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Labor Demand Dynamics: the Costa Rican case

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Fotografía de portada: “Presentes”, conjunto escultórico en bronce del artista costarricense Fernando Calvo Sánchez, año 1983. Colección del Banco Central de Costa Rica.

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Photography on the title page: “Presentes” (*Present*), set of sculptures from the Costa Rican artist Fernando Calvo Sánchez, 1983. Collection of the Central Bank of Costa Rica.

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Abstract

This paper studies the determinants of the labor demand in Costa Rica using firm level data. It also characterizes formal employment during the last 15 years through a set of stylized facts. The results suggest that: (i) the neoclassical theory of employment holds, (ii) wages are a stronger determinant for labor demand in the manufacturing and construction industries, (iii) employment is more persistent in larger firms, (iv) larger and more technological industries adjust their headcount more heavily to changes in wages and revenue and (v) Costa Rican labor is more sensitive to changes in wages but less to changes in production than similar economies.

Key words: Labor demand, labor-output elasticity, labor-wage elasticity, job creation, unemployment.

JEL codes: C23, J21, J23.

Resumen

El presente documento estudia los determinantes de la demanda laboral de la economía costarricense utilizando datos a nivel de firma. Además, describe el empleo formal mediante un set de hechos estilizados. Los resultados sugieren que: (i) la teoría neoclásica del empleo se cumple, (ii) los salarios son un determinante más fuerte de la demanda laboral en la industrias manufactureras y de construcción, (iii) el empleo es más persistente en las firmas grandes, (iv) las firmas más grandes y tecnológicas ajustan en mayor medida su planilla ante cambios en salarios e ingresos y (v) la demanda laboral costarricense es más sensible a cambios en los salarios pero menos a cambios en la producción que la de economías similares.

Palabras clave: Demanda laboral, elasticidad empleo-producto, elasticidad empleo-salario, creación de empleo, desempleo.

Clasificación JEL.: C23, J21, J23.

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Labor Demand Dynamics: the Costa Rican case

1 Introduction

The Central Bank of Costa Rica's strategic plan, 2015 - 2019, considers as a goal the better understanding of its economic growth; within it, the characterization of the labor market stands as a strategic action. So far, this task had only been accomplished using aggregated data due to the lack of firm level data. The pending research questions that are part of this agenda can now be addressed thanks to the availability of the Economic Variables Registry (REVEC by its Spanish acronym). With this database, more precise estimations are possible.

This study employs the REVEC database to understand the dynamics of Costa Rica's labor demand and estimates the labor-wage and the labor-product elasticities for the whole economy and across industries. Reliable estimations for the aforementioned elasticities and for the time-adjustment of labor market determinants after shocks serve as valuable inputs for the economic policy design.

The purpose of this analysis is twofold. It will describe, for the first time using microdata, the employment of the Costa Rican formal economy and estimate the responsiveness of labor demand to changes in its determinants, specifically to revenues and wage shocks.

Also, it is known that labor markets of developed economies have been thoroughly studied, but evidence for emerging economies is scarce, mainly, as acknowledged by Hamermesh (1993), because of the limited availability of producer microdata in such economies. Therefore, the results of this work will also enhance the empirical literature discussion across countries.

Among the existing literature, theoretical tools such as the neoclassical principles about employment convey an inverse relationship between labor costs and employment: when the

costs increase, employment falls because of the decreasing marginal utility of labor. Key studies in this field, such as the ones developed by Hamermesh (1988) and Arellano and Bond (1991), find a strong relationship between firms sales and employment. Following suit, wages and revenues will be examined in this paper as the main determinants of labor demand due to data disposal.

Global labor markets have experienced a turbulent period in recent years as consequence of the financial crisis. Costa Rican employment was no exception. For this country, so far, the employment research has been done using survey data. Therefore, being able to use administrative data of the quasi-universe of formal constituted firms embodies a valuable opportunity of providing estimates which characterize the dynamics of employment and the effect of the Great Recession on the labor market. In this fashion, it is important to consider the aggregated employment behaviour by economic categories of interest to unveil the sectors of the economy with the highest growth and the ones that were more vulnerable to the crisis.

The document is organized as follows: Section two provides an empirical framework by reviewing the findings of literature on employment and labor demand determinants for developed and emerging economies. It is complemented by Section three which in the interest of clarifying the theoretical context of labor demand determinants, introduces the specification used for the labor demand function. Section four, describes the data base and Section five, explains the econometric methodology used in the estimations. For the characterization of employment and its fluctuations through time, Section six describes employment by economic activity, firm size, intensity in the use of technology and geography, to be followed by Section seven, which shows the estimated labor demand elasticities and the average time-adjustment to shocks over its determinants. Finally, Section eight concludes.

2 Literature Review

Even though empirical evidence is plentiful for developed economies, estimations for labor demand in emerging countries, specially in Latin American economies, has been limited primarily by the lack of microdata; therefore, most of the research has been developed using aggregated data such as national household surveys.

Among the scarce literature, [Stallings and Weller \(2001\)](#) published a set of stylized facts about employment in Latin American countries throughout the nineties which pointed out that during that decade the services sector, along with the Wholesale and Retail industry, were the largest contributors to employment growth (34.8% and 32.7% of total new employment). Agriculture industry was the only one that saw its employment diminished (-4.3%) in this span of time. For a similar time period, nineties and early two thousands, [Guerrero de Lizardi \(2007\)](#)¹ documents that Costa Rica had the highest growth in production and new jobs within the Central American region, but the lowest growth in wages.

Also, [Gonzalez Pandiella \(2016\)](#) acknowledges for the local economy the structural change of the region's employment presented in [Stallings and Weller \(2001\)](#), as he points out that the local employment has experienced an increased duality. This means, that it has polarized between a traditional and less productive sector comprising Agriculture, Manufacturing, Construction and Domestic Services and a highly productive sector including Services and high technology exports whose growth has been far higher than that of the primary sector.

By compiling approximately 70 studies on developed economies, [Hamermesh \(1993\)](#) found that the results of the wage elasticity of the demand for labor lied within the $[-0.750, -0.150]$ interval, supporting the neoclassical theory of employment. The author also points out that this elasticity decreases with the qualification of the employment. In other words, the more qualified the jobs, the less responsive their demand is to changes in wages. In his work, the author also argues that energy is a substitute input of labor, whereas capital is a complementary one, and technological changes are complementary specifically to qualified labor.

Compiling data for six OECD countries, the same author has found evidence for a positive product elasticity of the labor demand, lying within a range between $[0.030$ and $0.710]$. In a more recent effort, [Hamermesh \(2004\)](#), with data from Latin American economies, such as Barbados, Brasil, Chile, Colombia, Mexico, Peru and Uruguay, found labor-wage elasticities between $[-0.690$ and $-0.170]$.

Research from [Bencosme \(2008\)](#), [Melognio and Porrás \(2013\)](#) and [Rodríguez \(2013\)](#) also show relevant findings for Latin American economies. They have used diverse method-

¹Appendix J shows an updated estimation of the Okuns law model worked by [Guerrero de Lizardi \(2007\)](#).

ologies to estimate the labor demand for different levels of data aggregation; their results will be compared and discussed with this research's estimates. Bencosme (2008) found for the Dominican Republic a labor-wage elasticity of -0.215 and labor-product elasticities of 0.802 , 0.665 and 0.140 for different sample periods using industry level data from 1991 to 2006.² Melognio and Porras (2013) estimated Uruguay's labor demand using workers survey data with a vector error correction model.³ Their estimates for labor-wage elasticities lie between -0.110 and -0.320 and labor-product elasticities between 0.680 and 1.090 , being the dependent workers with less working hours the most responsive to changes in production.

Finally for Colombia, Rodriguez (2013) uses an annual firm survey from 2000 until 2013, to estimate the labor demand with a two-stage systematic generalized method of moments for three types of workers within the Manufacturing sector: the unqualified, the administrative and the professional workers.⁴ He found that the demand for unqualified workers takes the longest time, on average, to adjust when its determinants change (around 6.6 years, 4.8 for administrative staff and 3.0 for professional workers) and that the demand for professional workers is the most responsive to changes in wages. The estimated long run labor-wage elasticities were -3.120 , -0.808 and -1.013 and the labor-product elasticities were 0.816 , 0.880 and 0.668 for the unqualified, administrative and professional workers respectively.

Regarding research on Costa Rica's labor market, Monge (2012) and Alvarez (2018) estimated production functions for the local economy using household survey data.⁵ Both find that the local economy is labor intensive: Monge (2012) found a product-employment elasticity of 0.560 (0.580 considering human capital as a determinant) and Alvarez (2018) of 0.710 . Despite their work not developing an estimation of the labor demand, their findings show a significant relation between production and employment.

Also for Costa Rica, Guerrero de Lizardi (2007) estimated the labor demand sector with panel data by economic activity for the 2001-2004 period. With a linear state space model,

²Bencosme (2008) estimates a panel data via two-stage least squares, controlling for the real exchange rate. She has three sample periods: 1991-1995, 1996-1999 and 2000-2006. Her results imply that labor demand has turned less sensitive to changes in production through time.

³They analyzed four models, one per each type of worker: all workers, private sector workers, not independent workers and not independent workers with more than 30 hours labored weekly.

⁴Administrative workers are involved in managerial tasks and professional workers are the qualified workers not involved in managing.

⁵Both authors use the Multiple Purpose Household Survey (EHPM) carried out by the Statistics and Census National Institute (INEC).

he found a positive labor-wage elasticity of 0.341 (using minimum wage) and 0.547 (using private wages), and labor-product elasticities of 0.848 and 0.849 respectively. The only other estimate of labor demand for this country, besides this paper, was performed by the Latin American Economic Commission (CEPAL) in 2002,⁶ using data on GDP, employment and minimum wage. Their estimated labor-wage elasticity was 0.436 for a 1980-2004 sample and 0.907 for a 1991-2001 sample; while the labor-product elasticity was 0.719 and 0.400 respectively for the mentioned sample periods. Both estimations, Guerrero de Lizardi (2007) and Comisión Económica para América Latina y el Caribe (2002), of the labor-wage elasticity are inconsistent with the neoclassical theory of employment and the empirical evidence found in the literature.

Given the regional and national context, the remarkable effort made by the Macroeconomic Statistics Department of the Central Bank of Costa Rica through the compilation of firm level data allows for more precise and updated estimations of Costa Rica's labor market characteristics. The new research contributes to the empirical literature, and serves as relevant information for public policy recommendations. Also, the novelty and completeness of this data, will allow for further analysis that includes the dynamics and heterogeneity of labor demand such as economic activity, firm size and technology use.

