using PSM is less than the biased difference-in-means t-test between treated and non-treated individuals discussed in Table 2. For example, the biased difference-in-means suggests that the labor income gap between workers whose opinions are taken into account and those who are ignored is somewhere around 36%, whereas the *local linear regression matching* indicates that such a gap is actually statistically non-significant (panel 5.c). This confirms that the PSM techniques used are correcting the bias that would result from the direct comparison between treated and non-treated workers.

The results for labor productivity in Table 6 are even clearer: we can't find any robust ATT effect for any job condition, except for fear of losing the job. Recall that the biased difference-in-means tests in Table 3 showed very large differences between treated and non-treated workers, but the PSM results indicate that the entire gap is due to selection. For example, we know that a strong correlate of good job conditions is having a college degree: the opinions of college educated workers are more likely to be taken into account, but education is also a key determinant of labor productivity. However, we do find very strong and significant results for fear of losing your job, which has a negative and significant ATT effect on imputed labor productivity under all four PSM techniques (panel 6.d). On average, facing this adverse job condition is associated with an imputed labor productivity gap of approximately 37%.

Up until this point, we have explored each job condition as a different treatment, although identity effects could result from the combination of all of them. According to Buckingham and Coffman (1999), some job conditions may behave as complementary practices, and thus their positive effect on firm performance and labor productivity will not arise if they are not simultaneously present in the workplace. We explore this possibility by defining two combined treatments. The first one is when the first three good job conditions (do your best, encouragement and opinions count) occur at the same time (panels 7.a and 8.a). The other one is when, on top of these three conditions, the worker has no fear of losing her job (panels 7.b and 8.b). Table 7 presents the PSM results for labor income and Table 8 for imputed labor productivity.

We find very strong effects when labor income is the outcome variable. Notice that the combined three good job conditions have positive and significant effects, not only using *local linear regression matching*, but also under the other three PSM techniques (panel 7.a). The result holds when job stability is added but, interestingly, the coefficients remain almost unchanged, suggesting that there is a cap on the cumulative effects of good job conditions (panel 7.b). When a worker has a working environment where she is able to do her best effort every day; is encouraged in the workplace and her supervisor takes her opinions into account, her labor income is approximately 16% higher than when none of these good job conditions are present.

The results for imputed labor productivity in Table 8 give partial support to the complementary practices hypothesis. Focusing on the *local linear regression matching* estimations we do find a positive and significant effect on imputed labor productivity only when all four good job conditions are present in the workplace (panel 8.b), but no effect when job stability is excluded from the analysis (panel 8.a). However, this result only holds under *kernell* and *local linear regression matching* estimators, according to which imputed labor productivity is approximately 47% higher when the full set good job conditions is present. So, when we use our imputed measure of labor productivity, the question of whether the full set of good job conditions are conducive to higher productivity is answered positively, but in a less robust way than when we use labor income directly as the outcome.

6 Discussion and conclusions

This paper has posited that good job conditions raise individual-level productivity and wages, using a theoretical framework based on Akerlof and Kranton (2005). Since firms should be expected to create different job conditions by type of worker depending on their bargaining power, abilities and human capital, these sources of variation must be taken into account in any estimation process.

Our empirical results give support to the hypothesis that good job conditions are conducive to higher income and productivity levels. Furthermore, the econometric results suggest that none of the four job conditions assessed is more important than the others: it is the combination of them which produces the strongest and most robust results. This may be due to the fact that individual workers have different psychological needs and therefore respond to different stimuli and incentives. We also find larger treatment effects in the estimations based on imputed productivity, which is consistent with the theoretical assumption that workers receive as pay only a fraction of their productivity, depending on their bargaining power. This could be further tested using narrower samples of workers' categories, but our sample size is already too small to pursue this line of research.

Although the measured effects in the productivity estimations are larger than those in the income estimations, the latter show higher significance levels and are more robust. This may be due to the larger measurement error in the imputed labor productivity variable, which is not observed directly. But there might be other alternative explanations. One, related to job search theory, is that job conditions that make workers more self-confident could change their bargaining power and help them get higher wages that are not supported on higher productivity.

