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Fixed or Open-ended? Labor Contract and Productivity in the Colombian Manufacturing Sector

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Abstract⁴

Using the Colombian Annual Manufacturing Survey (AMS) between 2000 and 2014, this paper investigates the effect of labor contract modalities on firm productivity within the industrial sector through a structural model. We find that temporary workers contribute to firms' labor productivity to a lower extent than permanent workers, while also having detrimental effects on TFP dynamics. We show this result is unlikely to be driven by the different skill composition of workers holding temporary contracts.

JEL Classification: C14, C52, D24, J23, J24, J41

Key words: labor contracts, temporary workers, skilled workers, firms' TFP

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1. Introduction

Over the past few years, as a result of the waning commodity boom, Latin America (LA) has been grappling with the puzzle of growth. Productivity has not played a remarkable role in this quest for stronger economic performance and has contributed instead to the gap with more advanced economies. On average, LA labor productivity is less than 30% of US.⁵

The growth of productivity in the economy as a whole depends not only on how fast productivity is rising in individual industries, but also on whether resources are moved in or out of those industries in response. Labor allocation and labor markets play an important role in it. Given the surge in temporary (fixed-term) modalities of contracting in advanced and emerging economies since the 1980s (Cazes and Laiglesia, 2015), the literature has investigated the effect of contractual terms on productivity growth.

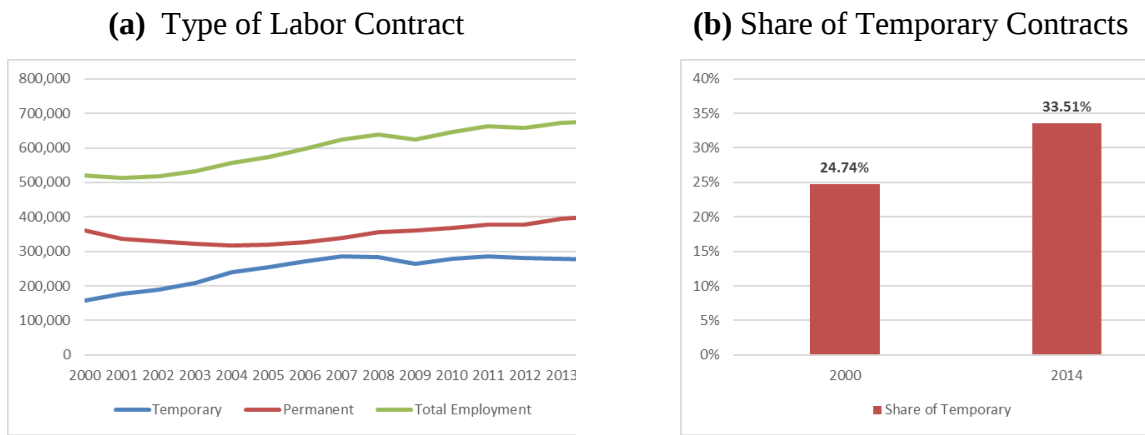
This paper explores the relationship between labor contracts and firm productivity in the Colombian industrial sector, using the information of the Annual Manufacturing Survey (AMS). In Colombia (Figure 1, panel a), total employment passed from around 519,247 in 2000 to 677,091 in 2014. Both workers with permanent (open-ended) contracts and workers with temporary (fixed term) contracts increased, but the share of temporary did so at a larger scale (Figure 1, panel b): in 2000, 24.7% of workers had temporary contracts vis- a vis 33.5% in 2014. When all the sectors in the economy are considered, Colombia exhibits one of the highest rates of temporary workers if compared to the rest of Latin America and the Caribbean,⁶ and OECD countries.⁷ This surge in temporary employment, often considered a way to curb high labor costs due to the rigidities of labor market regulations, has taken place across all subsectors within manufacturing, except basic metals (Figure 2).

⁵ Authors' calculations based on The Conference Board Total Economy Database, 2015.

⁶ Source: national household surveys, 2015.

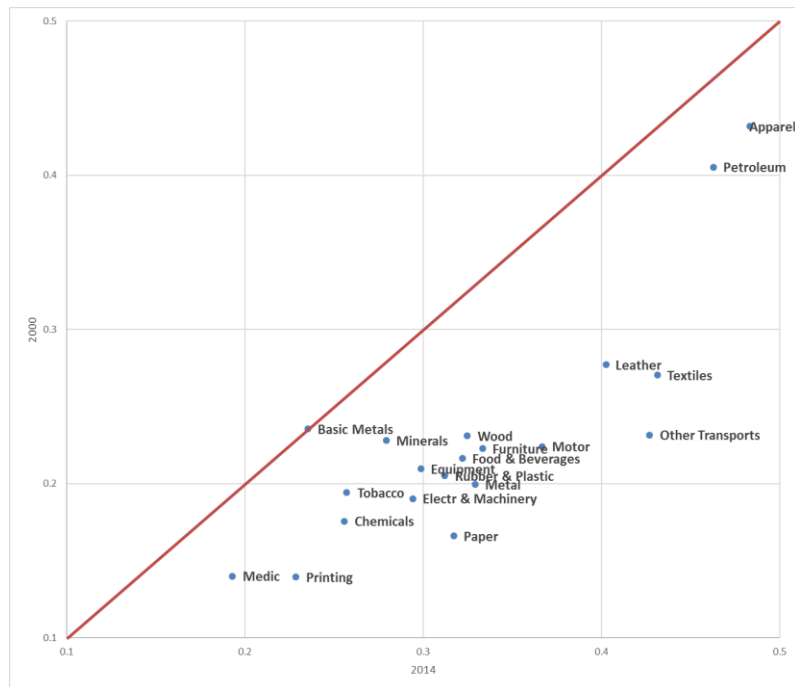
⁷ Source: OECD Data, 2015.

Figure 1. Total Manufacturing Employment



Source: Dane-AMS; authors' calculations.

Figure 2. Share of Temporary Contracts by Subsector in 2000 and 2014

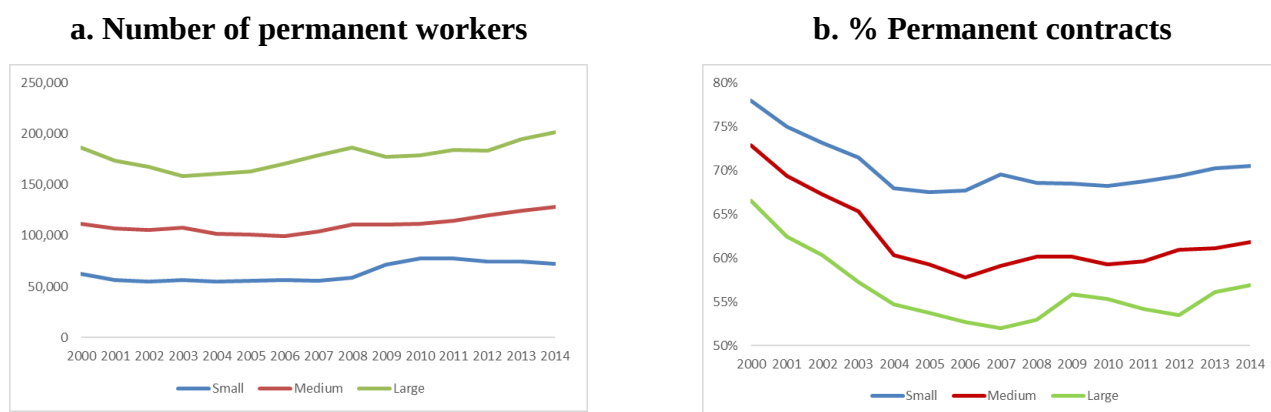


Source: Dane-AMS; authors' calculations.

Most firms in Colombia are small or medium, but the large firms generate most of the employment and most of the permanent positions. In 2014, 50% of permanent workers were hired

by large plants, 32% by medium ones, 18% by small (Figure 3, panel a).⁸ However, the larger the plant, the smaller is the share of permanent workers within the plant (Figure 3, panel b). Although large firms contribute the most to generating permanent positions, they hold lower shares of permanent workers. The percentage of plants hiring temporary workers also increases by plant size, and with exporting status.⁹

Figure 3. Permanent contracts by plant size



Source: Dane-AMS; authors' calculations.

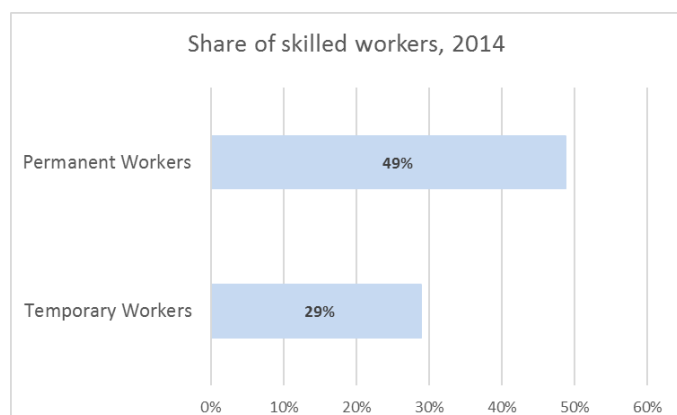
Permanent workers are more likely to be skilled and larger plants exhibit higher shares of skilled workers. Figure 4 depicts the share of skilled (vs. unskilled) workers by contract choice (panel A), by plant size (panel B), and by industry subsector (panel C). The comparison between Figures 2 and 4 shows that the subsectors with the highest share of skilled workers (chemicals, tobacco, basic metals, medical instruments) are also the ones with the highest proportion of permanent contracts. This is in line with the hypothesis that when their technologies require a more skilled labor force firms tend to hire on a longer-term basis as they value their workforce more (Eslava et al. 2014).

⁸ Firms are classified by size in small (between 10 and 49 employees), medium (between 50-200 employees), and large (more than 200 employees).

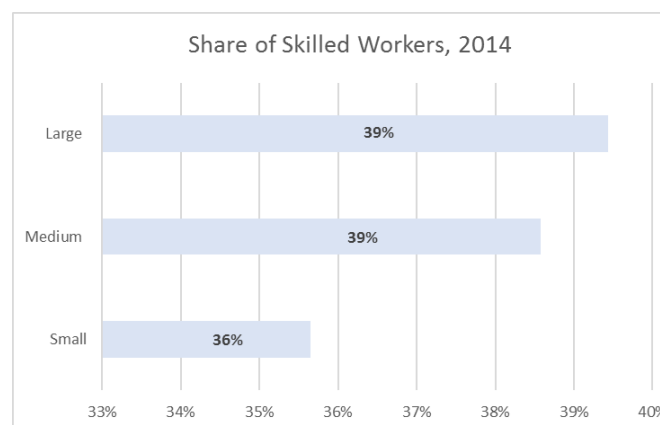
⁹ Exporting firms tend to be larger in size, more likely to be hiring temporary workers (82% of exporters hire temporary workers vs. 66% of non-exporters), and with higher shares of temporary workers (36% of workers are temporary in exporting firms vs. 23% in non-exporters).