3 Analytical framework

The *labor demand*, in this research, will follow the general definition stated by Hamermesh (1993) who delineates it as any decision taken by the employers concerning the headcount of the firm. The author argues that an appropriate way to obtain the labor demand is to start with a cost function that, as usual, depends on the factor's production costs. In what follows, it will be assumed that production is solely determined by labor and capital, with capital being fixed in the short run. This implies that the cost structure has a quasi fixed component, and as Schankerman and Nadiri (1984) suggest, a transformation function that connects the production (y) with a set of n variable inputs ($x = \{x_1, x_2, \dots, x_n\}$) and a set of m fixed inputs ($z = \{z_1, z_2, \dots, z_m\}$) can be expressed as $T(y, x, z) = 0$. Then, according to Lau (1976), if $T(y, x, z) = 0$ satisfies a series of regularity conditions and the

⁶The estimations made by Comisión Económica para América Latina y el Caribe (2002) for Central American countries can be found in Appendix A.

firm is trying to minimize the variable costs of employment, then cost can be expressed as a function of production (Y), fixed inputs (K) and variable costs (w):

$$C = C(w, Y, K), \quad \text{where :} \quad (3.1)$$

$$C_i > 0, \quad i = w, Y, K$$

On the other hand, Shephard's lemma shows that if a cost function is quasiconcave, the conditioned demand of one of its inputs can be obtained through the partial derivative of the cost function with respect of the cost of the input of interest.⁷ For example, the application of Shephard's lemma to equation 3.1 results in an expression for the demand for labor L^d :

$$L^d = \frac{\partial C(w, Y, K)}{\partial w} \quad (3.3)$$

It is important to notice that hiring in a firm has a lag; is not adjusted immediately after a shock due to restrictions in the hiring of new workers or due to the costs implied in firing existing workers. Job stability policies and training may also generate frictions during the headcount adjustment process. Arango and Rojas (2003) point that a convenient way of modelling the degree of this adjustment process is to add lags to the specification of labor demand. As it is known, at all times, the firm tries to maximize its profits. Thus, the optimality is achieved by maximizing the profit function. For a discrete-time model, Gould (1968) defines the optimal adjustment of a productive input, when the price of the product does not depend on time, by multiplying the gap, between the optimal employment level (L^*) and the first lag of its actual value, by its rate of adjustment, γ :

$$\dot{L}_t = \gamma(L^* - L_{t-1}) \quad (3.4)$$

By substituting the optimal employment level with a particular function in terms of a set of determinants X_t , where $(w_t, K_t, Y_t) \in X_t$, equation 3.5 is reached:

⁷More on Shephard's lemma can be found in Jehle (2001)

$$\dot{L}_t = \gamma(G(X_t) - L_{t-1}) \quad (3.5)$$

Arango and Rojas (2003) point out that if the function $G(X_t)$ is linear and its determinants do not depend on the labor demand, the expression 3.5 can be stated as:

$$L_t = \alpha L_{t-1} + \beta X_t + \epsilon_t \quad (3.6)$$

Where ϵ is an error term. Also, they argue that for its estimation it is necessary to assume that firms have static expectations; this implies that their hiring decisions only depend upon the contemporary determinants. They suggest to follow instead the model developed in Sargent (1978), as it similarly depends on the lags and future stock of the M determinants:

$$L_t = \alpha L_{t-1} + \sum_{m=1}^M \sum_{i=-\infty}^{\infty} \mu_{m,i} E_t(X_{m,t+i}) + \epsilon_t \quad (3.7)$$

where $\mu_{m,i}$ is the corresponding elasticity associated to determinant m lagged i periods (or i periods ahead). Keeping in mind that only past data is known, a convenient model to estimate labor demand is the following:

$$L_t = \alpha L_{t-1} + \sum_{m=1}^M \sum_{i=0}^N \mu_{m,i} X_{m,t-i} + \epsilon_t \quad (3.8)$$

where M denotes the amount of employment determinants and N their correspondent significant lags. Equation 3.9 is the optimal specification adopted in this research. For it, as stated by Esperança et al. (2011), the short run labor elasticity associated to shocks on the variable X_m in period i , is given by:

$$\mu_m^{SR} = \frac{\partial L_{i,t}}{\partial X_{i,t+i}} \quad (3.9)$$

The long run elasticity can be computed when considering the cumulative effect of a shock in X_m during t . Thus, if $|\alpha| < 1$:

$$\mu_m^{LR} = \sum_{i=0}^{\infty} \frac{\partial L_{i,t}}{\partial X_{i,t-j}} = \left(\sum_{i=0}^N \mu_{m,t-i} \right) \left(\frac{1}{1-\alpha} \right) \quad (3.10)$$

Finally, the average time that firms last adjusting their employment decisions after a change in their determinants, given by t^* which is the number of periods where the gap between the employment before the shock and the optimal employment decision after the shock is closed, will be approximated following Hamermesh (2004, p.558). For models with a single dependent variable, the author estimates the speed as the number of time periods “for half the gap between old and new equilibria to be traversed”. In these models with a lagged dependent variable this number is $t^* = \frac{\ln(0,5)}{\ln(\alpha)}$.

Hamermesh (1993) mentions that for small firms subject to a perfectly elastic labor supply, wage can be considered as a variable that will not be affected by individual firms. In this scenario, estimations for labor-wage elasticities allow to infer over exogenous changes in the wage observed by firms and over their labor demand. Despite the above, it is worth noting that the estimations validity may be affected by the influence firms may have in the labor market.

4 Data

This research makes use of the REVEC database, which is constructed by the BCCR and uses inputs from several institutional sources of Costa Rica. The two most important sources of information are the Treasury Ministry and the Social Security Fund (CCSS). Specifically, the former collects annual data on income and expenditure per firm and the latter monthly data on employment, which is averaged over the calendar year.

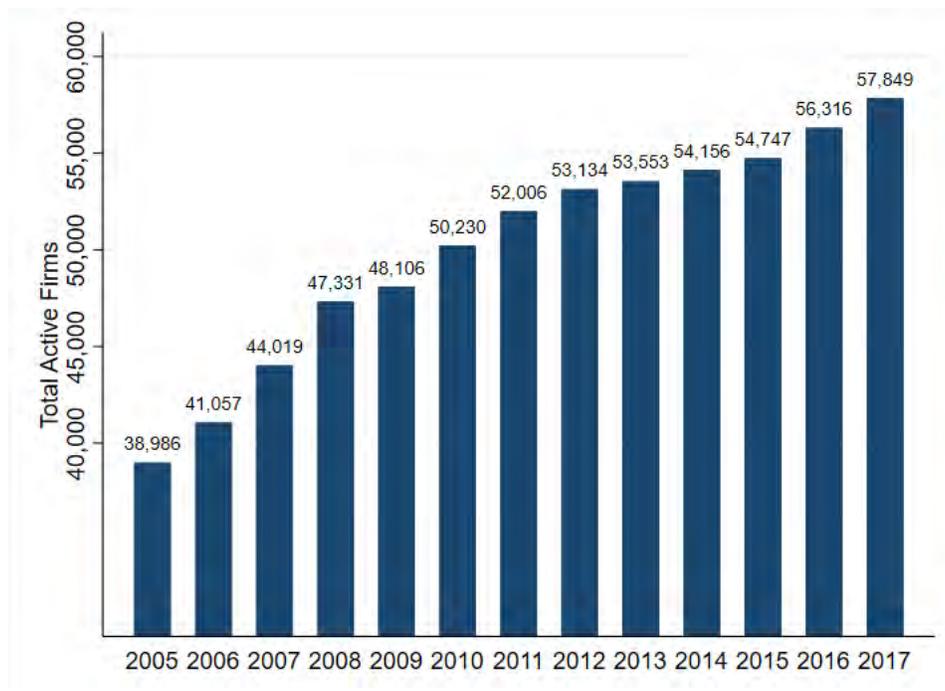
Formal constituted firms, including independent professionals that carry out formal economic activities, are obliged to register in the Treasury’s Single Taxpayers Registry, in which they inform their economic activity, income, expenditure, imports, exports and other information such as the location of their establishments.⁸ Given the firm’s identifica-

⁸This information is updated annually through the Sworn Income Tax Declaration form.

tion number a match is made with the employment data collected by CCSS, resulting in a longitudinal database with the most desirable characteristics for research on Costa Rica’s labor market.

In the aggregate, REVEC has annual data, from 2005 until 2017, for 237.057 firms from the formal sector.⁹ A firm is included in REVEC if it reported one (or more) employee(s) in at least one month during the time span. The number of active firms has increased uninterruptedly, from 38,986 in 2005 to 57,849 in 2017. Most of them, 62%, have an average between one to five employees, and approximately 2.7% have more than 100 employees. Finally, given their legal nature, out of the total firms, 60.1% (142,470) had a personal identification number.¹⁰

Figure 1: Active firms, 2005-2017



Source: own elaboration.

As stated in the analytical framework, the model characterizing the labor demand will include as independent variables: wages, capital stock and revenue. Also, and in absence

⁹In the database, employment is also accounted for if a firm is associated with an individual using his personal identification to conduct business.

¹⁰The others have a legal-person identification number.

of a variable for the level of production, income is used as proxy. Other variables such as customs regime and industry type are considered as controls. Table 1 gives a more detailed description of these variables.

Table 1: REVEC's variables of interest description

Variable	Description	Detail	Source
Employment	Firm's headcount	Firms average headcount during a year.	CCSS
Revenue	Declared income in tax form.	Annual cumulative in colones	Ministry of Treasury
Wages	Total labor costs	Annual cumulative in colones	CCSS
Capital	Reported value of fixed assets	Total value in colones	Ministry of Treasury
Customs Regime	Type of regime (Definitive, Special or Free Zone)	Cathegorical Variable	Ministry of Treasury
Industry	ISIC Categorization	4-digit classification	Ministry of Treasury

Source: own elaboration.

Additionally, variables are expressed in real terms; revenue and capital (fixed assets) are deflated with the implicit price index estimated by BCCR, while for wages, the consumer price index is used. In sum, the variables considered for the estimations are:

- Wages ($w_{i,t}$): natural logarithm of the arithmetic mean of annual real wages of firm i on year t .
- Capital ($k_{i,t}$): natural logarithm of deflated fixed assets of firm i on year t .
- Product ($Y_{i,t}$): natural logarithm of real income of firm i on year t .
- Employment ($\eta_{i,t}$): natural logarithm of the average headcount on year t of firm i .

5 Empirical Methodology

As mentioned in section 2, most estimations of labor demand elasticities for the local economy have been developed with cross-sectional data. Kuh (1959) had stated as limitations of the inferences from those estimations the structural incompleteness of data itself and the absence of an autoregressive component. Moreover, Arango and Rojas (2003) warned about the use of establishment level (instead of firm level data), as it implies an assumption

of optimality in the investment decisions of establishments, which is not necessarily the practice of business groups.

A linear model that depends on the production, the wages and a firm's capital as determinants for labor demand is adopted for this research. Given the considerations made in section 3 and the frequency of the available data, the model will also include lags of the variables production and wages. Specifically,¹¹

$$L_{i,t} = \alpha\eta_{i,t-1} + \sigma_0w_{(i,t)} + \sigma_1w_{(i,t-1)} + \epsilon_0Y_{(i,t)} + \epsilon_1Y_{(i,t-1)} + \phi K_{(i,t)} + T + u_{it} \quad (3.1)$$

Where $L_{i,t}$, $w_{i,t}$, $Y_{i,t}$ and $K_{i,t}$ denote the natural logarithm of the average headcount of employees, wages, revenue and fixed assets, working at the firm i in period t , respectively. The error term, $u_{i,t}$, is a stochastic shock over firm's i demand for labor in time t , while T is a control variable for time. The coefficients σ , ϵ and ϕ , represent the labor elasticity of their respective determinant.

Different empirical approaches used in the literature were considered. For example, [Nickell \(1981\)](#) and [Baltagi \(2008\)](#) mention that dynamic models such as this, have a temporal correlation and thus a severe bias if estimated through ordinary least squares. Even, the first difference estimator will be biased, as stated by [Anderson and Hsiao \(1982\)](#), because of the moving average model attained; still, it could be amended by including instrumental variables.

Subsequently, [Arellano and Bond \(1991\)](#), despite pointing that the Anderson-Hsiao estimator is consistent, argue that the instrumental variable approach does not take full advantage of the information in the sample as it does not account for all the potential orthogonality conditions. They affirm that through the Generalized Method of Moments (GMM) more efficient estimators can be attained, as long as internal instruments are included. Within the possible instruments, [Arellano and Bover \(1995\)](#) and [Blundell and Bond \(1998\)](#), note that the lags of the variables at levels perform poorly for the difference of the variable, so they recommend adding the lags of the differences of the variable as additional instruments. Comprising these considerations, [Arellano and Bover \(1995\)](#) argue that the Difference and System GMM's are the best estimators designed for models with

¹¹As will be discussed on section 7, after a general-to-specific modelling approach, a model with just one lag of the commented explanatory variables was chosen.

the following characteristics:

- data with few periods but many individuals,
- a linear econometric specification,
- a dynamic dependent variable,
- individual fixed effects, and
- independent variables that are not completely exogenous, meaning that they may be correlated with contemporary or past realizations of the error term.

Within this literature, there is another criterion that should be pondered. Nickell (1981) states that the estimated results from fixed effects for the autoregressive parameter in a dynamic model with the characteristics mentioned above, is upward biased. Hsiao (2014), on the other hand, argues that it is downward biased when estimated with ordinary least squares (OLS). Thus, the unbiased estimator for α should be bounded by the fixed effects and OLS estimators accordingly. Subsequently, Bond et al. (2001) suggest that if the Difference-GMM estimator for the autoregressive parameter is less than, or close to the fixed effects estimator, then, one may infer, that the System-GMM is highly preferred on behalf of efficiency.