The role of job conditions in workers' productivity is a fertile area for future research, especially in developing countries. To our knowledge, this is the first study that addresses the issue using individual-level data representative at the national level for a set of countries. Although we have applied a methodology in an attempt to tackle the selection issue present in the data, we do not claim to have given a definite answer to the question of whether, and to what extent, job conditions that arguably enhance workers' attachment to their jobs are good for the firms. Ideally, in order to further test these hypotheses, controlled experiments should be conducted inside firms, hopefully in those industries where labor productivity can be measured in a better way. A random group of workers would be submitted to a style of management under different job conditions and their performance and productivity results compared with a control group. Since experiments of this type occur almost daily within firms when new managers are appointed, this type of research is eminently doable and may be immensely profitable not just for academia but for the workers and firms that support it.

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Appendix – Second order condition for the worker's problem and properties of the optimal effort function

The second order condition for the worker's problem, using equation 4 as a starting point, is the following:

$$\beta F_{e,e}(\theta, e^*) - t < 0 \quad \Leftrightarrow \quad 0 < t - \beta F_{e,e}(\theta, e^*) \tag{A1}$$

which will hold given our assumptions about the worker's bargaining power and the diminishing marginal productivity of effort.

Comparative statics of the optimal effort function (e^*) are obtained by taking the corresponding derivatives from the worker's first order condition (equation 4).

- Worker's bargaining power, β: $F_e(\theta, e^*) + \beta F_{e,e}(\theta, e^*)\frac{\partial e^*}{\partial \beta} - t\frac{\partial e^*}{\partial \beta} = 0$

$$\Rightarrow \frac{\partial e^*}{\partial \beta} = \frac{F_e(\theta, e^*)}{\left[t - \beta F_{e,e}(\theta, e^*)\right]} > 0$$

- Worker's human capital, θ: $\beta\left[F_{e,\theta}(\theta, e^*) + F_{e,e}(\theta, e^*)\frac{\partial e^*}{\partial \theta}\right] - t\frac{\partial e^*}{\partial \theta} = 0$

$$\Rightarrow \frac{\partial e^*}{\partial \theta} = \frac{\beta F_{e,\theta}(\theta, e^*)}{\left[t - \beta F_{e,e}(\theta, e^*)\right]} > 0$$

- Quality of job conditions, t: $\beta F_{e,e}(\theta, e^*)\frac{\partial e^*}{\partial t} + e^{Ref} - e^* - t\frac{\partial e^*}{\partial t} = 0$

$$\Rightarrow \frac{\partial e^*}{\partial t} = \frac{\left[e^{Ref} - e^*\right]}{\left[t - \beta F_{e,e}(\theta, e^*)\right]}$$

Therefore, $\frac{\partial e^*}{\partial t} > 0$ as long as $e^{Ref} > e^*$.

Table 1 - Summary statistics from the Gallup World Poll of 2007

	All LAC	Sub-Sample	Restricted
Male = 1	0.45	0.61	0.62
Age (years)	39.1	35.6	32.1
Marital status: married	0.51	0.56	0.51
Urban = 1	0.60	0.69	0.81
Complete primary = 1	0.40	0.30	0.37
Complete secondary = 1	0.34	0.40	0.54
Complete college = 1	0.11	0.22	0.09
Currently employed = 1	0.42	1	1
Log of monthly labor income, US$ PPP of 2007	6.37	6.68	6.69
Number of Obsevations	22,187	3,360	1,967

Notes: "All LAC" column corresponds to all observations from 18 countries in Latin America and the Caribbean (N = 22,187). "Sub-sample" column corresponds to employed individuals who work for a firm under a supervisor and have non-missing labor income data (N = 3,360). "Restricted" column is derived from observations for which it was possible to calculate imputed labor productivity (N = 1,967). All data comes from from the Gallup World Poll of 2007.