Figure 4. Percentage of skilled and unskilled worker in 2014

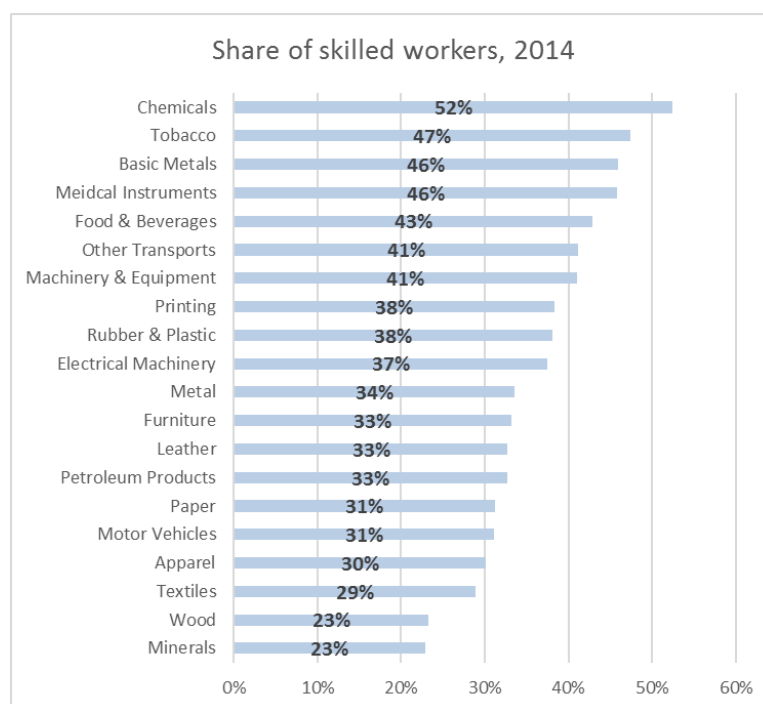
(a) by contract choice



(b) by plant size



(c) by subsector



Source: Dane-AMS; authors' calculations.

The reduction in the share of permanent workers between 2000 and 2014 may bear consequences for firm growth potential. The type of labor contract can affect workers' efforts through different channels. If a worker expects to stay in a work place for a short period, her willingness to exert efforts might diminish, which in turn can negatively affect the firm's

productivity. Moreover, the high turnover encouraged by temporary contracts may limit incentives for job trainings, further harming productivity. On the other hand, a temporary worker might exert more effort to be rewarded with a contract renewal or with a permanent contract. Temporary contracts might also have a positive effect on productivity as they allow for more flexibility, facilitating firms' allocative efficiency (hiring the right worker at the right time) and allowing for an easier adjustment of the workforce as needed. In a nutshell, the labor contract choice can affect productivity in either direction.

Temporary workers are significantly younger than permanent ones, irrespective of firm size, even though the gap in average age is greater in medium/large firms; they are also more likely to be female, but significantly more so in larger firms only.¹⁰ Besides being younger and female, temporary workers are also characterized by fewer years of education. Most of the workers in manufacturing are blue-collar and most of blue-collar workers are hired through temporary contracts, across all firm size. A striking difference is the proportion of formal jobs among temporary workers in small firms, as only half of them are affiliated to or pay social security contributions, while in larger firms they are approximately 90%. Moreover, temporary workers are remunerated significantly less than permanent ones, and the gap is larger in medium and large firms.¹¹

¹⁰ Source: Colombian Great Integrated Household Survey (Gran Encuesta Integrada de Hogares). We limit the sample to wage workers in the manufacturing sector between 15 and 64 years old in 2014. Given the way the survey was implemented, we are unable to distinguish between medium and large firms, so we will group the two categories together.

¹¹ The difference in pay could be a factor demotivating effort, hence the lower productivity level, but we cannot rule out the reverse causality either, i.e. that precisely because these workers are less productive, they are compensated with lower wages.

Table 1. Characteristics of Workers by Contract Type and Firm Size

		Small			S.E.	Medium/Large			S.E.
		Temporary	Permanent	Difference in Means		Temporary	Permanent	Difference in Means	
Age		33.22	36.01	-2.797***	0.861	32.42	36.66	-4.241***	0.614
Female		40.50%	37.20%	3.2	4.280	40.40%	35.00%	5.4*	3.160
Education	Years of Education	10.13	10.97	-0.84**	0.346	11.23	11.93	-0.69***	0.198
	No Education	0.45%	0.30%	0.2	0.350	0.02%	0.60%	-0.6**	0.271
	Primary Incomplete	4.11%	4.27%	-0.2	1.720	1.28%	2.31%	-1.0	0.780
	Primary Complete	9.13%	8.07%	1.06	2.490	5.76%	4.59%	1.17	1.530
	Secondary Incomplete	24.10%	17.90%	6.2*	3.530	11.00%	9.04%	2	1.890
	Secondary Complete	35.40%	31.40%	3.9	3.910	44.10%	35.70%	8.3***	3.180
	Tertiary Incomplete	6.73%	7.33%	-0.6	2.470	11.10%	7.65%	3.4*	1.890
	Tertiary Complete	18.30%	29.60%	-1.13***	3.660	24.90%	38.70%	-1.39***	2.880
Occupation:	Vocational/Technician	6.02%	12.00%	-6.0**	2.370	12.40%	14.60%	-2.2	2.090
	Director or Senior Officer	4.45%	5.11%	-0.7	2.170	1.40%	6.13%	-4.7***	1.180
	Administrative or intermediate level	10.20%	13.50%	-3.3	2.910	15.20%	15.00%	0.2	2.430
	Retailers and Sellers	7.44%	6.17%	1.27	1.910	9.20%	12.50%	-3.3*	1.810
	In Services	4.48%	4.67%	-0.2	1.740	8.53%	6.70%	1.82	1.930
	Farm Workers	0.08%	0.17%	-0.1	0.190	1.12%	2.31%	-1.2	0.879
	Blue-Collar (outside agriculture)	66.80%	58.30%	8.5**	4.170	52.00%	41.70%	10.3***	3.210
	Other	0.52%	0.00%	0.5*	0.303	0.13%	1.04%	-0.9	0.673
Formal		54.40%	93.80%	-3.94***	3.310	89.60%	98.10%	-8.4***	1.840
Part time		1.52%	0.05%	1.5**	0.701	0.28%	0.29%	-0.00	0.282
Wage		865,656	1,395,000	-529,523***	176,055	1,017,000	1,735,000	-718,009***	114,893

Source: Colombia Great Integrated Household Survey 2014.

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01.

In this paper, we first examine the plants' characteristics that explain the increase in labor productivity¹² observed between 2000-2014. By applying a Ñopo decomposition (2008), we find that increases in the share of temporary workers are related to decreases in productivity. Hence, we investigate how hiring through temporary contracts affects plant productivity. By applying Addessi's (2014) model, we find that temporary workers in the manufacturing sector increase plants' value added to a lower extent compared to permanent workers. This holds true in most of the subsectors, in exporting and non-exporting plants, in medium and large plants, in plants that own a website or have a greater internet connection bandwidth. In small plants and in a few

¹² Labor productivity is here defined as value added over employment.

subsectors, we find that temporary and permanent equally increase labor productivity. We find that our results are not driven by the difference in the skill composition of temporary and permanent workers, but by the contract modality itself.

The paper develops in seven sections beyond this introduction. The second section offers a brief literature review. The third presents the institutional background. The forth provides the data description. The fifth explains the empirical models, and the sixth describes the results. The seventh section concludes. The Appendix contains detailed information on the data cleaning process and definitions of variables.

2. Literature review

Much of the literature on the relationship among labor markets and productivity relates to the employment protection legislation (EPL)¹³ and to OECD countries,¹⁴ without being conclusive on the effect of contract modalities on productivity, nor providing much evidence beyond the OECD.

Generally, research acknowledges that different labor contracts might imply different levels of productivity and finds that the use of, or the regulations related to the use of, temporary contracts can have negative or non-significant effects on firms' productivity (Bassanini et al., 2009; Damiani and Pompei, 2010;¹⁵ Jona-Lasinio and Vallanti, 2011; Aguirregabiria and Alonso-

¹³ The indicators of employment protection legislation (EPL) outline conditions under which workers can be hired on both regular and temporary contracts.

¹⁴ The Employment Protection Legislation (EPL) methodology developed by the Organization for Economic Cooperation and Development (OECD) measures the degree of stringency of employment protection legislation of OECD and G201 countries, to determine, amongst others, its labor market impacts. The Inter-American Development Bank (IDB), in collaboration with the OECD, has applied this methodology to Latin American and Caribbean (LAC) countries.

¹⁵ Damiani and Pompei (2010) analyze the effect of labor protection on Total Factor Productivity (TFP) growth in 18 European countries between 1995 and 2005. They also control for the effect of growth in temporary employment on TFP, ending a negative and significant relation.

Borrego, 2014; Nielen and Schiersch, 2016;¹⁶ Cappellari et al., 2010;¹⁷ Addessi, 2014¹⁸). Dolado and Stucchi (2014) find that the effect of temporary contracts on TFP growth is negative when the conversion rate from temporary to permanent contracts is low, because the effort provided by temporary workers diminishes.

Using a natural experiment Autor and Houseman (2010) show that temporary-help positions reduce subsequent earnings and employment outcomes in the United States. With an eye to European labor markets, Blanchard and Landier (2002) and Cahuc and Postel-Vinay (2002) model temporary contracts as churning policies that affect negatively wage setting and may generate higher unemployment and lower productivity. According to Boeri and Garibaldi (2007), if fixed-term contracts are used as a buffer-stock to boost the number of hiring in a boom, employment may go up at least temporarily, but they find the use of fixed-term contracts in Italy to be associated with lower average productivity. The model by Cahuc et al. (2016) shows that the substitution of temporary jobs for permanent jobs induced by job protection does not change much total employment but reduces aggregate productivity.

However, according to Ichino et al. (2008) temporary contracts can be good screening devices and stepping stones into permanent jobs and therefore increase productivity. Giuliano et al. (2017), while not finding any significant effect of hiring through fixed-term contracts on firm competitiveness in the Belgian manufacturing sector, observe a positive and significant effect on labor productivity in services, which they attribute to some service subsectors being more labor intensive, in need of less sophisticated technology and less able to create stocks. Finally, Eslava et al. (2014) find that in Colombia the use of temporary contracts is associated with higher firms' productivity, particularly in businesses with lower skill needs. In the latter, a more intensive use of fixed term contracts plays as a shock absorber and leads to productivity gains. However, using

¹⁶ Bassanini et al. (2009) measure productivity as TFP and find no evidence of a productivity effect of facilitating the use of fixed-term contracts in the OECD; Damiani and Pompei (2010) find that fixed-term contracts can have detrimental effects on TFP growth; Jona-Lasinio and Vallanti (2011), Aguirregabiria and Alonso-Borrego (2014), and Nielen and Schiersch (2016) measure productivity as labor productivity.