Finally, the characteristics of REVEC allow for heterogeneity analysis on economic activity, technology use and firm size at birth. For the first, a twenty economic categories classification from the Uniform Industrial International Classification (ISIC) up to 4 digits is used. For the second, a categorization of four levels according to the intensity usage of technology is defined using the OECD criteria. And for the third, the firm size at birth, the Ministry of Industry, Economy and Trade's methodology is applied.¹²

¹²For a more detailed explanation on the MEIC and OECD industry classification methodologies on intensity in the use of technology and firm size, refer to appendix C

6 Stylized facts

6.1 Firm analysis

Costa Rica has experienced significant change in the composition of its economy during the last two decades. After the economic crisis experienced during the eighties, the economy shifted its productive model by diversifying the exports of goods and services. Since then, the tertiary sector has gained importance progressively, at the expense of the Agriculture and Manufacturing sectors which were affected the most; while the share of the number of firms in the Services industry has gone from 54.21% in 2005 to 60.29% in 2017, the share of agricultural firms decreased from 10.64% in 2005 to 6.83% in 2017, and the manufacturing share, went from 9.61% in 2005 to 7.27% in 2017, as showed in Table 2.

Table 2: Firm's composition by sector, 2005 and 2017

	2005	2017
Agriculture	10.64	6.83
Manufacturing	9.61	7.27
Wholesale and Retail	25.54	25.61
Services	54.21	60.29
Accommodation and Food Services	8.66	9.19
Professional, Scientific and Technical	7.21	8.64
Construction	6.29	5.72
Other Services	5.61	6.82
Transportation and Storage	5.30	6.09
Administrative and Support Services	4.24	5.03
Human Health and Social Work	3.41	4.49
Real Estate	3.23	3.27
Education	2.62	3.27
Information and Communication	1.60	1.99
Financial Activities	2.05	1.80
Art and Entertainment	1.36	1.55
Water Supply and Waste Management	0.80	1.03
Other Activities	0.98	0.70
Public Administration	0.46	0.35
Diplomatic Activities	0.23	0.21
Electricity and Gas	0.16	0.14

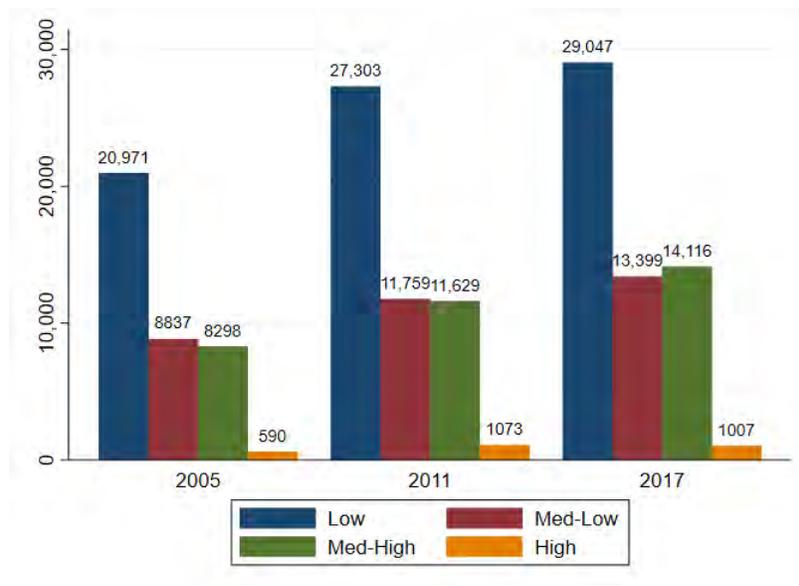
Source: own elaboration

Within these sectors, the economic activities which had a larger variation in the number of active firms (at the 4-digit ISIC aggregation), from 2005 until 2017, included restaurants, personal services activities, retail sale of food and beverages, and other food services. Firms from the information technology and computer services (376% increase in active

firms), electrical installation services (251%) and medical laboratories (222%) experienced a similar trend.¹³

In terms of technology usage, a significant fraction has turned to be high-technology with high-employment; they have almost doubled during this time span, signalling that the economy has transitioned to more technological-intense industries. Firms classified with low intensity were 54.2% of total firms in 2005, 52.7% in 2011 and 50,0% in 2017; meanwhile the ones with medium-high intensity, such as engineering and electric equipment manufacturing companies, have increased their share of total firms since 2005.

Figure 2: Active firms by their use of technology, 2005-2017



Source: own elaboration.

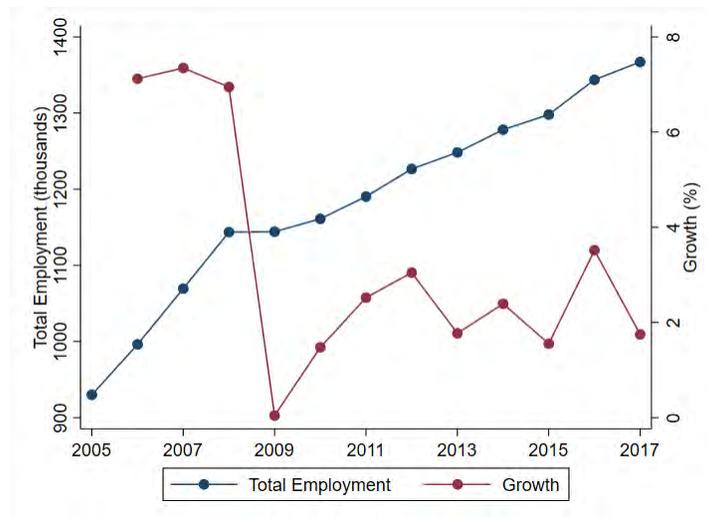
6.2 Employment analysis

According to the data recorded in REVEC, total employment increased 47% between 2005 and 2017, but not uniformly. The international financial crisis can be interpreted as a

¹³Appendix D shows the business groups with the highest gains and losses in terms of active firms between 2005 and 2017. In general, activities of less qualified work had the largest decreases. For example, the number of firms involved in the cultivation of plants used to prepare beverages and other non-perennial plants, decreased in 399 firms.

structural change for growth of employment. Before, from 2005 until 2008, its average growth was 7.15%, in 2009 it grew 0.04%, and afterwards, from 2010 until 2017, its average growth rate was 2.25%. Figure 3 shows employment level and year over year variations, while more detailed descriptions can be found in appendix E.

Figure 3: Employment level and growth, year over year variation, 2005-2017



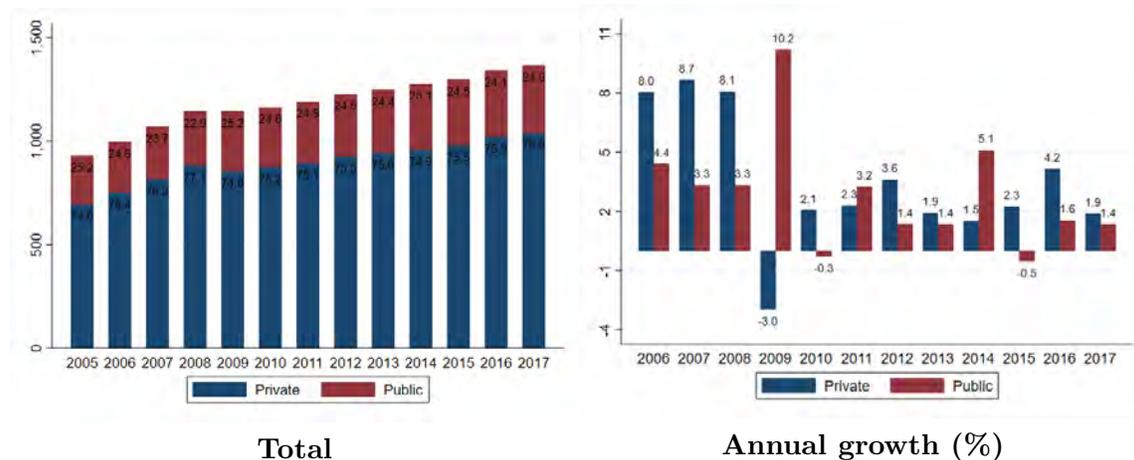
Source: own elaboration.

In Costa Rica, employment within the public sector has represented a quarter of total formal employment, approximately, for the past decade; between 2005 and 2008, it was 24.1% on average, and between 2009 and 2017 it was 24.6%. When comparing its behaviour to employment within the private sector, they seem contrasting most of the time as shown in the right chart of Figure 4. For example, as response to the negative impact on growth from the financial crisis, the Arias-Sánchez administration implemented a fiscal policy expansion which included a substantial and immediate increase in public employment, while the private employment suffered a significant contraction in 2009. For this year, public employment increased 10.2%, year over year, and the private employment decreased 3.0%.

Despite these differences, employment in both sectors have a common trait: after 2009 none of them has reached half the average growth rates experienced before the crisis: for the private employment it has gone from 8.3% for 2006-2008, to 2.5% after 2010, and for

public employment, from 3.7% to 1.7%.

Figure 4: Total employment and growth rates for public and private sector, 2005-2017



Source: own elaboration.

As in firms composition, most employment comes from the services industry with a clear upward trend. Whilst in 2005, 55.25% of total employees worked for a firm of Services, or as an independent workers within it, in 2017 its share was 59.99%. As suggested by Gonzalez Pandiella (2016), this happened at the cost of employment in industries with predominantly less qualified labor, such as Agriculture and Manufacturing. This duality is clear when comparing Agriculture with firms in the Professional, Scientific and Technical industry, Information and Communications and specially in the Administrative and Support Services.

Two other relevant industries in terms of employment are Public Administration¹⁴ and Wholesale and Retail, which as seen in table 3 represent 13.57% and 14.73% of total employment, in 2017, respectively¹⁵. Together, they account for more than a quarter of total labor, and their share has not changed significantly through time.

¹⁴Public Administration sector includes all business groups undertaking managing duties and comprehends a subset of the previously described public sector.

¹⁵Sectors that did not account for more than 1% of total employment in 2017 were not included. Thus, Real Estate, Arts and Entertainment, Water Supply and Waste Management, Diplomatic Activities and Others are not presented in table 3

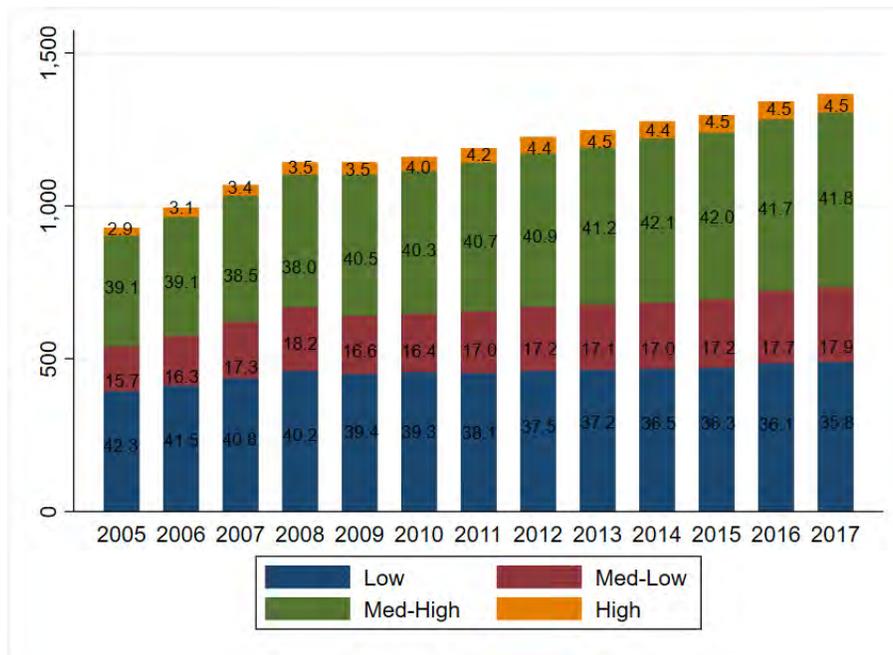
Table 3: Total employment per sector, 2005-2017 (shares in parenthesis)

Industry	2005	2011	2017
Public Administration	130,036 (13.98)	156,972 (13.19)	185,576 (13.57)
Wholesale and Retail	129,279 (13.90)	171,806 (14.43)	201,410 (14.73)
Manufacturing	120,291 (12.93)	137,526 (11.55)	144,874 (10.60)
Agriculture	102,235 (10.99)	102,943 (8.65)	104,402 (7.64)
Other Services	75,406 (8.11)	77,685 (6.53)	81,294 (5.95)
Administrative and Support Services	53,794 (5.78)	110,714 (9.30)	141,238 (10.33)
Human Health and Social Work	51,613 (5.55)	70,408 (5.91)	81,843 (5.99)
Accommodation and Food Services	39,312 (4.23)	52,481 (4.41)	62,560 (4.58)
Financial Activities	37,993 (4.09)	47,346 (3.98)	55,078 (4.03)
Education	34,464 (3.71)	51,253 (4.31)	60,834 (4.45)
Professional, Scientific and Technical	32,112 (3.45)	45,142 (3.79)	59,053 (4.32)
Transportation and Storage	30,516 (3.28)	40,373 (3.39)	50,309 (3.68)
Construction	29,261 (3.15)	38,868 (3.27)	49,165 (3.60)
Electricity and Gas	20,294 (2.18)	32,031 (2.69)	23,414 (1.71)
Information and Communication	12,587 (1.35)	20,486 (1.72)	28,953 (2.12)

Source: Own elaboration

The economy's increasing duality is evidenced by the changes in employment distribution given the intensity in the use of technology as shown in figure 5. Even when employment has increased in all categories of technology usage, total employment composition has changed in favor of technology intensive industries. In 2005, for example, 42.3% of total employment came from low-tech industries, but in 2017 35.8% did. Employment in medium-low and medium-high technology usage cover more than half of the total, and have increased almost 5% their proportion within these years. Meanwhile, high-intensive tech employment has more than doubled, but still represents a small share of total employment.