Table 2 - Differences in means between treated and non-treated workers, labor income

Labor income, monthly US$ PPP, logs		**In your work, do you have an opportunity to do what you do best every day, or not? (Do your best)**	**Is there someone at work who encourages your development, or not? (Encouragement)**	**At work, do your opinions seem to count, or not? (Opinions count)**	**Do you think you could lose your job in the next six months? (No job stability)**	**Do your best, encouragement, opinions count and job stability.**
Treated workers (Answered "Yes")	Average labor income	6.72	6.74	6.75	6.53	6.82
	Standard deviation	0.86	0.84	0.85	0.85	0.85
	Number of workers	2,967	2,570	2,821	719	1,495
Non-treated workers (Answered "No")	Average labor income	6.56	6.54	6.44	6.78	6.63
	Standard deviation	0.85	0.88	0.87	0.85	0.86
	Number of workers	465	845	640	2,215	1,394
	Difference-in-means	**0.16**	**0.20**	**0.31**	**-0.26**	**0.19**
	t statistic	-3.71	-5.86	-8.27	7.05	-6.01
	p value	0.00	0.00	0.00	0.00	0.00
	Proportion of workers exposed to treatment(s)	**86%**	**75%**	**82%**	**25%**	**52%**

Table 3 - Differences in means between treated and non-treated workers, imputed labor productivity

Imputed labor productivity, monthly US$ PPP, logs		In your work, do you have an opportunity to do what you do best every day, or not? (Do your best)	Is there someone at work who encourages your development, or not? (Encouragement)	At work, do your opinions seem to count, or not? (Opinions count)	Do you think you could lose your job in the next six months? (No job stability)	Do your best, encouragement, opinions count and job stability.
Treated workers (Answered "Yes")	Average labor productivity	7.48	7.52	7.52	7.05	7.61
	Standard deviation	2.10	2.04	2.06	2.24	2.04
	Number of workers	1,650	1,436	1,565	415	814
Non-treated workers (Answered "No")	Average labor productivity	6.96	7.08	6.90	7.51	7.20
	Standard deviation	2.02	2.22	2.14	2.04	2.16
	Number of workers	277	479	378	1,221	799
	Difference-in-means	**0.53**	**0.44**	**0.63**	**-0.47**	**0.41**
	t statistic	-3.90	-3.96	-5.28	3.92	-3.93
	p value	0.00	0.00	0.00	0.00	0.00
	Proportion of workers exposed to treatment(s)	**86%**	**75%**	**81%**	**25%**	**50%**