¹⁷ Cappellari et al. (2016) use 13,000 firm level observations of all Italian sectors between 2004 and 2007 to study the effects of deregulation reforms of apprenticeship and fixed-term contract. They find a small negative, but only weakly significant, effect of fixed-term employment on labor productivity, driven by the reduced job tenure and increased use of external collaborators that hampered the optimal allocation of resources

¹⁸ Addessi et al. (2014) develops a structural model that allows for the labor-contract choice to influence labor-augmenting factors and capture the effects on the evolution of the firm productivity process, and finds the use of temporary contracts to be detrimental to TFP growth.

fixed-term employment more intensively has a negative effect on TFP for the more high-skill intensity plants.

3. Institutional Background

Colombia is characterized by a dual labor market, where workers are entitled to different employment protection depending on the contract they hold. Fixed-term contracts in Colombia must be written and can last for a maximum duration of three years. However, they can be renewed indefinitely (Articles 45 and 46 of the Labor Code). Open-ended contracts instead have no time limit.

The other main difference with open-ended contracts is the dismissal payment: the employer who decides to dismiss a worker hired through an open-ended contract faces a dismissal cost. The dismissal compensation varies depending on the monthly salary (Article 64 Labor Code):

- If remuneration is lower than 10 minimum legal monthly salaries:
 - 30 days if tenure less than 1 year
 - 20 extra days for each subsequent year and in proportion per fraction of year
- If remuneration is above 10 minimum legal monthly salaries:
 - 20 days if tenure less than 1 year
 - 15 extra days for each subsequent year and in proportion per fraction of year

On the contrary, workers hired through a temporary contract can be dismissed at the end of the contract without dismissal compensation.

Firms in Colombia can also hire workers through a temporary work agency for services required on occasional, accidental or transitory basis, to replace workers which are on vacation, maternity or sickness leaves, to attend an increase in production, transport, sales of goods, stationary periods of harvest and in the provision of services. These contracts can last no longer than 6 months and are renewable for no longer than other 6 months.

Finally, workers can be hired through associative employment cooperatives, generating contracts for which there are no mandatory non-wage labor costs. This type of contracts is also fixed-term.

In the paper, we will not discriminate between the different forms of fixed-term contracts; we will focus on open-ended and fixed-term contracts.

4. Data Construction

We exploit panel information from the Annual Manufacturing Survey (AMS) conducted by the national statistical agency, DANE.¹⁹ The period spans from 2000 to 2014. The AMS is a census that covers information for all manufacturing establishments with 10 or more workers, or in the absence of this value with sales greater than a specific threshold, on labor, capital, consumption of intermediate goods, production, exports and department. The unit of observation is the plant. Particularly relevant for this study, it distinguishes between temporary and permanent contracts, as well as skilled and unskilled workers.

Initially there are 11,901 plants (11,307 firms)²⁰ in the period 2000-14.

We follow four rules to create the sample: 1) drop observations in the top/bottom 1% of value added; 2) exclude observations that show more than 400% growth from one year to the other in the total labor variable, as this level of growth in employment does not seem plausible; 3) exclude plants that consistently have fewer than 15 employees; and 4) drop firms from industries with too few observations (less than 70, i.e. tobacco and office & equipment).

Applying these rules, we are left with 9,961 plants (corresponding to 9,457 firms), for a total of 87,215 observations.

Since the estimation methodology we adopt requires the inclusion of variables up to their second-lag, we drop observations with missing values in the two lags of the variables of interest. Hence, we lose observations in the first two years of the sample.

Finally, when applying Olley and Pakes (1996) we also lose all the observations where investment is either missing or zero; while applying Levinsohn and Petrin (2003), we lose observations where electricity consumption is either missing or zero.

For the final sample used with Olley and Pakes (1996) we are left with 6,568 plants (6,206 firms), corresponding to 35,886 observations. As expected, the final sample for the Levinsohn and Petrin (2003) methodology is larger: 7,645 plants (8,056 firms), corresponding to 57,450 observations.

¹⁹ National Administrative Department of Statistics.

²⁰ 95,271 observations with non-missing industry values and with more than 10 employees.

We also had access to a special module of the survey on information and communication technologies in the 2012-4 period. Only part of the plants answered to this module,²¹ providing us with information on owning a website and the bandwidth used.

Further details about the sample construction and the definition of variables are presented in the Appendix.

5. Empirical Strategy

A. Ñopo (2008) Decomposition

Even though the change in labor productivity in Colombia was not comparable to US levels, we observe an increase in the 2002-2014 period. We adopt the Ñopo (2008) decomposition to determine which observable characteristics explain this increase. The Ñopo decomposition matches plants with the same observable characteristics in 2002 and 2014 and creates synthetic samples of identical plants that can be compared. The methodology allows understanding to what extent the labor productivity gap is explained by common characteristics of plants in the supports, to what extent by observable characteristics of plants outside the supports and how much by unobservable characteristics.

The productivity gap between 2002 and 2014 is quite substantial and amounts to 29.26% of the 2002 plants' labor productivity. The average productivity difference between plants in 2002 and 2014 (Δ) can be broken down into four components, three of which (Δ_X , Δ_{2014} , Δ_{2002}) can be attributed to differences in observable plant characteristics and the fourth (Δ_0) to the existence of non-observable differences:

$$\Delta Productivity = \Delta_X + \Delta_{2002} + \Delta_{2014} + \Delta_0 \quad (1)$$

Δ_X is the part of the productivity gap explained by common characteristics of plants in 2002 and 2014; it accounts for the expected increase in productivity for plants in 2014 when their observable characteristics follow the distribution of characteristics of 2002 plants.

Δ_{2000} (Δ_{2014}) is the part of the productivity gap explained by the fact that there are some combinations of 2002 (2014) plant characteristics that cannot be found in 2014 (2002) plant characteristics.

²¹ 6,631 plants in 2012, 6,515 in 2013, 2,641 in 2014.

Δ_0 is the amount of productivity increase that cannot be explained by the observable characteristics available in the data and is left unexplained.

It is important to know that all components Δ_{2014} , Δ_{2000} , Δ_X and Δ_0 add up to 100% of the change in productivity between 2002 and 2014. Thus, when the methodology does not control enough for observable characteristics, unobservables collect most of the changes in productivity.

B. Addessi's model

Our empirical strategy adopts the theoretical model proposed by Addessi (2014), where different labor contracts are introduced. Empirically the model follows the Olley and Pakes (1996) (here after OP) approach while also tackling the multicollinearity problem described in Akerberg et al. (2006) (here after AFC). The production function is a Cobb-Douglas and labor services are perfect substitutes that can be characterized by different labor-augmenting factors. The dynamics are introduced in the model by assuming that the TFP follows a controlled Markov chain process that can be influenced by the labor-contract choice with a time period lag. Our contribution is to explore the effects of labor contract choice on both the labor-augmenting and the TFP-augmenting in a context different from the advanced economies that have usually dominated the literature. Alternatively, we investigate the Levinsohn and Petrin (2003) (here after LP) approach, taking in consideration the multicollinearity and endogenous problem observed in AFC. The benefits of adopting LP are twofold. First, the investment proxy is only valid for establishments that exhibit non-zero investments, which amounts to losing a great deal of data compared to using intermediate inputs as a proxy. Second, adjustment costs may lead to kink points in the investment demand function, i.e. plants will not fully respond to some productivity shocks, while adjustment of the intermediate inputs to the productivity shock may be entire, eliminating the correlation between the error term and the regressors.

OP and LP with the AFC interdependence problem correction

The Cobb-Douglas value added production function is:

$$Y_t = e^{\omega_t} K_t^{\beta_k} L_t^{\beta_l} \quad (2)$$

where Y_t is value added, e^{ω_t} is a technology factor, K_t is capital and L_t is labor.

The logarithmic form of the value-added production function is:

$$y_t = \omega_t + \beta_k k_t + \beta_l l_t + \eta_t \quad (3)$$

where y_t and k_t are the log transformations of Y_t and K_t and η_t is an untransmitted shock. ω_t is unobserved productivity that enters in the firm's decision problem, while η_t is either measurement error or a shock to productivity which is not forecastable. The endogeneity arises because decisions on input choices are influenced by the firm's beliefs on ω_t , biasing upward OLS estimates of input coefficients, β_k and β_l .

OP and LP propose alternatives to proxy productivity: OP use investment expenditure, i_t , and LP intermediate goods (electricity, fuel, or materials), represented by m_t . In this paper, we will use electricity consumption.

To allow the possibility that contracts induce a static difference in labor productivity, we follow Addessi (2014) and define labor as $(P_t + sT_t)$, where P_t are workers with permanent contracts and T_t temporary ones.

Hence, the logarithmic form of the value-added production function becomes:

$$y_t = \omega_t + \beta_k k_t + \beta_l \ln(P + sT) + \eta_t \quad (4)$$

The other effect of labor contract choice is dynamic and affects TFP growth. Let us define $X_t = P_t/(P_t + T_t)$, and assume that TFP follows a first-order Markov process:

$$\omega_t = g(\omega_{t-1}) + \gamma X_{t-1} + \mu_t \quad (5)$$

where $\mu_t \sim N(0, \sigma_\mu)$ and $g(\cdot)$ is a function relating TFP to its previous period.

The investment demand is presented by OP as a polynomial function of the unobserved productivity shock and capital. We follow Addessi to take into consideration the different labor contract types and define investment as a function of the different contract types, $i_t = f(\omega_t, x_t, p_t, k_t)$, where x_t and p_t are log transformations of X and P_t .²² The inclusion of x_t and P_t follows the intuition that investment is a forward looking variable and that the current level of x_t and P_t affects future TFP and consequently investment. Since under certain assumptions investment is strictly increasing in productivity, it is possible to invert it and define productivity as a function of observables, $\omega_t = f^{-1}(i_t, x_t, p_t, k_t)$.

LP adopt a similar approach, but use the demand of intermediate goods as a function of ω_t , hence in this case $\omega_t = f^{-1}(m_t, x_t, p_t, k_t)$.²³

²² $i_t = f(\omega_t, x_t, p_t, k_t)$ is defined on permanent contracts and labor contract composition, not on temporary contracts. This is because once we control for x_t and P_t , we also control for T_t . (Addessi, 2014).

²³ In this case $m_t = f(\omega_t, x_t, p_t, k_t)$ is justified by the idea that the intermediate inputs are the last ones to be chosen, hence the demand for m depends on x_t, p_t, t_t . Controlling for x_t and P_t is equivalent to controlling for x_t, P_t, T_t .

Addressi's methodology requires a two-step procedure, each stage corresponding to a different moment condition. However, to have consistent estimates we also need to control for selection bias; hence, we follow OP (1996) and introduce a further step to estimate survival probabilities.