Figure 5: Employment distribution given the use of technology, 2005-2017 (headcount in thousands)



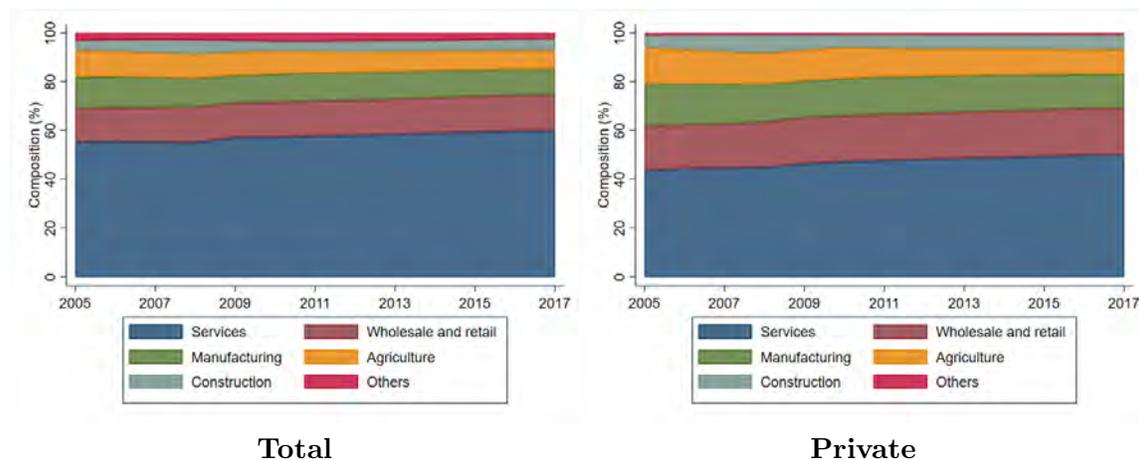
Note: labels inside bars show to the employment share of the respective category.

Source: own elaboration.

Most of manufacturing and agricultural activities are categorized as low-tech industries. As expected, their share of total employment has reduced at the expense of employment in Services, which accounts for most of employment in the tech-intensive firms. As evidenced in figure 6, which shows employment composition through time for total and private employment, the share of private total employment in Agriculture and Manufacturing di-

minished from 11.0% and 17.3% in 2005 to 10.0% and 13.9% in 2017 respectively. On the other hand, private employment in the Services industry increased its share from 43.6% to 50.0% during the same period. Thus, there has been a clear change in employment composition in favor of the Services sector that strengthened in 2009 and that has been driven specially by the private sector.

Figure 6: Employment composition by industry, 2005-2017



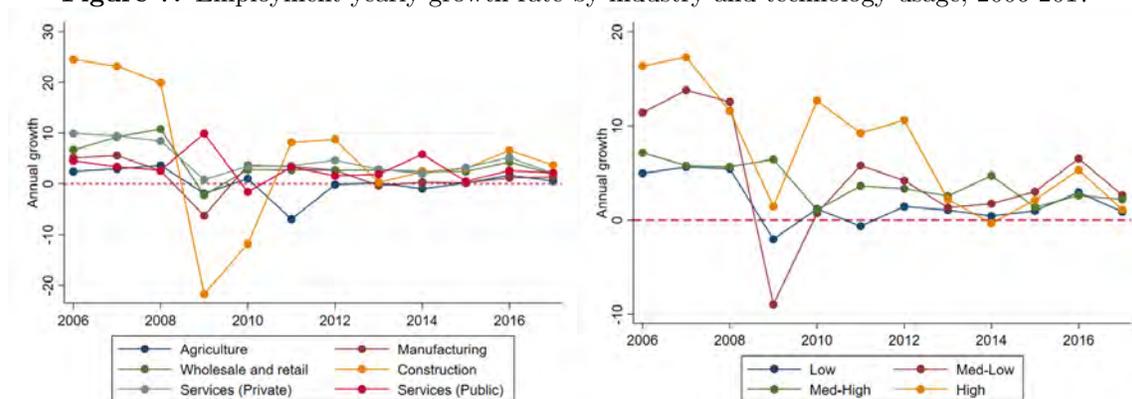
Source: own elaboration.

During this time, growth has been heterogeneous among industries. For the Construction sector, the financial crisis had a deep impact; before 2009 its employment grew above 20% annually, but afterwards, in 2010, it decreased 21.8%.

As shown in figure 7, employment was also lessened in sectors as Wholesale and Retail, Manufacturing and Agriculture, which are low-tech and med-low technology intensive industries, as there were 14,412 net job losses.¹⁶ However, in the overall employment of the economy, there was a positive change in 2009 explained by the expansionary fiscal policy: public services employment grew 9.9%, when its average growth rate was of 3% prior to 2009. After the crisis, employment growth rates in the main industries were higher but still, lower than half their growth rates before it. Construction, for example, recovered slightly after 2010 and had considerable boost in 2016.

¹⁶As explained in appendix C, most of construction and manufacturing firms are classified as med-low tech firms, and agricultural firms as low-tech.

Figure 7: Employment yearly growth rate by industry and technology usage, 2006-2017



Industry

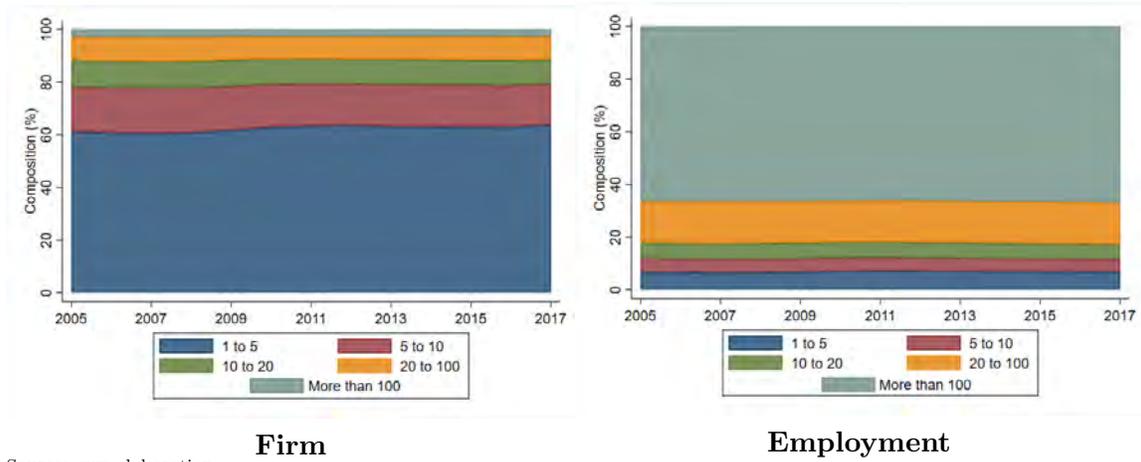
Intensity in the use of technology

Source: own elaboration.

As shown by Criscuolo et al. (2014), the majority of firms in OECD countries have less than 10 employees, approximately 80% of total firms in Italy, Finland, New Zealand, Spain, Hungary and the Netherlands. In Costa Rica, in 2005, 78.16% of active firms had between one and ten employees, and for the year 2017 a 79.30% of total did. Meanwhile, firms with more than 100 workers have been 2.7% on average. Even when their percentage is low, given the total number of firms, 66.5% of workers in the private sector, on average, pertain to firms with more than 100 employees. Smaller firms account only for 6.8% of the employment. As seen in figure 8, composition of firms have changed slightly in favor of smallest firms, opposite to what has happened to employment composition by firm size.

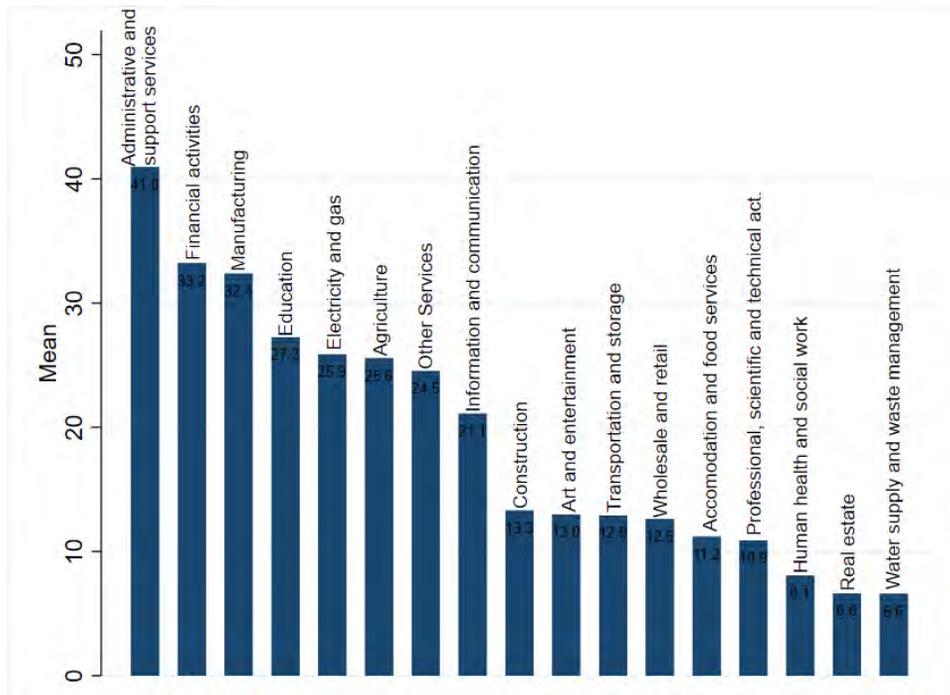
Considering the average number of workers per firm within the private sector, as shown in Figure 9, Administrative and Support Services show the highest average headcount at 41. This industry, considers firms in activities such as security services, travel agencies, building cleaning services and other human resources, and call centers. The latter has an average of 273 employees, which explain the category headcount mean. Appendix F shows that this mean has not changed significantly over time. Finally, appendix K compares REVEC and Employment Continuous Survey (ECE) formal employment aggregates.

Figure 8: Firm and employment composition by headcount in the private sector, 2005-2017



Source: own elaboration.

Figure 9: Employment mean by industry within the private sector (2005-2017)



Source: own elaboration.