Table 4 - Logit models for propensity scores

	(1) Dependent variable: Do your best	(2) Dependent variable: Encouragement	(3) Dependent variable: Opinions count	(4) Dependent variable: No job stability	(5) Dependent variable: All together
Male	0.109	-0.104	-0.0383	0.141	-0.140
	(0.122)	(0.0997)	(0.113)	(0.109)	(0.0930)
Age (years)	-0.0177	-0.0231	0.0207	-0.0123	0.0207
	(0.0313)	(0.0230)	(0.0252)	(0.0257)	(0.0219)
Marital status: married	-0.0452	0.241**	0.0951	-0.0512	0.175
	(0.147)	(0.119)	(0.134)	(0.126)	(0.109)
Marital status: divorced	-0.347	-0.119	0.197	0.0776	-0.107
	(0.233)	(0.190)	(0.231)	(0.220)	(0.188)
Marital status: widowed	-0.260	-0.119	-0.161	0.0777	0.0416
	(0.445)	(0.336)	(0.377)	(0.430)	(0.360)
Has one child	0.145	-0.0840	-0.108	0.0477	-0.0172
	(0.159)	(0.125)	(0.144)	(0.135)	(0.116)
Has two or more children	0.102	0.0510	-0.0594	-0.0294	0.0674
	(0.148)	(0.121)	(0.137)	(0.129)	(0.111)
Lives in urban area	0.0143	0.120	0.223*	-0.221**	0.158
	(0.132)	(0.104)	(0.117)	(0.110)	(0.0965)
Complete primary education	0.189	0.0826	0.0892	-0.218	0.184
	(0.248)	(0.198)	(0.210)	(0.208)	(0.195)
Complete secondary education	0.468*	0.202	0.330	-0.502**	0.446**
	(0.250)	(0.199)	(0.214)	(0.210)	(0.195)
Complete college education	0.618**	0.546**	0.955***	-0.929***	0.690***
	(0.281)	(0.225)	(0.256)	(0.241)	(0.215)
Has basic computer skills	-0.101	0.201*	0.244*	0.118	0.149
	(0.135)	(0.109)	(0.127)	(0.118)	(0.100)
Donated money	-0.0390	0.108	0.0613	-0.0849	0.170*
	(0.138)	(0.111)	(0.129)	(0.118)	(0.100)
Volunteered time	0.179	-0.131	0.0676	0.130	-0.206*
	(0.156)	(0.120)	(0.144)	(0.128)	(0.110)
Helped a stranger	0.0953	0.174*	0.196*	-0.130	0.0364
	(0.125)	(0.101)	(0.114)	(0.108)	(0.0935)
Voiced a public official	0.207	0.303***	0.417***	-0.222*	0.252**
	(0.141)	(0.112)	(0.133)	(0.119)	(0.0996)
Life satisfaction, 5 years ago	0.0258	-0.00308	0.0173	-0.0405*	0.0135
	(0.0239)	(0.0194)	(0.0219)	(0.0208)	(0.0181)
Constant	0.591	0.343	-0.00125	0.237	-1.701***
	(0.641)	(0.500)	(0.548)	(0.540)	(0.477)
Observations	2767	2748	2784	2369	2335
Country dummies	Yes	Yes	Yes	Yes	Yes
Pseudo R Squared	0.0440	0.0475	0.0626	0.0393	0.0376
Log-likelihood	-1032	-1439	-1182	-1237	-1550

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Age squared included but not reported. Do your best: "In your work, do you have an opportunity to do your best every day?" / Encouragement: "Is there someone at work who encourages your development?" / Opinions count: "At work, do your opinions seem to count?" / Lacks job stability: "Do you think you could lose your job in the next six months?" / All together: Do your best = yes, Encouragement = yes, Opinions count = yes, Has job stability = yes. "Donated money", "Volunteered time", "Helped a stranger" and "Voiced a public official" correspond to the answers to the following questions: "Have you donated money to a charity in the past month?" / "Have you volunteered your time to an organization in the last month?" / "Have you helped a stranger or someone you didn't know who needed help in the last month?" / "Have you voiced your opinion to a public official in the last month?". For the saturated logistic models (not reported), all variables where interacted with country dummy variables. The excluded marital status category is "single". The excluded education category is "incomplete primary education". All regressions include country fixed effects. The countries are Argentina, Brazil, Belize, Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru and Uruguay. The excluded country category is Argentina. All data from the Gallup World Poll of 2007.

Table 5 - Propensity Score Matching results for labor income (pure treatments)

5.a - In your work, do you have an opportunity to do what you do best every day, or not? **(Do your best)**

Outcome: labor income, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	186	183	235	186
Treated obs.	1,348	647	1,348	1,348
ATT effect	**0.13**	**0.09**	**0.10**	**0.16**
std. error	0.19	0.09	0.08	0.07
t statistic	0.68	0.98	1.30	2.43

5.b - Is there someone at work who encourages your development, or not? **(Encouragement)**

Outcome: labor income, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	286	318	400	286
Treated obs.	1,214	818	1,214	1,214
ATT effect	**0.15**	**0.17**	**0.12**	**0.11**
std. error	0.08	0.07	0.06	0.07
t statistic	1.78	2.45	2.03	1.63

5.c - At work, do your opinions seem to count, or not? **(Opinions count)**				
Outcome: <u>labor income</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	207	217	298	207
Treated obs.	1,284	648	1,284	1,284
ATT effect	**0.14**	**0.11**	**0.19**	**0.16**
std. error	0.16	0.08	0.07	0.12
t statistic	0.89	1.26	2.54	1.31

5.d - Do you think you could lose your job in the next six months? **(No job stability)**				
Outcome: <u>labor income</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	228	534	1,021	228
Treated obs.	349	257	349	349
ATT effect	**-0.24**	**-0.20**	**-0.19**	**-0.19**
std. error	0.07	0.07	0.06	0.07
t statistic	-3.16	-2.83	-3.28	-2.76

ATT: Average Treatment effect on the Treated.