First, we define $\phi_t = \omega_t + \beta_k k_t + \beta_l \ln(P + sT) = f^{-1}(i_t, x_t, p_t, k_t) + \beta_k k_t + \beta_l \ln(P + sT) = \phi_t(i_t, x_t, p_t, k_t)$ and substitute in the production function to obtain the first stages:

$$\textbf{OP-ACF:} \quad y_t = \phi_t(i_t, x_t, p_t, k_t) + \eta_t \quad (6)$$

$$\textbf{LP-ACF:} \quad y_t = \phi_t(m_t, x_t, p_t, k_t) + \eta_t \quad (7)$$

While in standard OP and LP, $\hat{\beta}_l$ would be identified in the first stage, according to ACF there are functional dependence problems that impede the estimation of input coefficients in the first step²⁴ (for details see Akerberg et al., 2016).²⁵ Hence, in the first stage we run a non-parametric regression of y_t on $\phi_t(\cdot)$ and estimate $\hat{\phi}_t(\cdot) = y_t - \hat{\eta}_t$, but not yet $\hat{\beta}_l$.

In a *second stage* we estimate the probability of survival by fitting a probit model of a survival dummy on $i_{t-1}, x_{t-1}, p_{t-1}, k_{t-1}$. We call the predicted probabilities from this model $\widehat{Pr}_t$.

Input coefficients are estimated in the *third stage*. Since $\omega_t = E[\omega_t | \Omega_{t-1}] + \varepsilon_t = E[\omega_t | \omega_{t-1}, X_{t-1}] + \varepsilon_t = g(\omega_{t-1}) + \gamma X_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim N(0, \sigma_\varepsilon)$, the second stages of OP and LP are given by:

$$\begin{aligned} \textbf{OP-AFC:} \quad \hat{\phi}_t &= \beta_k k_t + \beta_l \ln(P_t + sT_t) \\ &+ g(\hat{\phi}_{t-1} - \beta_k k_{t-1} - \beta_l \ln(P_{t-1} + sT_{t-1}), \widehat{Pr}_t) \\ &+ \gamma X_{t-1} + \varepsilon_t \end{aligned} \quad (8)$$

$$\begin{aligned} \textbf{LP-AFC:} \quad \hat{\phi}_t &= \beta_k k_t + \beta_l \ln(P_t + sT_t) \\ &+ g(\hat{\phi}_{t-1} - \beta_k k_{t-1} - \beta_l \ln(P_{t-1} + sT_{t-1}), \widehat{Pr}_t) \\ &+ \gamma X_{t-1} + \varepsilon_t \end{aligned} \quad (9)$$

where $g(\cdot)$ is a non-linear function of the fourth order. We estimate the third stage by a nonlinear least squares regression. We refer to the procedures implementing the 2-steps of the structural

²⁴ $\hat{\beta}_l$ is well identified only under some specific conditions in the data-generating process.

²⁵ AFC propose to invert conditional rather than unconditional input demand functions to control for unobserved productivity. Hence, the first stage moment condition is $E[\eta_t | \Omega_{t-1}] = E[y_t - \phi_t(\cdot) | \Omega_{t-1}] = 0$ rather than $E[\eta_t | \Omega_{t-1}] = E[y_t - \beta_l l_t - \phi_t(i_t, k_t) | \Omega_{t-1}] = 0$. As a consequence, β_l cannot be estimated.

model in Addressi (2014) as *Bench1* and *Bench2*. *Bench2* differs from *Bench1* in the fact that the labor-contract choice at $t-1$ is instrumented with its lag.

Since the predicted values have been used for $\hat{\phi}_t$, the standard errors need to be corrected by bootstrap.

To explore further the role of skills composition, we divide temporary and permanent workers into skilled and unskilled. Our third stages become:

$$\begin{aligned} \text{OP-AFC: } \hat{\phi}_t = & \beta_k k_t + \beta_l \ln(P_sk_t + s_{ts}T_sk_t + s_{pu}P_unsk_t + s_{tu}T_unsk_t) \\ & + g(\hat{\phi}_{t-1} - \beta_k k_{t-1} \\ & - \beta_l \ln(P_sk_{t-1} + s_{ts}T_sk_{t-1} + s_{pu}P_unsk_{t-1} \\ & + s_{tu}T_unsk_{t-1}), \widehat{Pr}_t) + \gamma_s X_sk_{t-1} + \gamma_u X_unsk_{t-1} + \varepsilon_t \end{aligned} \quad (10)$$

$$\begin{aligned} \text{LP-AFC: } \hat{\phi}_t = & \beta_k k_t + \beta_l \ln(P_sk_t + s_{ts}T_sk_t + s_{pu}P_unsk_t + s_{tu}T_unsk_t) \\ & + g(\hat{\phi}_{t-1} - \beta_k k_{t-1} \\ & - \beta_l \ln(P_sk_{t-1} + s_{ts}T_sk_{t-1} + s_{pu}P_unsk_{t-1} \\ & + s_{tu}T_unsk_{t-1}), \widehat{Pr}_t) + \gamma_s X_sk_{t-1} + \gamma_u X_unsk_{t-1} + \varepsilon_t \end{aligned} \quad (11)$$

where P_{sk} (T_{sk}) are the skilled workers with permanent (temporary) contracts, and P_{unsk} (T_{unsk}) the unskilled workers with permanent (temporary) contracts; X_{sk} (X_{unsk}) is the share of skilled (unskilled) workers with permanent contracts within the skilled (unskilled).

6. Results

A. Ñopo decomposition

The labor productivity gap (Δ_Y) between 2002 and 2014 amounts to 29.26% of the labor productivity average in 2002 (Table 2). We examine how relevant plant characteristics explains this gap.²⁶

Capital accounts for 12.62% of this gap is (table 2).²⁷ A positive Δ_X means that an increase in the number of plants with larger amounts of capital across time is associated with an increase in labor productivity. When adding a dummy identifying plants whose share of temporary workers

²⁶ We insert characteristics one by one, to isolate the effect of each component. Every time we add a characteristic, we verify what happens when we also control for hiring temporary workers.

²⁷ A dummy is equal to 1 when the capital of the firm is above the median levels, calculated by pooling observations of 2002 and 2014 together.

is above the median, the productivity gap explained by common observable characteristics, Δ_X , does not vary much.

We also want to control for labor. Hence, we add dummies identifying the size of the plant (medium, large) as defined by the number of workers. In Column (2) Δ_X increases, which implies that the plants' size helps explaining the labor productivity gap. Interestingly, when in Column (3) we add the dummy identifying plants whose share of temporary workers is above the median, Δ_X decreases. This means that controlling for temporary workers decreases the explanatory power of the observable characteristics included so far. We also know that plants increase their shares of temporary workers across time. Hence, the larger shares of temporary workers are negatively associated with productivity.

In Column (4) we control for plants with skilled workers above the median, whose increase in 2014 helps to explain the increase in productivity (Δ_X increases to 18.15%). Once again, when we also control for plants with a share of temporary workers above the median in Column (5), the explained gap decreases, reinforcing the idea that higher shares of temporary workers are negatively associated with productivity.

Controlling for plants with the share of skilled workers within temporary above the median decreases the productivity gap explained by observable characteristics (Column 6), but controlling again for temporary workers decreases it even further (Column 7).

In Column (8) we control for the number of exporting plants. Δ_X now decreases, probably led by the number of exporting plants decreasing across time. We find the same pattern when we add temporary workers to the decomposition (Column 9).

Finally, we add subsector dummies (Columns 10-11). By doing so we lose many observations from the common support (16.91% in 2002, and 9.32% in 2014). Δ_{2014} is now -3.75%, Δ_{2002} is 10.73% and Δ_X 4.69%. The fact that Δ_{2014} is negative means that the characteristics of plants in 2014 that are outside the common support decrease the productivity gap and these are the plants characterized by shares of temporary workers higher than the median.

The fact that Δ_0 is always large and significantly different from 0 implies that observable characteristics fail to explain most of the labor productivity gap. What is more relevant to us is that an increase in the number of plants with higher shares of temporary workers is associated with a decrease in productivity, even though the magnitude of this relationship tends to be small. To

understand whether the link is causal we estimate the value-added production function endogenizing the TFP process.

B. Addessi's model

Tables 2-8 show the estimated β_k , β_l , s , and γ from equation (8). s and γ are the parameters of most interest in this paper. If $s < 1$, permanent workers contribute more to labor productivity;²⁸ if $s > 1$, temporary workers are the productive ones. The results are interesting to understand how the composition of permanent and temporary workers affects productivity. γ shows how the composition of permanent and temporary workers affects TFP dynamics.

The OLS estimation is a standard ordinary least square regression which ignores three main elements: (i) input services are correlated with the unobserved productivity, (ii) labor services are not homogenous, and (iii) productivity follows a Markov process; hence, $s = 1$, while $g(\cdot)$ and γ are not estimated. The estimation called 2-steps applies the procedure previously exposed except for considering productivity as an exogenous Markov process (i.e., not including labor-service composition, X , in TFP); it includes estimation of $g(\cdot)$. *Bench1* and *Bench2* are consistent with the procedure and the hypotheses presented in the previous section. They differ in the time reference of X . In *Bench1*, X is not instrumented since there is no reason to expect correlation between the composition of the labor contracts at time $t-1$ and the productivity shock at time t , while in *Bench2* X is instrumented with its lagged value.

Table 3 shows the results for the entire sample and by plant size. Table 4 divides plants between exporters and non-exporters. Table 5 presents the results by geographical area, while Table 6 by use of information and communication technology.

As we can see in Table 3, estimating an OLS regression in the manufacturing sample, the elasticities of value added with respect to capital and labor services, β_k and β_l , are 0.365 and 0.682.

When moving beyond the OLS procedure, we need to guess an initial value for the parameters to be estimated; our guess is 0.4 for β_k , 0.6 for β_l , 1 for s (i.e. temporary and permanent contracts are characterized by the same labor-augmenting factor) and 0 for γ (i.e. labor-contract composition has no effect on the dynamic generation process of TFP).

²⁸ s is the labor-augmenting factor of temporary contracts. If $s=1$, workers with temporary contracts contribute to value added to the same extent of permanent contracts; this translates into an equal contribution to labor productivity, defined as value added per worker.

When we split labor into temporary and permanent workers and run the 2-steps estimation, β_k and β_l are 0.129 (s.e. 0.011) and 0.776 (0.007), while s is 0.887 (s.e. 0.014), suggesting that labor contracts induce a static difference in labor productivity.

Unlike in Addessi (2014), introducing the labor-contract composition in the TFP dynamics does not change the estimated coefficients in our setting. When we estimate the model through *Bench1*, we find that s is 0.887 (s.e. 0.014), significant at 1% level. The finding is confirmed under *Bench2* estimation.²⁹ This means that temporary workers are less productivity-enhancing than permanent workers. The estimated γ is not significantly different from zero, but this hides important differences at a more disaggregated level.