6.3 Job creation and destruction

Harmonized panel data from firm registers allow to separate net job creation into job creation and destruction indicators. Following Criscuolo et al. (2014), gross job creation in a specific year t can be quantified as the sum of all positive variations ($\Delta E_{i,t}^+$) in firms headcount from year $t - 1$ to year t :

$$GJC_t = \sum_i^N \Delta E_{i,t}^+ \quad (6.3.1)$$

Similarly, job destruction can be gauged as the absolute value of the sum of the negative variations in headcount, i.e. $|\Delta E_{i,t}^-|$:

$$GJD_t = \sum_i^N |\Delta E_{i,t}^-| \quad (6.3.2)$$

Finally, net job creation is the difference between job creation and job destruction:

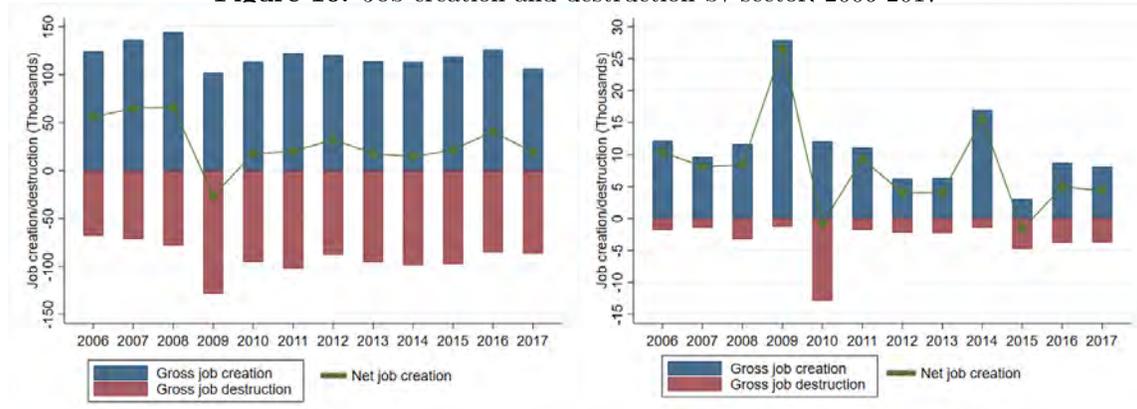
$$NJC_t = GJC_t - GJD_t \quad (6.3.3)$$

As discussed before, net job creation has differed for the private and public sectors. Private gross job creation grew at rates of 10% in 2007 and 5.7% in 2008, but shrank 29.2% in 2009. The opposite happened in the public sector during 2009. As consequence of the expansionary fiscal policy, job creation had a year over year change of 140.2%, going from 11,635 gross jobs created in 2008 to 27,941 in 2009.

After 2009 private employment has experienced a positive net growth, but it has been lower than the net growth rate it had before the crisis. Figure 10 shows that the net job creation (private job creation to destruction ratio) has remained quite stable since 2010 for the private sector. On the contrary, employment in the public sector has been more volatile. For example, Figure 10 shows how immediately in 2010 public gross job destruction increased by 890.8%, and how in 2014, public job creation almost three folded with respect to the prior year.

It is relevant to consider that the gross figures showed in Figure 10 take into account the contribution of exiting firms in job destruction and entering firms for job creation. However, most of job creation and destruction happens in incumbent firms, thus it is

Figure 10: Job creation and destruction by sector, 2006-2017



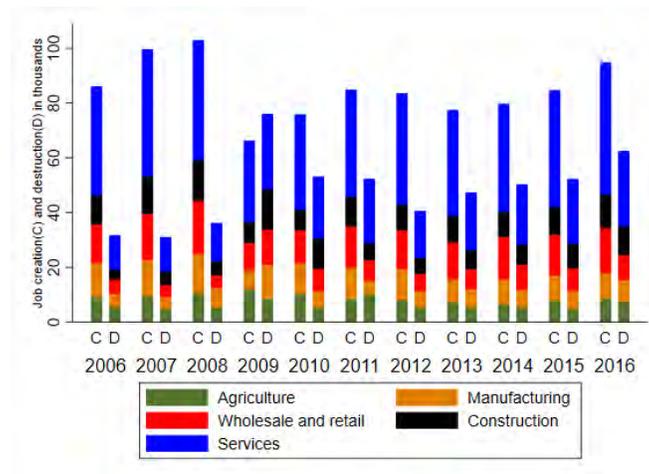
Private

Public

Source: own elaboration.

necessary to extend this analysis for incumbent firms only. Figure 11 displays job creation and destruction from incumbent firms in the private sector for five industries. It shows a high degree of job rotation implied in the high job destruction figures. It also shows, how Construction was the most badly affected sector by the financial crisis given the amount of dismissed positions. This outcome, also implies an increase in job losses for med-low tech firms.

Figure 11: Private incumbent firms: job creation and destruction by industry, 2006-2016

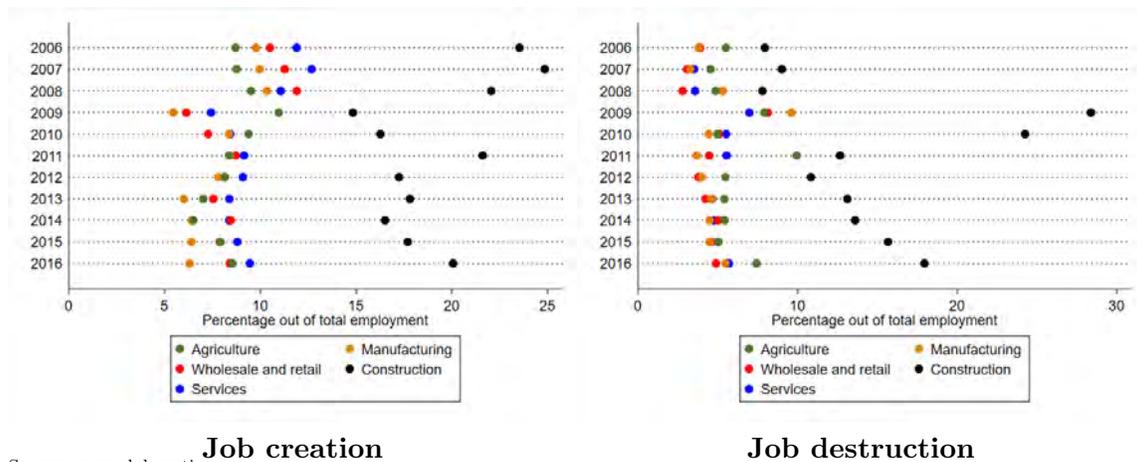


Note: Employment from firms classified in “Other Industries” is not accounted for in the industries graph.

Source: own elaboration.

Employment in the Construction industry is far more volatile than in the rest of industries. Job destruction in incumbent construction firms represented during 2009 a 28.4% of its total employment, substantially higher than the 7.9%, 9.6%, 8.0% and 4.2% in Agriculture, Manufacturing, Wholesale and Retail and Services industries respectively. However, despite this figure being comparably high, this was not a particular phenomenon for 2009, as seen in Figure 12, the percentage that the job creation and destruction represent out of total employment for this industry is significantly higher than for the rest of sectors.

Figure 12: Percentage of job creation and destruction out of total employment by industry, 2006-2016



Source: own elaboration.

For Agriculture, an average of 80.2% of new jobs are created by incumbent firms, and for Manufacturing the share is of 83.9%. Services and Wholesale and Retail follow with a 70.3% and 70.0 % respectively.¹⁷ However, a considerably higher fraction of new employment in construction is created by new firms, making the indicator substantially lower at 62.9%. On the other hand, the share of incumbent firms in total job destruction is also high in the construction industry (averaging 60.3% of total job destruction). Manufacturing incumbent firms also contribute considerably to job destruction, with a 66.5% of total. Wholesale and Retail (56.7%) and Agriculture (54.4%) follow. This share is considerably lower for the Services industry (43.6%).

From this evidence, there are three remarks to be made. First, job destruction in the most technology intensive firms has been strongly surpassed by job creation, and thus

¹⁷Refer to appendix G for detailed graphs.

its employment has experienced a larger growth than the employment of low-tech firms. Second, job rotation is linked to economic cycles in all industries, but more evidently in construction firms. And third, most of the new jobs come from incumbent firms, specially in less qualified industries such as Agriculture and Manufacturing, while incumbent firms in industries related to more qualified jobs contribute less to job destruction than industries related to less qualified employment.

6.4 Wages and revenue in the private sector

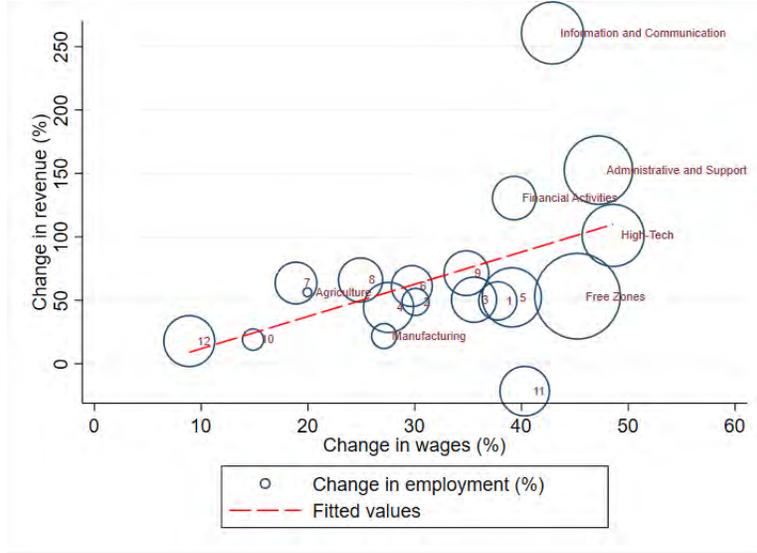
Kapsos (2006) and Khan et al. (2007) show empirical evidence of the positive relationship between production and total employment in several economies, on this line, for Costa Rica, Figure 13 depicts the percentage change of average wages, total employment and revenue by categories from 2005 until 2017. Employment growth was higher the more intensively used is the technology in that sector: high-tech employment grew 133%, med-high employment 85.8%, med-low 69.7% and employment in low-tech firms just a 24.2%. As seen earlier in this section, and detailed in appendix C, high-technology firms include those that develop activities such as pharmaceutical, electronic and medical devices manufacturing, which despite having a substantial growth during the last decade still hire a small share of the workforce. On the other hand, employment in industries such as Information and Communication (132.9%) and Administrative and Support Services (162.2%), which are classified as medium-high tech intensive firms, have had the largest growth by the 4-digit ISIC industries aggregation. Contrarily, employment in Agriculture (2.1%), Manufacturing (20.4%) and Art and Entertainment (14.6%) had the smallest growth rate.

For the Costa Rican data, there is evidence of a high and positive correlation between income and wages: larger income growth apparently translates into a larger average of wages growth. Within them, high-technology firms show the highest growth in both, influenced by growth in financial and information, and communication activities. On the contrary, firms with the lowest technology intensity had the lowest growth in revenue and wages. On average, wages in agricultural firms, for example, grew less than half than those in high-technology firms, and firms in the educational field, which are among the lowest income-growth activities, had the smallest average wages growth.

Within the financial and information and communication industries, businesses such as computer programming (108.6%), insurance brokers (183.2%) and financial leasing (141%)

experienced the largest growth in average wages among high employing industries. The former was the activity with the largest revenue growth: 568% in programming related activities. Contrarily, private college (-42.5%), high school(-26.8%) and primary (-13.8%) education centers experienced a substantial contraction in average wages.