Table 6 - Propensity Score Matching results for imputed labor productivity (pure treatments)

6.a - In your work, do you have an opportunity to do what you do best every day, or not? **(Do your best)**

Outcome: imputed labor productivity, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	186	183	235	186
Treated obs.	1,348	647	1,348	1,348
ATT effect	**0.13**	**0.21**	**0.19**	**0.35**
std. error	0.49	0.23	0.19	0.20
t statistic	0.27	0.94	1.00	1.77

6.b - Is there someone at work who encourages your development, or not? **(Encouragement)**

Outcome: imputed labor productivity, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	286	318	400	286
Treated obs.	1,214	818	1,214	1,214
ATT effect	**0.25**	**0.30**	**0.20**	**0.15**
std. error	0.23	0.18	0.16	0.18
t statistic	1.09	1.65	1.27	0.81

6.c - At work, do your opinions seem to count, or not? **(Opinions count)**				
Outcome: <u>imputed labor productivity</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	207	217	298	207
Treated obs.	1,284	648	1,284	1,284
ATT effect	**0.45**	**0.17**	**0.38**	**0.39**
std. error	0.42	0.23	0.20	0.36
t statistic	1.08	0.73	1.91	1.10

6.d - Do you think you could lose your job in the next six months? **(No job stability)**				
Outcome: <u>imputed labor productivity</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	228	534	1,021	228
Treated obs.	349	257	349	349
ATT effect	**-0.52**	**-0.48**	**-0.41**	**-0.41**
std. error	0.19	0.18	0.16	0.15
t statistic	-2.76	-2.72	-2.67	-2.65

ATT: Average Treatment effect on the Treated.

Table 7 - Propensity Score Matching results for labor income (combined treatments)

7.a - Treatment: Do your best, encouragement and opinions taken into account

Outcome: <u>labor income</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	345	468	597	345
Treated obs.	1,017	750	1,017	1,017
ATT effect	**0.15**	**0.15**	**0.15**	**0.16**
std. error	0.07	0.06	0.05	0.05
t statistic	2.28	2.73	2.92	3.19

7.b - Treatment: Do your best, encouragement, opinions count and job stability

Outcome: <u>labor income</u>, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	302	450	653	302
Treated obs.	696	497	696	696
ATT effect	**0.15**	**0.08**	**0.15**	**0.16**
std. error	0.08	0.06	0.05	0.06
t statistic	1.97	1.36	2.71	2.82

ATT: Average Treatment effect on the Treated.

Table 8 - Propensity Score Matching results for imputed labor productivity (combined treatments)

8.a - Treatment: Do your best, encouragement and opinions taken into account				
Outcome: imputed labor productivity, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	345	468	597	345
Treated obs.	1,017	750	1,017	1,017
ATT effect	**0.21**	**0.39**	**0.27**	**0.25**
std. error	0.19	0.16	0.13	0.19
t statistic	1.09	2.49	2.04	1.35

8.b - Treatment: Do your best, encouragement, opinions count and job stability				
Outcome: imputed labor productivity, monthly US$ PPP, logs	*Nearest-Neighbor matching*	*Radius matching (r = 0.001)*	*Kernel matching, normal distribution*	*Local Linear Regression matching, bootstraped errors, 100 iter.*
Control obs.	302	450	653	302
Treated obs.	696	497	696	696
ATT effect	**0.32**	**0.17**	**0.37**	**0.40**
std. error	0.21	0.17	0.14	0.16
t statistic	1.51	1.02	2.61	2.45

ATT: Average Treatment effect on the Treated.