By size, we find that the larger the plant, the lower the parameter s . While temporary workers in small plants contribute to productivity to the same extent as permanent workers (s is not significantly different from 1), temporary workers in medium size plants are less productive than permanent workers, and they are even less in large plants. According to *Bench1* estimations, s is 0.995 (s.e. 0.020), 0.819 (s.e. 0.021) and 0.639 (s.e. 0.052) for small, medium and large companies respectively. The coefficient γ indicates that the incidence of permanent contracts in total contracts has a positive effect on TFP dynamics in medium and large plants, while it does not in small plants. Medium and large plants hire sizable proportions of temporary workers (38% and 44% on average,³⁰ respectively), but this seems to affect negatively both productivity in the current year and TFP growth.

In the case of exporters, temporary workers are less productive than permanent workers, with the gap being larger than in non-exporter plants (Table 4): according to *Bench1* model, the estimation of s is 0.918 (s.e. 0.019) for non-exporters and 0.815 (s.e. 0.018) for exporters. In TFP dynamics we observe a positive effect from a higher share of permanent contracts in exporting plants.

We also examine whether temporary workers are characterized by a different level of productivity depending on the geographical area where plants operate. To do so, we divide the sample into two groups: plants operating in the most populous departments, where we assume greater possibilities of networking among plants (Bogota D.C, Antioquia and Valle del Cauca), and plants operating in the remaining departments. We do not find substantial differences in the

²⁹ According to *Bench2* estimates, s is 0.887 (s.e. 0.014).

³⁰ Aggregating observations over the 2000-2014 time span.

productivity of temporary workers between the two areas: s is 0.872 (s.e. 0.014) in the most densely populated areas and 0.919 (s.e. 0.030) in the remaining areas (Table 5); γ is not significantly different from zero in either group.

We now assess whether internet speed amplifies the productivity gap of the different labor contract types, by making the productive workers even more productive. Among plants that use internet, those who have a greater bandwidth are the plants where temporary workers contribute the least to increasing value added, even though long-run effects on TFP dynamics are not significantly different from zero (Table 6). More in general, we also explore whether labor contracts have a different effect on productivity in plants with different inclinations to adopt technology, using ‘ownership of a webpage’ as an indicator of the latter. In plants that are more technology-friendly (i.e. have a webpage),³¹ temporary workers contribute to labor productivity to a lower extent than permanent workers, but in the long-run the productivity gap is null (γ is not significantly different from zero).

Overall, it seems that temporary workers are most often characterized by a lower (or in the best-case scenario not significantly different) labor-augmenting factor compared to permanent workers. To assess whether this result is driven by the lower shares of skilled workers among the temporary, we estimate equation 10. Results are presented in Tables 7-8.

In the aggregate manufacturing sector, we find that permanent unskilled workers are as productive as permanent skilled workers ($s_{pu} = 1.035$, s.e. 0.022), while both skilled and unskilled temporary workers are dragging productivity down compared to permanent workers ($s_{ts} = 0.879$, s.e. 0.030; $s_{tu} = 0.921$, s.e. 0.026).

Let us recall that we found that temporary workers are as productive as permanent workers in small plants. When we disentangle workers by skill levels too, we find that workers in each category are equally productive: s_{ts} is 1.006 (s.e. 0.056), s_{pu} is 1.073 (s.e. 0.031), and s_{tu} is 1.061 (s.e. 0.035), i.e. none of the parameters is significantly different from 1 at 1% significance level. In medium and large plants, we found that temporary workers increase value added to a lower extent than permanent. Once we differentiate skilled and unskilled, we see that this distinction

³¹ 15,740 plants have non-missing information on ownership of a webpage; 76.03% of them use the webpage, 23.97% do not. In the sample where we estimate TFP through OP, 8,136 plants in the 2012-4 period have information on the webpage: 85.54% of the plants use it, 15.46% do not.

does not matter: temporary workers, both skilled and unskilled, always exhibit lower levels of labor productivity compared to permanent workers.³²

We find the same pattern when we replicate the exercise in exporting plants (Table 8): while permanent unskilled workers are as productive as permanent skilled ones (s_{pu} is 1.018 -s.e. 0.034- in exporting plants), both skilled and unskilled temporary workers are less productive than permanent (s_{ts} is 0.837 -s.e. 0.041, and s_{tu} is 0.823 -s.e. 0.029-). In non-exporting plants, permanent unskilled are as productive as permanent skilled workers (s_{pu} is 1.048 -s.e. 0.026-); while skilled workers hired through a temporary contract are less productive (s_{ts} is 0.892 -s.e. 0.039-).

In a nutshell, when temporary workers are less productive than permanent workers, this is not driven by their skill composition.

Furthermore, the non-significant effect of permanent contracts in TFP dynamics in the aggregate could have been hiding positive effects of permanent contracts within skilled workers and negative effects within the unskilled, or vice versa. Instead γ_{sk} and γ_{unsk} in Tables 7-8 are never significantly different from zero, meaning that it is neither within the skilled or the unskilled workers that permanent contracts have a significant impact in the long run.

Finally, when we allow the production function to differ across subsectors (Table A1), estimations differ depending on the methodology adopted (OP/LP), which makes it hard to draw robust conclusions.

A. Robustness Checks

First, it is reassuring to note that *Bench1* and *Bench2* estimates are almost identical. Our estimates are robust to changing the degree of the polynomial used in the estimation of the first and third steps, to changing the propensity score, to calculating the first stage distinguishing by skills, to changing the number of replications used for bootstrapping errors, to using consumption of all intermediate good rather than electricity only, to varying the initial parameters' values assigned in non-linear squares estimations.

³² Estimates for s_{ts} are 0.814 (s.e. 0.032) and 0.542 (s.e. 0.074), s_{pu} are 0.991 (s.e. 0.030) and 0.887 (s.e. 0.077), and s_{tu} are 0.813 (s.e. 0.029) and 0.605 (s.e. 0.055) respectively in medium and large firms.

The same applies for the estimate of the s and γ parameters when we re-conduct all the analysis through LP (Tables A2-A4). Only the findings across subsectors are not robust, hence we do not rely on them.

7. Conclusion

The rise in temporary contracts in Colombia raises questions on its consequences on firm productivity. To estimate the effects of hiring workers through temporary rather than open-ended contracts, we follow Addressi (2014) and apply an Olley and Pakes (1996) structural model in three steps, including the Akerberg et al. (2016) correction and endogenizing TFP. We also use the Levisohn and Petrin (2003) approach. We find that temporary workers in the manufacturing sector in 2000-14 contribute to plants' labor productivity less than permanent workers. When allowing the production function to differ by plant size, exporting status and use of information and communication technology, this pattern holds in most cases (in medium and large plants, exporters, tech-friendly plants or with a greater internet connection bandwidth). Only in small plants, non-exporters, and in firms that make less use of information and communication technology, temporary and permanent workers equally contribute to labor productivity.

We analyze whether the lower productivity of fixed-term contracts is driven by a higher proportion of unskilled workers holding those contracts and do not find support for this thesis as results seem to be driven exclusively by the contract type itself.

Moreover, when exploring the effects of the contract mix on TFP dynamics, we find that in many cases a higher share of permanent contracts has a positive influence on TFP growth: this is true in the aggregate manufacturing sector, in medium/large size plants, in exporters; the reverse is hardly true.

Even though we are unable to measure the temporary-to-permanent conversion rate, the large share of temporary workers that prevails in Colombia is suggestive of temporary contracts being a dead-end cost-reduction device rather than a stepping stone for workers to become permanent, with negative effects on productivity. In the OECD, there have been proposals to replace dual labor markets with a single open-ended contract,³³ where termination costs that increase smoothly with job tenure allow the gains of both fixed-term and permanent contracts

³³ In Spain, Italy, and France.

(Blanchard and Tirole, 2003, Boeri and Garibaldi 2008, Dolado 2012, Bentolila et al. 2012b, Cahuc 2012, OECD 2014, IMF 2014, 2015, 2017). Due to the low degree of employment protection in the initial period, this instrument can be used as a screening device, but as employment protection becomes more stringent with job tenure, it also serves as an incentive for plants to invest in training for all workers and search for the right matches. Given the similar EPL that characterizes Colombia, this single open-ended contract could be a tool to fight a segmented labor market that slows productivity down. At the same time, fixed term contracts should not be eliminated, which might have other unintended consequences, but rather restricted to replacements or seasonal work.

Table 2. Ñopo's Productivity Decomposition

	(1) Capital	(2) Capital, Size	(3) (2) + Temp	(4) Capital, Size, Skilled	(5) (4) + Temp	(6) Capital, Size, Skilled, Skilled within Temp	(7) (6) + Temp	(8) Capital, Size, Skilled, Skilled within Temp, Exports	(9) (8) + Temp	(10) Capital, Size, Skilled, Skilled within Temp, Exports, Subsector	(1) (10) + Temp
Δ_Y	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%	29.26%
Δ_0	16.63%	13.10%	14.39%	11.11%	12.30%	14.49%	15.32%	14.99%	16.21%	19.59%	17.58%
Δ_{2002}	.	.	.	.	.	.	0.00%	.	1.31%	6.46%	10.73%
Δ_{2014}	.	.	.	.	0.02%	0.00%	0.00%	0.00%	0.5%	-3.21%	-3.75%
Δ_X	12.62%	16.15%	14.87%	18.15%	16.75%	14.71%	13.42%	14.18%	11.23%	6.41%	4.69%
Percent 2002	100%	100%	100%	100%	100%	100%	99.72%	100%	99.33%	88.33%	83.09%
Percent 2014	100%	100%	100%	100%	99.69%	99.90%	99.44%	98.85%	98.83%	94.55%	90.68%

Notes: The Ñopo decomposition matches plants with the same observable characteristics in 2002 and 2014 and creates synthetic samples of identical plants that can be compared. Δ_X is the part of the productivity gap explained by common characteristics of plants in 2002 and 2014; Δ_{2000} (Δ_{2014}) is the part of the productivity gap explained by the fact that there are some combinations of 2002 (2014) plant characteristics that cannot be found in 2014 (2002) plant characteristics. Δ_0 is the amount of productivity increase that cannot be explained by the observable characteristics available in the data and is left unexplained. Each column corresponds to the characteristics based on which plants are matched (in column 1 plants are matched based on capital values, etc.). The columns in blue we also add the share of temporary workers within the plant.