Figure 13: Average wages, total income and total employment changes from 2005 to 2017

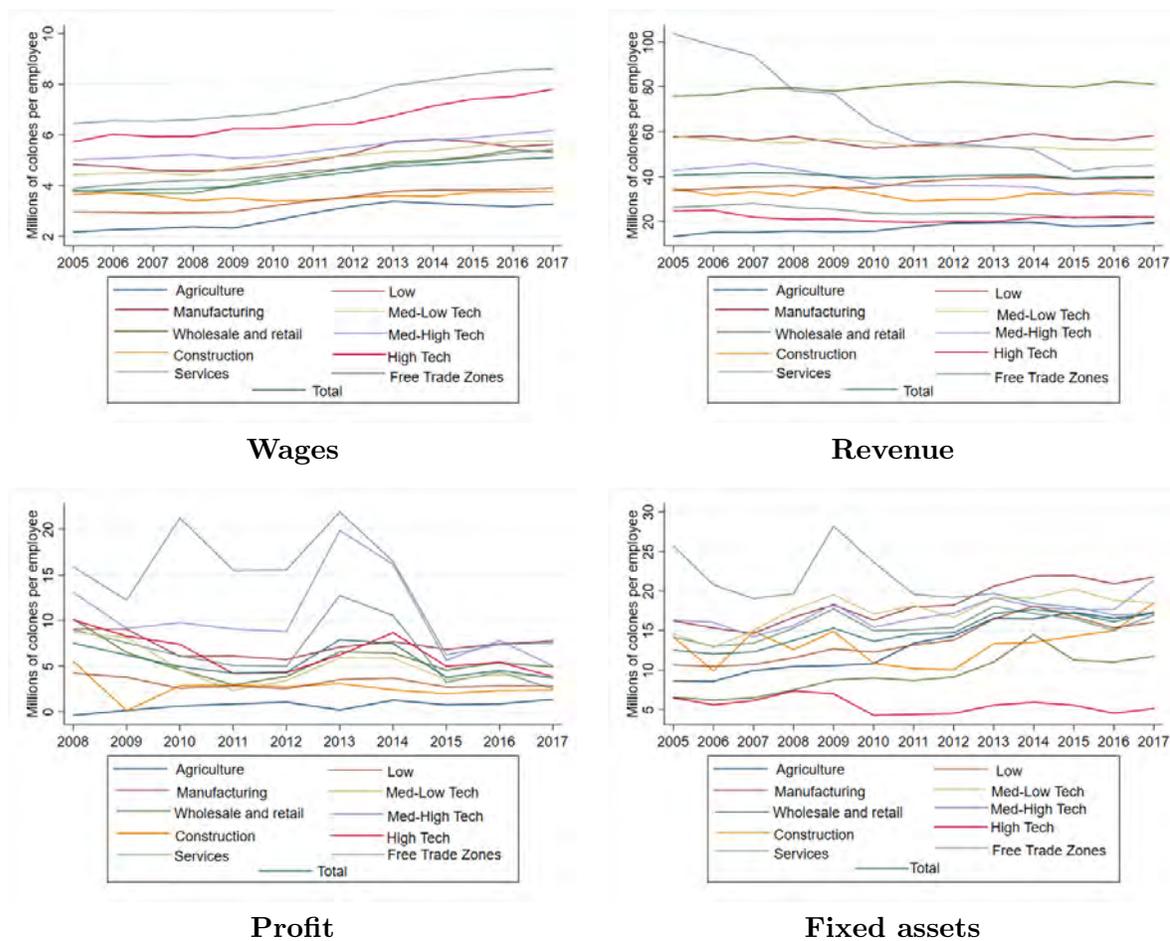


1.Total, 2.Low-Tech, 3.Med-Low Tech, 4.Med-High Tech, 5. Human Health and Social Work, 6.Wholesale and Retail, 7.Accommodation and food services, 8.Transportation and Storage, 9.Construction, 10.Art and Entertainment, 11.Professional, Scientific and Technical, 12.Education.
Source: own elaboration.

Figure 14 shows wages, revenue, profit and fixed assets per employee in the private sector. It exhibits that high-tech firms' average wage more than doubles that of the low-tech firms. However, this does not translate into absolute higher profits, as the most profitable businesses are related to finance and insurance, which are classified as medium-high tech firms. In terms of profits,¹⁸ services and manufacturing have a high return, and low-tech firms are less profitable, specially agricultural firms which in certain years even had losses. Finally, fixed assets per employee are inversely proportional to the intensity in the use of technology.

¹⁸Defined as total revenue minus total expenses.

Figure 14: Annual average wages, income, profit and fixed assets per employee, 2005-2017



Source: own elaboration.

Employment in Free Trade Zones (FTZ's) has increased from a 28,339 headcount (3.0% of total employment) in 2005 to 100,034 (7.3%) in 2017. While the number of firms increased from 137 to 313. In general, these firms' indicators such as revenue, wages and employment growth rates, have a higher and more volatile behaviour than the rest of the economy.¹⁹ They also pay the highest wages, are the most profitable and have had the highest fixed assets per employee for most part of the last decade.

¹⁹In Costa Rica, firms in the free trade zone are exempt of taxes on local purchases of goods and services, on imports and exports. They also pay a lower income tax, and depending on the FTZ's geographical location they might be completely exempt of it.

An important final remark should be made towards public employment. Given the high percentage of qualified activities within the public sector, its wages have been substantially higher than the private sector average; from 2005 until 2017, average public wages grew 45.9%, whilst average wages in the private sector grew a 37.8%.

6.5 Geography of employment

Costa Rica's urban area is defined as the Greater Metropolitan Area (GMA)²⁰. It has experienced immigration from rural areas, and has experienced a differentiated expansion in population and growth. In terms of employment density, the difference is substantial: for 2017, in rural cantons, such as La Cruz and Golfito, the average is 1.3 worker per square kilometer, while in the capital city it averages 10,875.

For 2005, the first year for which there is information in the database, 727,019 (78.2% of total employment) worked for firms within the GMA, and in 2017 there was a total headcount of 887,313 (79.5%). Between these years, the cantons of Heredia, Santa Ana, Escazú and Curridabat increased their share of total employment in 2.3%, 1.8%, 1.6% and 0.8% respectively. On the other hand, between 2005 and 2017, employment in rural cantons such as Pérez Zeledón and San Ramón, decreased their share of total employment from a 2.4% and 2.3% to 1.7% for both.

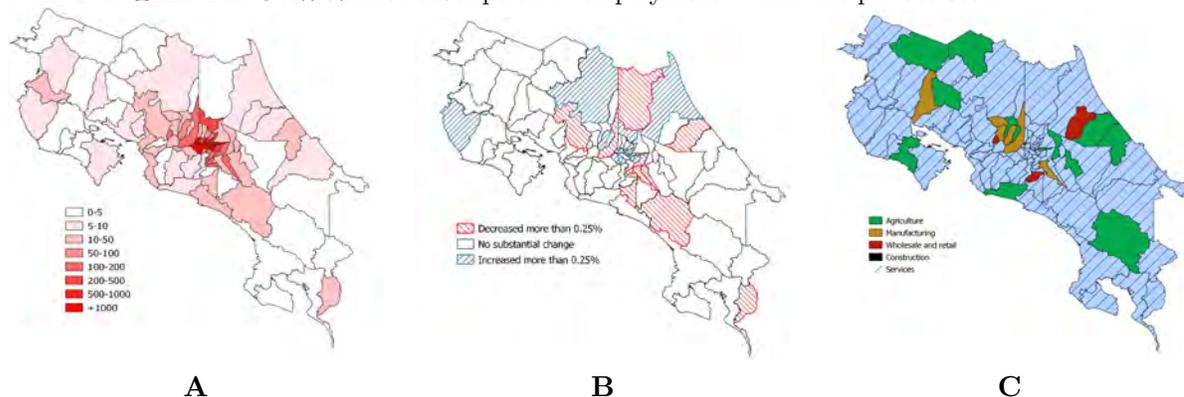
Economic activities also differ among cantons. In 2005 only 45 cantons out of 81 had services as its predominant employer. For 2017, the number had increased to 58 out of the 82²¹ (or 25 out of the 31 cantons in GMA) mainly because of the change from Manufacturing and Wholesale and Retail to Services. Santa Ana, Cartago and Belén are among the cantons whose employment in Services relevance increased the most.

The GMA also entails almost all of the public sector's employment (94.5%), high employing activities with high average wages. For example, computer programming firms (96.5%), administrative office services (96.4%) and financial leasing (97.4%) concentrate almost all of its hiring in the GMA and are among the better paying industries. Thus, Belén, Flores, Santa Ana, San José and Escazú have the highest average wages (for the private sector),

²⁰The GMA is the main conurbation of Costa Rica. It comprehends most of urban cantons in the province of San José, the capital city, and in the surrounding provinces: Cartago, Alajuela and Heredia.

²¹ Before 2017 there were 81 cantons but, in that year Río Cuarto was declared as an independent canton from Grecia. Thus, REVEC does not differentiate between firms in them.

Figure 15: Geographical description of employment within the private sector



A) Shows employment in 2017 per square kilometer.
 B) Shows the cantons that acquire (or lost) more of the 0.25% of total employment in 2017 in comparison to 2005.
 C) Shows the economic activities that had the most employment in 2017.
 Source: own elaboration.

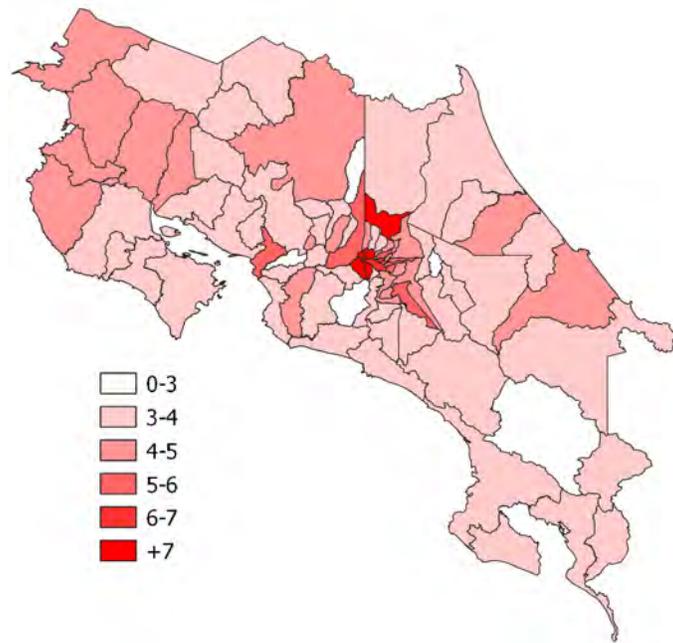
which are three times higher than the average wage of Buenos Aires and Nandayure, cantons with the lowest average wage. These two cantons have agriculture as its main activity. There is a significant (almost double) difference between the wages cantons in the GMA and the rest of almost double, which are depicted in the choropleth map, Figure 16.

7 Results

The empirical framework presented in Section 3 is valid in the context of private markets. Therefore, this research will exclude from the database two cases where employment decisions consider primarily factors other than market forces. The first one is public employment, which is strongly related to political outcomes, and the second one is the banking industry, where financial market imperfections (such as the primary role of the government as owner of the main commercial banks) also have a substantial impact over employment decisions. Hence, the sample used for estimation purposes considers only non-financial private firms. Otherwise, the inclusion of all firms would underestimate the effect of market conditions over employment.

Additionally, the estimation sample only considers firms with a median employment greater

Figure 16: Choropleth of annual average wages (millions of colones)



Note: Due to the lack of information for the Rio Cuarto specified in footnote 21, it appears in the map as with a null average wage.
Source: own elaboration.

than five because the inclusion of smaller operations such as self-employed individuals or very small firms that lack enough data to be considered for analysis may generate a downward bias of real effects of wage and revenue changes over employment.²²

As data is in levels, stationarity tests are required, among them, Baltagi (2008) stated that for the sake of robustness it is necessary to perform several unit-root tests and to distinguish between the different properties of each. Therefore, all variables of the model (employment, average wages, revenue and fixed assets) were tested using Levin, Lin and Chu (LLC), Breitung, Im, Pesaran and Shin (IPS), ADF-Fisher and Phillips-Perron-Fisher (PPF).

Most of them, rejected the null hypothesis of data being a unit-root process, with the exception of the Breitung test. Because this assessment and the LLC assume that all

²²Alternative estimations considering firms with median greater than three employees are shown in appendix I.

unit-root stochastic processes are equal,²³ this result is not troubling, as the data comes from a panel, and the condition stated by Baltagi (2008) for them to be valid ($\frac{\sqrt{N_t}}{T}$ must asymptotically approach zero)²⁴ does not hold, considering that this dataset has over 12,000 firms over twelve years. Results are shown in table 4.

Table 4: Unit root tests

Test	Levin, Lin & Chu	Breitung	Im, Pesaran & Shin	ADF-Fisher	PP-Fisher
Employment ($L_{i,t}$)	0,0000	1,0000	0,0000	0,0000	0,0000
Wages ($w_{i,t}$)	0,0000	0,0000	0,0000	0,0000	0,0000
Revenue ($Y_{i,t}$)	0,0000	1,0000	0,0000	0,0000	0,0000
Fixed assets ($K_{i,t}$)	0,0000	1,0000	0,0000	0,0000	0,0000

Source: own estimations.

The model presented in section 5 was chosen, and due to the lack of information contributed by further lags, it was decided to include just one lagged period.²⁵ The results of estimating the model for the specified categories are summarized in table 5, considering only categories with over 500 firms within the sample.

In terms of methodology, the OLS, fixed-effects and first-difference GMM estimators were compared to assess the autoregressive parameter of the latter. As seen in table 5, the observed first lag parameter of the first-difference GMM model for all firms is 0.851; a result bounded by the fixed effects (0.483) and the OLS (0.859) estimated coefficients. However, this does not hold for the remaining estimations, which suggests as a best strategy to follow Bond et al. (2001) who stated that different models are chosen to elicit the coefficients of interest based on the OLS-fixed effects criteria.

In accordance, elasticities for the Manufacturing, Wholesale and Retail industries and micro firms at birth are inferred over the first-difference GMM estimator. Furthermore, both GMM autorregressive coefficients for the estimations of the Accommodation and Food Services, and Information and Communication, were outside the specified threshold. For those cases, the System GMM is preferred. Notwithstanding, when comparing first-differences and system GMM models, the estimated coefficients do not differ considerably.

Additionally, the exogeneity and autocorrelation tests indicate that residuals show first-

²³In contrast, in the remaining tests each group is assumed to have different components in their stochastic processes.

²⁴where N_t is the amount of cross-sections and T refers to the periods of time

²⁵Models with up to four lags of the independent variables were considered, as well as a general to specific approach.

order autocorrelation (but not any further) and the instruments are exogenous. Finally, in order to correct the underestimation of the standard errors of the two-step estimators the suggestion by Windmeijer (2005) is followed.

Given the model results, Costa Rican labor demand elasticities are within the range showed by Hamermesh (1993) and close to those of Latin American related literature. In general terms, considering all firms, an increase of a percentage point in their revenue causes an increase of 0.435% in next year's employment. Analogously, an increase of one percent in firms wages leads to a 0.358% decrease in the following years' employment. When considering different characteristics of the firms, the estimated elasticities have the expected sign but are heterogeneous in magnitude. For the included industries, there is a significant heterogeneity in the relationship of the firms' size at birth and intensity in the use of technology to employment.

Estimated industries' adjustment to changes in revenue is quite different. Firms in the Construction, Accommodation and Storage, and Administrative and Support Services seem to adjust employment substantially more after shocks in revenue than firms in Agriculture and in Transportation and Storage activities. However, the higher the firms' intensity in the use of technology, the higher the labor elasticity associated to revenue. Another feature suggested by the results is that the larger the firm size at birth, the more it adjusts its employment to changes in revenue. The elasticities of employment derived from 1% increase in revenue, lie within a range of 0.361% increase for the micro firms and 0.462% increase for the larger firms.

The results show that a percentage point increase in wages has a negative effect on employment in a 0.358% a year afterwards. However, a negative causal relationship between wage rate increases and employment was not found for all industries and firm categories. For those industries where it is the case, results are quite heterogeneous. When comparing, larger labor-wage short run elasticities were found for industries with less qualified jobs in a larger proportion. For the Construction and Manufacturing industries, for example, there were of -0.949 and -0.749 respectively, while for Professional, Scientific and Technical activities, -0.326, and Administrative and Support Services, -0.308.

Given the higher labor-wage elasticity in the Construction industry, and its importance in the medium-low intensity technology usage classification, other industries' elasticities within the same group were biased upwards. Still, firms classified as high intensity in the

Table 5: Labor demand elasticities

Category	Estimated coefficients			Groups
	$L_{i,t-1}$	ϵ_0	σ_0	
All firms	0.851***	0.435***	-0.358***	12,846
Industry categories				
Agriculture ⊗	0.817***	0.130**	0.044	953
Manufacturing ⊙	0.737***	0.401***	-0.749***	1097
Construction ⊗	0.513***	0.513***	-0.949***	762
Wholesale and Retail ⊙	0.616***	0.407***	-0.381**	2052
All Services ⊗	0.792***	0.515***	-0.081	5417
<i>Transportation and Storage</i> ⊗	0.855***	0.228***	-0.157	781
<i>Accommodation and Food Services</i> ⊗	0.749***	0.502***	-0.134	1124
<i>Information and Communication</i> ⊗	0.860***	0.371***	-0.047	545
<i>Professional, Scientific and Technical</i> ⊗	0.669***	0.474***	-0.326***	1044
<i>Administrative and Support Services</i> ⊗	0.841***	0.687***	-0.308***	1018
Categories by intensity in the use of technology				
Low ⊗	0.800***	0.256***	-0.149	5875
Medium-Low ⊗	0.788***	0.496***	-0.604***	3648
Medium-High ⊗	0.652***	0.507***	-0.368***	4127
High ⊗	0.840***	0.766***	-0.537***	531
Firm size at birth categories				
Micro ⊙	0.365***	0.313***	-0.214	2158
Small ⊗	0.806***	0.384***	-0.169	5473
Medium ⊗	0.897***	0.399***	-0.195***	3148
Large ⊗	0.924***	0.462***	-0.569***	2066
Free Trade Zones				
Free trade zones ⊗	0.905***	0.332***	-1.004***	303

Note: system-GMM estimations are identified with ⊗ and first-difference GMM estimations with ⊙.
Source: own estimations

use of technology also seem to adjust significantly its employment to changes in wages.

When considering the size of the firm, no association could be established for small firms, but substantial labor-wage elasticities were estimated for large firms. Furthermore, free trade zones seem to be very elastic to changes in wages in the short run, as their elasticity is larger than one: when wages increase in one percent, they decrease their employment more than one percent in subsequent years.

The estimations, given the results of the autoregressive parameter, show that employment persistence in Costa Rica is close to the results from the literature. This research finds an autorregressive parameter of 0.851, while Blundell and Bond (1998) got a result of 0.810 for the United Kingdom, and Rodriguez (2013) found for the Colombian manufacturing

sector a result of 0.901 for blue-collar workers, 0.866 for administrative staff and 0.797 for professional staff. When considering the firms' size, larger firms seem to have more persistent employment, whereas when considering the intensity in the use of technology, there is no evidence of a relationship with employment persistence.

The mean adjustment time to shocks in labor demand determinants is of 4.3 years, indicating a more rigid labor market when compared to the United Kingdom as [Blundell and Bond \(1998\)](#) estimated its mean adjustment time as 3.3 years, but not as rigid as the estimated mean adjustment time of 5.3 years found by [Esperança et al. \(2011\)](#) for the Portuguese economy. The results for the Costa Rican labor market differentiating by industry, technology usage, firm size and Free Trade Zone, are shown in table 6. In general, the main differences does not seem to be from the type of industry nor the technology intensiveness but the firm size. The larger the firms, the more persistent the employment and thus, the longer it lasts to reach the new headcount equilibrium.

Table 6: Mean adjustment time and long run elasticities

Category	Mean adjustment time (years)	Long run ϵ	Long run σ
All firms	4.3	0.457	-0.235
Industry categories			
Agriculture	3.4	0.557	-
Manufacturing	2.3	1.399	-0.563
Construction	1.0	0.564	-0.805
Wholesale and Retail	1.4	0.591	-0.188
All Services	3.0	0.683	-
<i>Transportation and Storage</i>	4.4	0.607	-
<i>Accommodation and Support Services</i>	2.4	0.697	-
<i>Information and Communication</i>	4.6	0.671	-
<i>Professional, Scientific and Technical</i>	1.7	0.574	-0.184
<i>Administrative and Support Services</i>	4.0	0.923	-0.277
Categories by intensity in the use of technology			
Low	3.1	0.385	-
Medium-Low	2.9	0.533	-0.472
Medium-High	1.6	0.675	-0.443
High	4.0	0.850	-0.644
Firm size at birth categories			
Micro	0.7	0.472	-
Small	3.2	0.397	-
Medium	6.4	0.441	-0.914
Large	8.8	0.463	-2.540
Free Trade Zones			
Free Trade Zones	6.9	0.274	-0.400

Source: own estimations.

To conclude this analysis of Costa Rica's labor market, it is necessary to look at the long run elasticities. For all categories, effects of changes in revenue seem to be slightly larger in the long run²⁶. For the whole economy a one percentage increase in revenue leads to a 0.457% increase in employment in the long run, marginally higher from the short run elasticity which was 0.435. The difference is substantially larger in the manufacturing industry, for the labor-revenue elasticity, as the long run elasticity three folds the short run.

Seems appropriate to clarify that employment persistence does not necessarily imply higher long run labor-wage elasticities for all industries, as results show that the response of labor demand is greater in the short run than in the long run, suggesting that firms may overreact to wage rate increases, but the effect is slightly offset as time passes by. Negative effects of wage increases seem to be persistent for large firms and those with a higher intensity in the use of technology. Those firms labor demand show a larger long-term response to wage changes due to their considerably higher job persistence.

8 Conclusions

This paper uses a novel dataset to study labor market dynamics for the Costa Rican economy, and contributes to the literature of labor demand in two main areas. First, it characterizes the formal labor market for the period where the data is available, and second, it estimates a labor demand equation where the elasticity results comply with the neoclassical theory and complements its results by analyzing long run responses considering labor persistence.

On the first contribution, total formal employment, average wages, and revenues for the firms were characterized for a twelve year span that encompasses the most recent international financial crisis, from 2005 until 2018. During this period, the relative importance of the services industry has increased significantly, driven specially by technology and knowledge intensive industries, whereas sectors in which less qualified labor prevails, such as manufacturing and agriculture, reduced their relative importance. However, all industries had a common trait: they had higher employment growth rates in the years prior to the

²⁶Long run elasticities were estimated only for categories for which contemporaneous wages resulted to be significant at least at the 10% level.

financial crisis than afterwards.

In terms of firm size, employment had a quite homogeneous structure during this period. Few large firms concentrated most of the employment in an economy full of small firms. As most of these large firms are located in the Great Metropolitan Area, employment is more concentrated there and the headcount has increased in highly intensive knowledge activities, thus higher average wages are paid in this area, GMA.

When considering job rotation, it seems to be present in all of the analyzed industries, but is considerably higher in the Construction, for which most of new jobs go to *newborn* firms. For Agriculture and Manufacturing, most new jobs come from incumbent firms. The incumbent firms, in general, in industries related to more qualified jobs contribute less to job destruction, thus it might be said that incumbent firms in Services have a much more stable headcount over time than the rest of industries.

On the second contribution, the estimation for the labor demand of the entire economy had the expected sign predicted by neoclassical employment theory. Results show a labor elasticity of 0.435 associated to revenue and a -0.358 response to wages. Still, it turned to be significant to study it while considering different characteristics as important differences were showcased across industries, for example. Given the results of this research, the responsiveness of employment to changes over revenue and wages seems to be correlated to firm's size in the short and long run. Firm size also seems to determine the estimated mean adjustment time of employment, as it was 4.3 years when considering all firms, but it turned significantly longer for larger firms. When analyzing the persistence of the negative effects of wage increases there is also a difference by firm size, as it is larger in the long run for larger firms. For the rest of the business groups this negative effect was slightly offset in time.

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Appendices

A CEPAL (2002) labor demand elasticities for Central American countries

Table A1: Labor-product (ϵ) and labor-wage elasticities (σ) estimations for Central American countries

Country	ϵ_y CEPAL (2002)	Years	ϵ_y	ϵ_w	R^2	Observations
Costa Rica	0,80	1980-2004	0,719 (15,20)	0,436 (6,22)	0,960	25
		1991-2001	0,400 (1,99)	0,907 (3,00)	0,873	11
El Salvador	1,42	1994-2002	0,614 (14,48)	0,193 (2,35)	0,936	9
		1980-2004	0,347 (6,94)	0,443 (4,57)	0,927	25
Guatemala	0,86	1980-2004	0,963 (14,02)	0,007 (0,06)	0,914	25
		1986-2003	0,613 (5,29)	0,519 (2,55)	0,794	18
Honduras	1,61	1985-2004	1,187 (15,71)	-0,629 (-4,40)	0,915	20
		1995-2003	1,005 (14,83)	-0,278 (-2,15)	0,900	9
Nicaragua	0,05	1991-2004	0,660 (2,26)	0,082 (0,20)	0,865	14
Panama	1,08	1991-2002	0,672 (3,64)	0,128 (0,35)	0,947 0,947	12

Source: Guerrero de Lizardi (2007).