Table 3. Results in the Aggregate and by Plant Size

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
All plants	0.365***	0.129***	0.129***	0.129***	0.682***	0.776***	0.776***	0.776***	0.887***	0.887***	0.887***	0.003	0.003
N=35,781	(0.010)	(0.011)	(0.011)	(0.011)	(0.017)	(0.007)	(0.007)	(0.007)	(0.014)	(0.014)	(0.014)	(0.003)	(0.003)
Small	0.353***	0.093***	0.093***	0.093***	0.634***	0.748***	0.747***	0.747***	0.995***	0.995***	0.995***	0.004	0.003
N= 15,250	(0.018)	(0.011)	(0.011)	(0.011)	(0.036)	(0.013)	(0.013)	(0.013)	(0.020)	(0.020)	(0.020)	(0.005)	(0.004)
Medium	0.348***	0.143***	0.144***	0.143***	0.757***	0.777***	0.775***	0.776***	0.819***	0.819***	0.821***	0.022***	0.019***
N=14,788	(0.011)	(0.016)	(0.016)	(0.016)	(0.033)	(0.014)	(0.014)	(0.014)	(0.021)	(0.021)	(0.022)	(0.004)	(0.004)
Large	0.419***	0.204***	0.204***	0.203***	0.462***	0.700***	0.701***	0.701***	0.638***	0.639***	0.641***	0.013	0.020***
N=5,743	(0.019)	(0.025)	(0.025)	(0.025)	(0.062)	(0.025)	(0.025)	(0.025)	(0.052)	(0.052)	(0.052)	(0.008)	(0.007)

Notes: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Results by Exporting Status of the Plant

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
No													
Exporter	0.334***	0.127***	0.127***	0.127***	0.731***	0.773***	0.773***	0.773***	0.918***	0.918***	0.918***	-0.000	0.001
N=22,615	(0.012)	(0.011)	(0.011)	(0.011)	(0.019)	(0.011)	(0.011)	(0.011)	(0.019)	(0.019)	(0.019)	(0.004)	(0.003)
Exporter	0.402***	0.132***	0.132***	0.132***	0.550***	0.781***	0.783***	0.782***	0.816***	0.815***	0.816***	0.010**	0.008*
N=13,166	(0.014)	(0.021)	(0.021)	(0.021)	(0.024)	(0.015)	(0.015)	(0.015)	(0.018)	(0.018)	(0.019)	(0.004)	(0.004)

Notes: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Results by Area

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
More densely N=24,952	0.317*** (0.011)	0.111*** (0.013)	0.111*** (0.013)	0.111*** (0.013)	0.744*** (0.017)	0.807*** (0.011)	0.808*** (0.011)	0.808*** (0.011)	0.873*** (0.014)	0.872*** (0.014)	0.873*** (0.014)	0.005 (0.003)	0.005 (0.003)
Less densely N=10,829	0.440*** (0.016)	0.159*** (0.025)	0.159*** (0.026)	0.159*** (0.026)	0.583*** (0.029)	0.711*** (0.017)	0.711*** (0.017)	0.712*** (0.017)	0.920*** (0.031)	0.919*** (0.030)	0.919*** (0.030)	0.005 (0.006)	0.006 (0.006)

Notes: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6. Results by Use of Information and Communication Technology

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
Bandwidth <1024 Kbps N=794	0.244*** (0.027)	0.325*** (0.103)	0.326*** (0.106)	0.327*** (0.105)	0.796*** (0.044)	0.785*** (0.049)	0.787*** (0.048)	0.787*** (0.049)	0.908*** (0.057)	0.913*** (0.059)	0.916*** (0.058)	0.019 (0.016)	0.028 (0.018)
Bandwidth [1025-2048 Kbps] N=2,603	0.279*** (0.018)	0.114*** (0.038)	0.114*** (0.035)	0.114*** (0.035)	0.736*** (0.034)	0.804*** (0.032)	0.803*** (0.030)	0.804*** (0.032)	0.880*** (0.045)	0.880*** (0.045)	0.880*** (0.044)	-0.009 (0.009)	-0.002 (0.008)
Bandwidth >2049 Kbps N=4,735	0.369*** (0.016)	0.358*** (0.016)	0.183*** (0.027)	0.183*** (0.029)	0.643*** (0.032)	0.673*** (0.033)	0.692*** (0.027)	0.693*** (0.028)	0.676*** (0.045)	0.865*** (0.040)	0.864*** (0.039)	0.008 (0.008)	0.008 (0.008)
Web Page N=10,063	0.312*** (0.014)	0.154*** (0.011)	0.154*** (0.012)	0.154*** (0.011)	0.750*** (0.021)	0.785*** (0.013)	0.785*** (0.014)	0.785*** (0.013)	0.880*** (0.019)	0.880*** (0.020)	0.880*** (0.019)	-0.002 (0.006)	-0.003 (0.005)
No Web Page N=2,696	0.235*** (0.017)	0.115*** (0.028)	0.115*** (0.028)	0.115*** (0.033)	0.896*** (0.035)	0.803*** (0.019)	0.802*** (0.019)	0.803*** (0.020)	0.974*** (0.031)	0.975*** (0.031)	0.974*** (0.032)	-0.010 (0.009)	0.001 (0.008)

Notes: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Results on Skilled vs Unskilled in the Aggregate and by Plant Size

	$\beta_{perm,sk}$			$s_{temp,sk}$			$s_{perm,unsk}$			$s_{temp,unsk}$			$Y_{skilled}$		$Y_{unskilled}$	
	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2
All plants N=35,781	0.775*** (0.007)	0.775*** (0.007)	0.776*** (0.007)	0.883*** (0.030)	0.879*** (0.030)	0.882*** (0.030)	1.041*** (0.022)	1.035*** (0.022)	1.041*** (0.022)	0.922*** (0.027)	0.921*** (0.026)	0.923*** (0.027)	-5.687 (11.724)	0.022** (0.010)	-5.706 (11.725)	0.006 (0.010)
Small N=5,250	0.747*** (0.013)	0.748*** (0.013)	0.748*** (0.013)	1.009*** (0.057)	1.006*** (0.056)	1.008*** (0.057)	1.075*** (0.032)	1.073*** (0.031)	1.079*** (0.032)	1.059*** (0.035)	1.059*** (0.035)	1.061*** (0.035)	2.557 (14.635)	0.025 (0.018)	2.557 (14.635)	0.025 (0.018)
Medium N=14,788	0.777*** (0.014)	0.776*** (0.014)	0.776*** (0.014)	0.817*** (0.032)	0.814*** (0.032)	0.815*** (0.032)	0.994*** (0.031)	0.991*** (0.030)	0.995*** (0.031)	0.814*** (0.029)	0.813*** (0.029)	0.815*** (0.029)	-2.522 (10.474)	0.002 (0.016)	-2.534 (10.474)	-0.009 (0.016)
Large N=5,743	0.701*** (0.025)	0.699*** (0.025)	0.699*** (0.025)	0.549*** (0.073)	0.542*** (0.074)	0.546*** (0.074)	0.896*** (0.078)	0.887*** (0.077)	0.897*** (0.078)	0.609*** (0.055)	0.605*** (0.055)	0.610*** (0.056)	-2.497 (18.441)	0.021 (0.051)	-2.526 (18.441)	-0.003 (0.055)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8. Results on Skilled vs Unskilled by Exporting Status

	$\beta_{perm,sk}$			$s_{temp,sk}$			$s_{perm,unsk}$			$s_{temp,unsk}$			$Y_{skilled}$		$Y_{unskilled}$	
	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2
No Exporter N=22,615	0.772*** (0.011)	0.773*** (0.011)	0.773*** (0.011)	0.897*** (0.039)	0.892*** (0.039)	0.895*** (0.039)	1.054*** (0.026)	1.048*** (0.026)	1.054*** (0.026)	0.973*** (0.030)	0.971*** (0.030)	0.974*** (0.029)	0.611 (14.454)	0.019 (0.012)	0.591 (14.453)	0.001 (0.012)
Exporter N=13,166	0.781*** (0.015)	0.781*** (0.015)	0.781*** (0.015)	0.840*** (0.041)	0.837*** (0.041)	0.839*** (0.041)	1.021*** (0.034)	1.018*** (0.034)	1.022*** (0.034)	0.823*** (0.029)	0.823*** (0.029)	0.824*** (0.029)	14.955 (13.437)	0.027 (0.026)	14.942 (13.437)	0.015 (0.025)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

References

- Akerberg, D., Caves, D., Frazer, G. 2006. "Structural identification of production functions." *MPRA Paper 38349*. University Library of Munich.
- Addessi, W. 2014. "The productivity effect of permanent and temporary labor contracts in the Italian manufacturing sector." *Economic Modelling* 36, 666-672.
- Aguirregabiria, V., and Alonso-Borrego, C., 2014. "Labor contracts and flexibility: evidence from a labor market reform in Spain." *Economic Inquiry*, 522, pp.930-957.
- Alba-Ramirez, A. 1994. "Formal Training, Temporary Contracts, Productivity and Wages in Spain." *Oxford Bulletin of Economics and Statistics*, 562, 151–170.
- Alonso-Borrego, C. 2010, "Firm Behaviour, Market Deregulation and Productivity in Spain." Banco de Espana, Documento de Trabajo 1035.
- Auer, P., Berg, J. and Coulibaly, I. 2005. "Is a stable workforce good for productivity?" *International Labour Review*, 144: 319–343. doi:10.1111/j.1564-913X.2005.tb00571.x
- Autor, D., Kerr, W., and Kugler, A. 2007. "Do Employment Protection Reduce Productivity? Evidence from US States." *The Economic Journal*, 117, F189–F217.
- Autor, D. H., and Houseman S. N. 2010. "Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from" Work First". *American Economic Journal: Applied Economics*: 96-128.
- Bartelsman E. J., Hinloopen J. 2005. "Unleashing animal spirits: ICT and economic growth", in L. Soete e B. ter Weel eds., *The Economics of the Digital Economy*, Edward Elgar Publishing.
- Bassanini, A., L. Nunziata and D. Venn 2009. "Job Protection Legislation and Productivity Growth in OECD Countries." *Economic Policy*, 24, 349-402.
- Beaudry, P. , Doms, M. and E. Lewis 2010. "Endogenous Skill-Bias in Technology Adoption: City Level Evidence from the IT Revolution." *Journal of Political Economy*, 118, 988-1036.
- Belot, M., Boone, J., and J. Van Ours 2007: "Welfare Effects of Employment Protection", *Economica*, 74, 381-396.
- Bentolila, S., Dolado, J. and J. F. Jimeno 2008. "Two-tier Employment Protection Reforms: The Spanish Experience" CES-Ifo-DICE, *Journal for International Comparisons*, 6, 49-56
- Bentolila, S., P. Cahuc, J. Dolado, and T. Le Barbanchon 2012a. "Two-Tier Labour Markets in a Deep Recession: France vs. Spain," *The Economic Journal*, 122, 155-187.

- Bentolila, S, T Boeri and P Cahuc 2012b, “Ending the Scourge of Dual Labour Markets in Europe”, *VoxEU*, 12 July.
- Blanchard, O. J., and A. Landier 2002. “The Perverse Effects of Partial Labor Market Reform: Fixed Duration Contracts in France.” *The Economic Journal*, 112, 214–244.
- Blanchard, O. J., and J. Tirole 2003. “Contours of Employment Protection Reform”, MIT Department of Economics Working Paper, No. 03-35.
- Boeri, T., and P. Garibaldi 2007. “Two Tier Reforms of Employment Protection: A Honeymoon Effect?” *The Economic Journal*, 117, 357–385.
- Boeri, T., and Garibaldi, P. 2008. Un Nuovo Contratto per Tutti. *Chiarelettere*, Torino.
- Booth, A. L., Francesconi, M., & Frank, J. 2002. “Temporary jobs: stepping stones or dead ends?.” *The Economic Journal*, 112480, F189-F213.
- Cahuc, P 2012, “For a unified contract”, *European Labour Law Journal*, 33: 190–205.
- Cahuc, P., A., Cheron and F. Mahlebert 2016. “Explaining the Spread of Temporary Jobs and its Impact on Labor Turnover.” *International Economic Review*, 572, 533-572.
- Cahuc, P., and F. Postel-Vinay 2002. “Temporary Jobs, Employment Protection and Labor Market Performance.” *Labour Economics*, 9, 63–91.
- Cappellari, L., Dell’Arlinga, C. and M. Leonardi 2012. “Temporary Employment, Job Flows and Productivity. A Tale of Two Reforms.” *The Economic Journal*, 122, 188-215.
- Cazes and Laiglesia, 2015. “Temporary Contracts, Labour Market Segmentation and Wage Inequality” in: *Labor Markets, Institutions and Inequality*, chapter 6, 147-183, Edward Elgar Publishing.
- Cingano, F., M. Leonardi, J. Messina and G. Pica, 2010. “Employment Protection Legislation, Productivity and Investment. Evidence from Italy.” *Economic Policy*, 25, 117-163.
- Damiani, M., Pompei, F., 2010. “Labour protection and productivity in EU economies: 1995–2005.” *Eur. J. Comp. Econ.* 7 2, 373–411.
- Dolado, J. 2012. “The Pros and Cons of the Latest Labour Market Reform in Spain.” *Spanish Labour Law and Employment Relations Journal*, 1, 22–30.
- Dolado, J.J., Stucchi, R., 2014. “Do temporary contracts affect TFP? Evidence from Spanish manufacturing firms.” IZA Discussion Paper N. 3832.
- Engellandt, A., and R. T. Riphahn 2005. “Temporary Contracts and Employee Effort.” *Labour Economics*, 123, 281–299.

- Eslava, M., Haltiwanger, J., Kugler, A. and Kugler, M., 2014. “The effects of regulations and business cycles on temporary contracts, the organization of firms and productivity.” Documentos de Trabajo del CEDLAS.
- Hall, R. 1988. “The Relation between Price and Marginal Cost in U.S. Industry.” *Journal of Political Economy*, 96, 921–947.
- Hopenhayn, H., and J.P. Nicolini 1997. “Optimal Unemployment Insurance.” *Journal of Political Economy*, 105, 412-438.
- Hopenhayn, H., and R. Rogerson 1993. “Job Turnover and Policy Evaluation. A General Equilibrium Analysis.” *Journal of Political Economy*, 101, 915-938.
- Ichino, A., Mealli, F., & Nannicini, T. 2008. “From temporary help jobs to permanent employment: What can we learn from matching estimators and their sensitivity?” *Journal of Applied Econometrics*, 23, 305-327.
- Giuliano, R., Kampelmann, S., Mahy, B. and Rycx, F., 2017. “Short notice, big difference? The effect of temporary employment on firm competitiveness across sectors”, IZA Discussion Paper Series.
- Ichino, A., and R. Riphahn 2005. “The Effect of Employment Protection on Worker Effort: A Comparison of Absenteeism During and After Probation.” *Journal of the European Economic Association*, 3, 120–143.
- IMF 2014. “Italy; Staff Report for the 2014 Article IV Consultation,” IMF Staff Country Reports 14/283, International Monetary Fund.
- IMF 2015. “France; Selected Issues,” IMF Staff Country Reports 15/179, International Monetary Fund.
- IMF 2017. “Spain; 2016 Article IV Consultation-Press Release; Staff Report; Informational Annex; Staff Statement; and Statement by the Executive Director for Spain.” IMF Staff Country Reports 17/23, International Monetary Fund.
- Jona-Lasinio, C., Vallanti, G., 2011. “Reforms, Labour Market Functioning and Productivity Dynamics: a Sectoral Analysis for Italy.” Working Papers LuissLab, 1193.
- Kleinknecht, A., R. M. Oostendorp, M. P. Pradhan, and C. W. M. Naastepad, 2006. “Flexible labour, firm performance and the Dutch job creation miracle.” *International Review of Applied Economics*, 2002, 171-187.
- Lagos, R. 2006. “A Model of TFP.” *Review of Economic Studies*, 73, 983-1007.

- Lazear, E. and S. Rosen 1981. "Rank-Order Tournaments as Optimal Contracts." *Journal of Political Economy*, 89, 841-864.
- Levinsohn, J. and A. Petrin 2003. "Estimating Production Functions Using Inputs as Controls for Unobservables." *Review of Economic Studies*, 70, 317-342.
- MacLeod, W. B., & Nakavachara, V. 2007. "Can wrongful discharge law enhance employment?" *The Economic Journal*, 117521, F218-F278.
- Michelacci, C. and J. Pijoan-Mas 2012: "Intertemporal Labor Supply with Search Frictions." *Review of Economic Studies*, 79, 899-931.
- Nielen, S. and Schiersch, 2016. "Productivity in German manufacturing firms: Does fixed-term employment matter?" *The International Labour Review*, Vol.155, No. 4.
- OECD 2014, *Employment Outlook 2014*.
- Olley G.S. and A. Pakes 1996. "The Dynamic of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64, 1263-1297
- Poschke, M. 2009. "Employment protection, firm selection, and growth." *Journal of Monetary Economics*, 568, 1074-1085.
- Saint-Paul, G. 1997, "Is Labour Rigidity Harming Europe's Competitiveness? The Effect of Job Protection on the Pattern of Trade and Welfare." *European Economic Review*, 41, 499-506.
- Scarpetta S. and T. Tressel, 2004. "Boosting Productivity via Innovation and Adoption of New Technologies: Any Role for Labor Market Institutions?" World Bank Policy Research Working Papers WPS3273.
- Wasmer, E. 2006. "General Versus Specific Skills in Labour Markets with Search Frictions and Firing Costs." *American Economic Review*, 963, 811-31.

8. Appendix: Data and definition of variables

A. Sample Selection

Initially there are 11,901 plants (11,307 firms), corresponding to 95,271 observations with non-missing industry values and with more than 10 employees in the period 2000-14.

First, we drop observations in the top/bottom 1% of value added; and we are left with 11,820 plants (11,234 firms) and 93,300 observations.

We also exclude observations that show more than 400% growth from one year to the other in the total labor variable, as this level of growth in employment does not seem plausible: we are left with 11,820 plants (corresponding to the same number of firms, and 93,251 observations).

Following Eslava *et al.* (2014), we also drop plants that consistently have fewer than 15 employees: we are left with 9,973 plants (9,467 firms), corresponding to 87,318 observations.

We remove firms from industries with too few observations (less than 70): tobacco (58 observations) and office & equipment (45 observations); we are left with 9,959 plants (9,454 firms) and 87,215 observations.

Since in *Bench2* estimations we need to include variables up to their second-lag and since we prefer to use the same sample for all estimations (OLS, 2-steps, *Bench1*, *Bench2*) to obtain comparable results, we need to drop observations that do not have up to two lags in the variables of interest. Hence, we lose observations in the first two years of the sample: our regression will relate to the period 2002-2014. We also lose observations for firms with missing values in the two previous lags in any of the variables entering the regressions.

Finally, when applying OP we also lose all the observations in which investment is either missing or zero; while applying LP we lose observations in which consumption of electricity is either missing or zero.

For OP we are left with 6,557 plants (6,194 firms), corresponding to 35,781 observations. The sample when running LP estimates is larger: 8,058 plants (7,654 firms), corresponding to 57,477 observations.

The module on information and communication technologies provides data for some of the plants in our dataset: 6,631 plants in 2012, 6,515 in 2013, 62,641 in 2014. From this module, we will use information on whether the plant has a webpage or the bandwidth it uses. 15,740 plants have non-missing information on having/not having a webpage; 15,787 have non-missing information for the bandwidth.

B. Variable Definitions

Value Added: it is the total revenue received from the use of inputs (land, capital, labor, business organization) involved in the production function. The DANE calculates the value added as the difference between gross output and intermediate consumption.

Gross Output: the value of gross output is equal to the “Value of all the establishment’s manufactured goods”, plus the “Revenues from industrial subcontracting made for others”, plus the “Value of the electric energy sold”, plus the value of the revenue from CERT³⁴, plus the “Value of stocks of the products in the manufacturing process at the start of the year”, minus the “Value of the products in the manufacturing process at the end of the year”, plus the value of other operating revenues, such as those generated by rent of goods produced and the installation, maintenance and repair of products manufactured by the establishment.

Capital: book value of fixed assets; it corresponds to all the fixed assets of the establishment, defined as those relatively durable goods not to be sold, for the use of the establishment and the development of its industrial activity; it includes all the physical assets that are expected to have a productive life longer than one year, and all those extensions, additions or improvements and major reforms that extend the life or normal economic efficiency of the assets (land, buildings, machinery and equipment, on-going construction, office equipment, etc.).

Gross Investment: includes the sum of the investments in new and used fixed assets, manufactured for their own use or received in transfer from other establishments, less sales, withdrawals and transfers of fixed assets owned by the plant.

Energy Consumption: value of electric power purchased (only the one attributable to the manufacturing process); it corresponds to the value in kwh. acquired by the establishment for its operation.

Permanent Personnel: corresponds to the yearly average of payroll personnel or plant personnel with a direct labor link with the establishment through an indefinite term contract.

Temporary Personnel: temporary staff hired directly by the establishment (corresponds to the yearly average staff hired through fixed-term contract to accomplish specific tasks under an agreed remuneration), and temporary staff hired by companies specialized in the supply of personnel (corresponds to yearly average staff without either a labor or contractual relationship

³⁴ Discounts caused during the year by exports of products y and subproducts prepared by the establishment.

with the plant, hired through agencies specialized in the supply of personnel to carry out specific tasks in the industrial establishment.

Skilled personnel: professionals, technicians and production technologists (national and foreign; it refers to persons directly linked to productive activities or tasks directly related with production; this category includes mechanical, chemical, industrial, electrical, mining and oil engineers, etc., and technicians and technologists who work directly in the production process), and administration and sales staff (the people who lead the economic, financial and administrative aspects of the establishment and responsible for the elaboration and conduction of the general policy of the company, as managers, sub-managers and paid directors; this includes: heads of the administrative staff, supervisors, security guards, staff that do not work in the area of production, vendors, distributors and/or delivery agents, if their remuneration is borne by the establishment; it does not include warehouse staff, administrative offices, management, warehouses and other auxiliary units not directly linked to the establishment or located in a place different from the productive plant).

Unskilled personnel: production workers (it corresponds to workers dedicated to manufacturing, processing, assembling, maintenance, inspection, storage, packing, loading such as: internal delivery couriers, chauffeurs, cleaning machines personnel, supervisors and foremen who work manually, drivers of vehicles for transport of raw materials, materials or products only within the establishment, workers dedicated to maintenance and repair (mechanical, electrical, etc.) of the machinery and industrial equipment; administrative supervisors, supervisors dedicated mainly to the supervision of the workers, surveillance personnel, guards, staff working in production area).

Deflators: variables are adjusted with the producer price index (PPI) for each two-digit ISIC (International Standard Industrial Classification of All Economic Activities) sector; December values are taken for each year; base period December 2014 = 100. As PPI is at the sector level (not plant level), what we measure is TFPR (“revenue” productivity).

Appendix Tables

Table A1. Results by Industrial Subsector (OP)

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
Food&Beverage	0.417***	0.418***	0.417***	0.417***	0.651***	0.641***	0.641***	0.641***	1.174***	1.154***	1.159***	-0.010	-0.008
N=6,880	(0.017)	(0.009)	(0.010)	(0.010)	(0.028)	(0.013)	(0.013)	(0.013)	(0.040)	(0.053)	(0.052)	(0.012)	(0.012)
Textiles	0.177***	0.066	0.071	0.068	0.721***	0.690***	0.696***	0.693***	0.665***	0.659***	0.661***	-0.027	-0.015
N=1,466	(0.060)	(0.046)	(0.044)	(0.045)	(0.079)	(0.063)	(0.062)	(0.062)	(0.048)	(0.047)	(0.046)	(0.018)	(0.017)
Apparel	0.139***	0.102***	0.102***	0.102***	0.763***	0.790***	0.791***	0.791***	0.779***	0.800***	0.794***	0.021	0.017
N=2,145	(0.036)	(0.017)	(0.017)	(0.017)	(0.036)	(0.017)	(0.017)	(0.017)	(0.034)	(0.047)	(0.044)	(0.021)	(0.020)
Leather	0.157***	0.153***	0.159***	0.157***	0.863***	0.829***	0.822***	0.824***	1.142***	1.121***	1.122***	-0.052**	-0.044**
N=730	(0.040)	(0.015)	(0.016)	(0.015)	(0.045)	(0.028)	(0.027)	(0.027)	(0.051)	(0.046)	(0.047)	(0.025)	(0.022)
Wood	0.301***	0.098	0.099	0.099	0.874***	0.911***	1.007***	1.006***	0.878***	0.866***	0.865***	-0.021	-0.023
N=341	(0.103)	(0.061)	(0.060)	(0.060)	(0.139)	(0.141)	(0.055)	(0.054)	(0.092)	(0.105)	(0.103)	(0.038)	(0.038)
Paper	0.413***	0.394***	0.387***	0.392***	0.674***	0.731***	0.741***	0.734***	0.995***	1.033***	1.009***	0.048*	0.023
N=1,001	(0.042)	(0.087)	(0.078)	(0.084)	(0.083)	(0.058)	(0.058)	(0.056)	(0.100)	(0.091)	(0.097)	(0.026)	(0.026)
Printing	0.168***	0.094***	0.095***	0.095***	0.969***	1.003***	1.004***	1.003***	0.793***	0.803***	0.797***	0.020	0.007
N=1,994	(0.047)	(0.032)	(0.032)	(0.032)	(0.062)	(0.033)	(0.032)	(0.033)	(0.039)	(0.044)	(0.044)	(0.020)	(0.018)
Petroleum	0.769***	0.424**	0.422**	0.432**	0.750**	0.958***	0.956***	0.952***	1.202	1.171	1.257	-0.054	0.114
N=152	(0.192)	(0.195)	(0.202)	(0.193)	(0.330)	(0.198)	(0.192)	(0.186)	(11.240)	(14.284)	(0.764)	(0.135)	(0.112)
Chemicals	0.399***	0.287***	0.284***	0.285***	0.597***	0.735***	0.736***	0.736***	0.671***	0.650***	0.650***	-0.028*	-0.028**
N=3,688	(0.028)	(0.026)	(0.043)	(0.043)	(0.048)	(0.026)	(0.026)	(0.026)	(0.040)	(0.044)	(0.040)	(0.017)	(0.014)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A1. Results by Industrial Subsector (OP - continuation)

	β_k				β_l				s			γ	
	OLS	2-steps	Bench1	Bench2	OLS	2-steps	Bench1	Bench2	2-steps	Bench1	Bench2	Bench1	Bench2
Rubb&Plastic	0.307***	0.170**	0.171**	0.170**	0.704***	0.785***	0.786***	0.785***	0.870***	0.871***	0.870***	0.003	0.001
N=3,027	(0.031)	(0.078)	(0.078)	(0.078)	(0.046)	(0.042)	(0.042)	(0.042)	(0.043)	(0.037)	(0.037)	(0.018)	(0.015)
Minerals	0.509***	0.464***	0.467***	0.466***	0.527***	0.552***	0.554***	0.553***	0.902***	0.939***	0.916***	0.030	0.012
N=1,986	(0.040)	(0.040)	(0.039)	(0.041)	(0.066)	(0.036)	(0.034)	(0.036)	(0.081)	(0.071)	(0.076)	(0.020)	(0.018)
Basic Metals	0.274***	0.333***	0.334***	0.334***	0.781***	0.722***	0.724***	0.724***	0.707***	0.753***	0.763***	0.047	0.055
N=630	(0.049)	(0.025)	(0.025)	(0.025)	(0.099)	(0.043)	(0.043)	(0.043)	(0.086)	(0.105)	(0.100)	(0.046)	(0.039)
Metal	0.307***	0.254***	0.254***	0.254***	0.659***	0.707***	0.708***	0.709***	0.891***	0.907***	0.913***	0.016	0.022
N=1,948	(0.037)	(0.039)	(0.038)	(0.038)	(0.062)	(0.059)	(0.059)	(0.059)	(0.049)	(0.060)	(0.052)	(0.017)	(0.014)
Equipment	0.171***	0.152***	0.151***	0.151***	0.838***	0.878***	0.877***	0.877***	0.743***	0.732***	0.732***	-0.015	-0.016
N=1,771	(0.044)	(0.013)	(0.013)	(0.013)	(0.052)	(0.019)	(0.019)	(0.018)	(0.025)	(0.031)	(0.032)	(0.017)	(0.018)
Elect Machinery	0.246***	0.266***	0.264***	0.265***	0.773***	0.803***	0.805***	0.804***	1.207***	1.138***	1.155***	-0.051	-0.042
N=784	(0.048)	(0.071)	(0.079)	(0.071)	(0.068)	(0.049)	(0.051)	(0.048)	(0.113)	(0.141)	(0.125)	(0.034)	(0.033)
Medic. Instrum.	0.156**	0.113	0.114	0.113	0.983***	0.977***	0.976***	0.978***	0.575***	0.552***	0.571***	-0.045	-0.011
N=258	(0.068)	(0.078)	(0.076)	(0.084)	(0.131)	(0.069)	(0.069)	(0.071)	(0.111)	(0.135)	(0.115)	(0.127)	(0.065)
Vehicles	0.174**	0.080	0.080	0.080	1.034***	1.026***	1.024***	1.026***	0.863***	0.854***	0.867***	-0.019	0.009
N=721	(0.068)	(0.086)	(0.085)	(0.086)	(0.098)	(0.057)	(0.055)	(0.058)	(0.074)	(0.073)	(0.079)	(0.038)	(0.034)
Other Transp.	0.476***	0.453*	0.444**	0.447**	0.829***	0.817***	0.802***	0.798***	0.576	0.912	0.888	0.297	0.281
N=181	(0.128)	(0.232)	(0.208)	(0.220)	(0.204)	(0.143)	(0.149)	(0.138)	(1.511)	(0.800)	(0.809)	(0.238)	(0.190)
Furniture	0.189***	0.151***	0.150***	0.151***	0.904***	0.942***	0.939***	0.939***	0.913***	0.894***	0.896***	-0.026	-0.024
N=1,779	(0.036)	(0.013)	(0.012)	(0.012)	(0.049)	(0.041)	(0.041)	(0.039)	(0.033)	(0.030)	(0.031)	(0.017)	(0.014)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A2. Results in the Aggregate and by Plant Size (LP)

	β_k		β_l		s		γ	
	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2
All Plants	0.144***	0.144***	0.809***	0.809***	0.889***	0.888***	-0.004**	-0.002
N=57,477	(0.011)	(0.011)	(0.006)	(0.006)	(0.010)	(0.010)	(0.001)	(0.002)
Small	0.127***	0.127***	0.812***	0.812***	0.964***	0.963***	-0.004	-0.004
N=30,042	(0.020)	(0.020)	(0.007)	(0.007)	(0.013)	(0.013)	(0.003)	(0.003)
Medium	0.164***	0.164***	0.790***	0.790***	0.812***	0.814***	0.013***	0.014***
N=20,306	(0.013)	(0.013)	(0.011)	(0.011)	(0.014)	(0.014)	(0.003)	(0.003)
Large	0.149***	0.149***	0.724***	0.724***	0.671***	0.672***	0.009*	0.012**
N=7,129	(0.032)	(0.032)	(0.017)	(0.018)	(0.042)	(0.042)	(0.005)	(0.006)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A3. Results by Exporter (LP)

	β_k		β_l		s		γ	
	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2
No Exporter	0.144***	0.144***	0.811***	0.811***	0.917***	0.916***	-0.004*	-0.002
N=39,179	(0.014)	(0.014)	(0.008)	(0.008)	(0.013)	(0.013)	(0.002)	(0.002)
Exporter	0.142***	0.142***	0.806***	0.806***	0.815***	0.815***	0.000	-0.000
N=18,298	(0.021)	(0.021)	(0.010)	(0.010)	(0.017)	(0.017)	(0.003)	(0.003)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A4. Results by Area (LP)

	β_k		β_l		s		γ	
	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2	Bench1	Bench2
More densely pop	0.169***	0.169***	0.750***	0.750***	0.934***	0.934***	-0.001	-0.001
N=40,547	(0.023)	(0.023)	(0.014)	(0.014)	(0.021)	(0.021)	(0.003)	(0.004)
Less densely pop	0.131***	0.131***	0.835***	0.835***	0.872***	0.871***	-0.004*	-0.002
N=16,930	(0.010)	(0.010)	(0.006)	(0.006)	(0.010)	(0.011)	(0.002)	(0.002)

Notes: Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1