B Profit function approach in a continuous-time model

In a continuous-time model, a way of getting such specification, following Hamermesh (1990), is to assume quadratic costs:

$$C(\dot{L}) = a\dot{L} + b\dot{L}^2, \quad \text{where } a > 0 \quad \text{and} \quad b > 0 \quad (\text{B1})$$

where, \dot{L} denotes the percentage change of headcount over time. Then, equation B2 shows the marginal costs of an additional worker:

$$CMg(\dot{L}) = \frac{\partial C(\dot{L})}{\partial \dot{L}} = a + 2b\dot{L} \quad (\text{B2})$$

Gould (1968) proposes B3 as a profit function approach for a continuous-time model:

$$\max_{L_t} \quad \Pi = \int_0^{\infty} e^{-rt} (F(L_t) - wL_t - C(\dot{L})) \quad dt \quad (\text{B3})$$

where w denotes the wages (and only variable cost of the model), r the discount rate for profits, and $F(L_t)$ the production function. This function shows positive but decreasing marginal returns, i.e. $F'(L) > 0$ and $F''(L) < 0$. In this case, the first order condition for the inter-temporal problem will be the corresponding Euler equation:

$$2b\ddot{L}_t - 2br\dot{L}_t + F'(L_t) - w - ra = 0 \quad (\text{B4})$$

which implies that in the steady-state, the optimum employment level must satisfy equation B5:

$$F'(L^*) = w + ra \tag{B5}$$

In models without rigidities, the optimality condition establishes that the worker's marginal production must be equal to its marginal cost, measured by the wage level. As shown in B5, for this case, marginal costs are higher as “ ra ” is strictly positive; therefore, the optimal employment will be lower.

C Firm categorization methodologies

In order to describe employment and its behaviour to changes on its determinants on different type of firms, some classifications were used. The methodologies used to classify firms by industry, technology intensity and firm size are explained in what follows.

C.1 Categorization by industry

Twenty industries were defined based on the 4-digits International Standard Industrial Classification (ISIC). The categories were based on the Clasificación de Actividades Económicas de Costa Rica (CAECR-2011). However, the *Mining and Quarrying* industry proposed on the CAECR-2011 includes the firms that does not have an ISIC code associated and is called as *Others*. Finally, an additional classification that includes all the services industries is proposed. Table C1 shows how industries were classified.

Table C1: Industry classification

Industry	ISIC 2-digit code	Observations
Agriculture	01-03	Includes cattle raising, fishing and forestry.
Manufacturing	10-33	
Electricity and Gas	35	Includes electricity, gas and steam suppliers and air conditioning activities.
Water Supply, Sewerage and Waste Management	36-39	Includes wastewater evacuation, waste management and decontamination.
Construction	41-43	
Wholesale and Retail	45-47	
Transportation and Storage	46-53	
Accommodation and Food Services	55-56	
Information and Communication	58-63	
Real Estate	68	
Professional, Scientific and Technical	69-75	
Administrative and Support Services	77-82	
Education	85	
Human Health and Social Work	86-88	
Art and Entertainment	90-93	
Other Services	94-96	
Financial Activities	64-66	
Public Administration	84	
Diplomatic Activities	99	
Others	Not previously classified	Includes mining and quarrying.
Services	<i>Code > 49</i>	

Source: own elaboration.

C.2 Technology intensity

This classification is based on the OECD proposal, which has two different criteria to classify manufacturing and services firms. The fraction of profits invested in research and development is the criteria used for the manufacturing industries, while the classification for services firms is based on the qualification of its workforce and the intensity in the use of high technology (known as a knowledge-intensive criteria). The details are further explained in Hatzichronoglou (1997) and in Abdal et al. (2016). Table C2 describes the ISIC codes OECD establishes for the four different classifications.

Table C2: Technology intensity classification

Low intensity	
Activity	ISIC 2-digit code
Agriculture, livestock, hunting and related service activities	1
Forestry and timber extraction	2
Fisheries and aquaculture	3
Production of food products	10
Preparation of beverages	11
Manufacture of tobacco products	12
Manufacture of textile products	13
Manufacture of leather products	15
Production of wood, wood products (except furniture) and straw	16
Manufacture of paper and paper products	17
Printing and playback of recordings	18
Furniture manufacturing	31
Other manufacturing industries	32
Wholesale and retail	45-47
Land transport and pipelines	49
Postal services and courier services	53
Accommodation and food services	55-56
Rental and leasing activities	77
Recruiting activities	78
Activities of associations	94
Personal service activities	96
Households as employers of domestic work	97
Activities of organizations and extraterritorial bodies	99

Medium-Low intensity	
Activity	ISIC 2-digit code
Mining and quarrying	5-9
Manufacture of coke and refined petroleum products	19
Manufacture of rubber and plastic products	22
Manufacture of metal products (Except machinery and equipment)	25
Manufacture of other transport equipment	30
Repair and installation of machinery and equipment	33
Electricity and gas	35
Water supply and treatment	36-39
Construction	41
Transportation and storage	52
Real estate	68
Tour operators	79
Service activities for buildings and landscapes	81
Administrative and support services	82
Repair of computers and appliances for personal and domestic use	95
Medium-High intensity	
Activity	ISIC 2-digit code
Manufacture of chemical substances and products	20
Manufacture of common metals	24
Manufacture of metal products (except machinery and equipment)	25
Manufacture of electrical equipment	27
Manufacture of machinery and equipment (not previously classified)	28
Manufacture of automotive vehicles and trailers	29
Civil engineering	42
Water transport	50
Transportation by air	51
Information and communication	58-63
Insurance	65
Auxiliary activities of financial services	66
Legal and accounting activities	69
Architecture and engineering	71
Scientific research and development	72
Advertising and marketing	73
Security	80
Public Administration	84
Education	85
Human health and social work	86
Institutional services	87-89

Art and entertainment	90-93
High intensity	
Activity	ISIC 2-digit code
Manufacture of pharmaceutical, chemical and medicinal products	21
Manufacture of computer, electronic and optical products	26
Consulting services	70
Professional, scientific and technical activities	74

Source: own elaboration.

C.3 MEIC

A last classification is based on the 4 categories established by the Costa Rican Economics, Industry and Trade Ministry. This methodology calculates a $Score_i$ as a function of the average firm employment (PE), net annual sales (VAN) and the firms total assets value (ATE). Firms sector i defines the formula applied to calculate the score. For the services and wholesale and retail firms the next formula applies:

$$Score_{C\&S} = 100 \quad X \quad \left[\frac{0,6PE}{30} + \frac{0,3VAN}{3.084.000.000} + \frac{0,1ATE}{964.000.000} \right] \quad (C1)$$

For the information technology firms the following formula is applied:

$$Score_{ATE} = 100 \quad X \quad \left[\frac{0,6PE}{50} + \frac{0,3VAN}{3.084.000.000} + \frac{0,1ATE}{964.000.000} \right] \quad (C2)$$

Finally, for the industrial firms the score is estimated as follows:

$$Score_{IND} = 100 \quad X \quad \left[\frac{0,6PE}{100} + \frac{0,3VAN}{1.785.000.000} + \frac{0,1ATE}{1.095.000.000} \right] \quad (C3)$$

Once the score is estimated, firms are categorized then in the following classes:

Table C3: MEIC size classifications

Classification	Score
Micro firms	$Score_i \leq 10$
Small firms	$10 < Score_i \leq 35$
Mid-sized firms	$35 < Score_i \leq 100$
Large firms	$Score_i > 100$

Source: own elaboration based on MEIC data.

D Largest changes in firms by ISIC-4 digit classification

Table D1: Firms with most increases and decreases in active firms from 2005 to 2017

Industry	ISIC Code	Increase	Decrease
Larger increases			
(1) Restaurants and mobile food services	5610	1495	-
(2) Personal services activities	9609	952	-
(3) Retail sales of food and beverages	4781	811	-
(4) Building construction	4100	803	-
(5) Retail of food and beverages in specialized establishments	4721	792	-
Larger decreases			
(1) Cultivation of plants used to prepare beverages	0127	-	199
(2) Cultivation of other non-perennial plants	0119	-	156
(3) Load handling	5224	-	120
(4) Plant propagation	0130	-	48
(5) Wood chips and particles production	1610	-	44

Source: Own elaboration

E Employment descriptive statistics

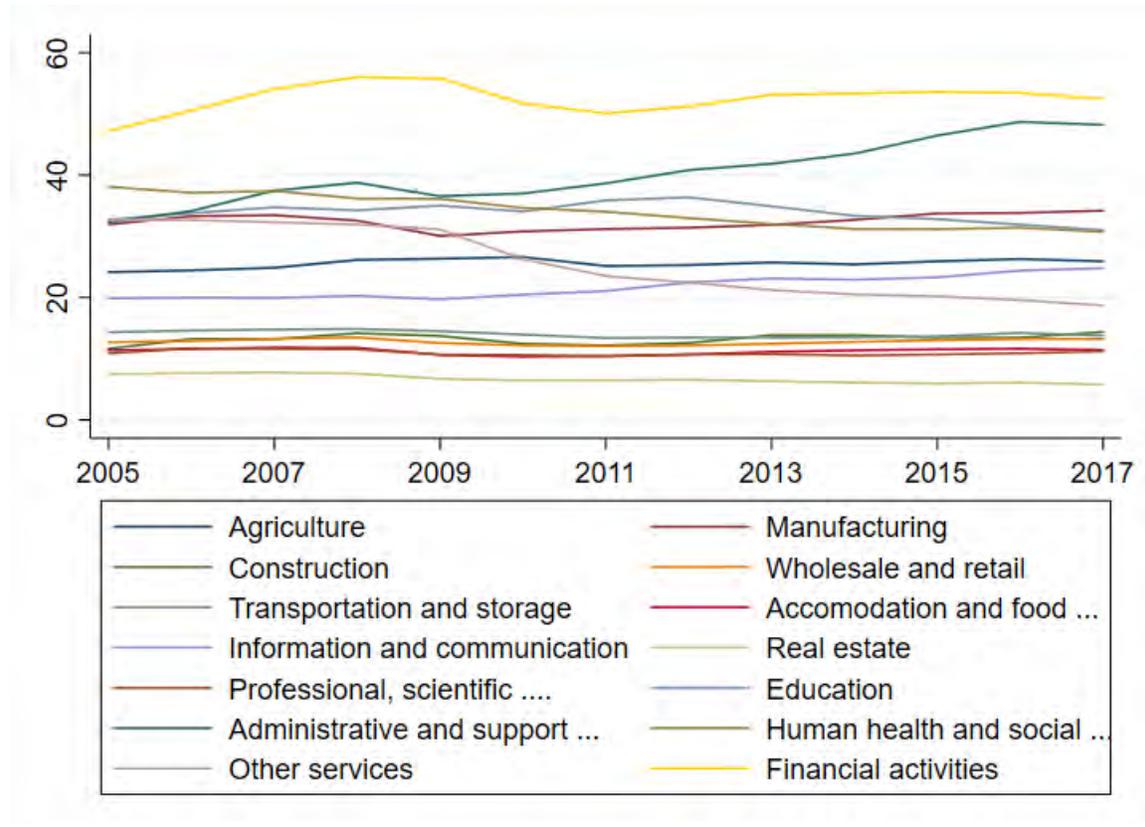
Table E1: Employment descriptive statistics, 2005-2017

Year	Total	Growth	Firm Average	St. Dev.	Maximum
2005	929,972	-	23.4	448.0	68,081
2006	996,205	7.12	23.8	465.6	74,065
2007	1,069,388	7.35	23.8	461.3	74,935
2008	1,143,682	6.95	23.7	449.4	73,300
2009	1,144,175	0.04	23.3	500.4	85,622
2010	1,161,067	1.48	22.6	463.3	75,037
2011	1,190,327	2.52	22.4	472.4	79,291
2012	1,226,588	3.05	22.5	472.2	80,592
2013	1,248,317	1.77	22.7	476.5	82,026
2014	1,278,169	2.39	23.0	515.3	94,302
2015	1,298,025	1.55	23.1	511.0	94,265
2016	1,343,689	3.52	23.2	519.9	97,249
2017	1,367,171	1.75	23.1	520.5	99,868

Source: Own elaboration

F Industries employment mean

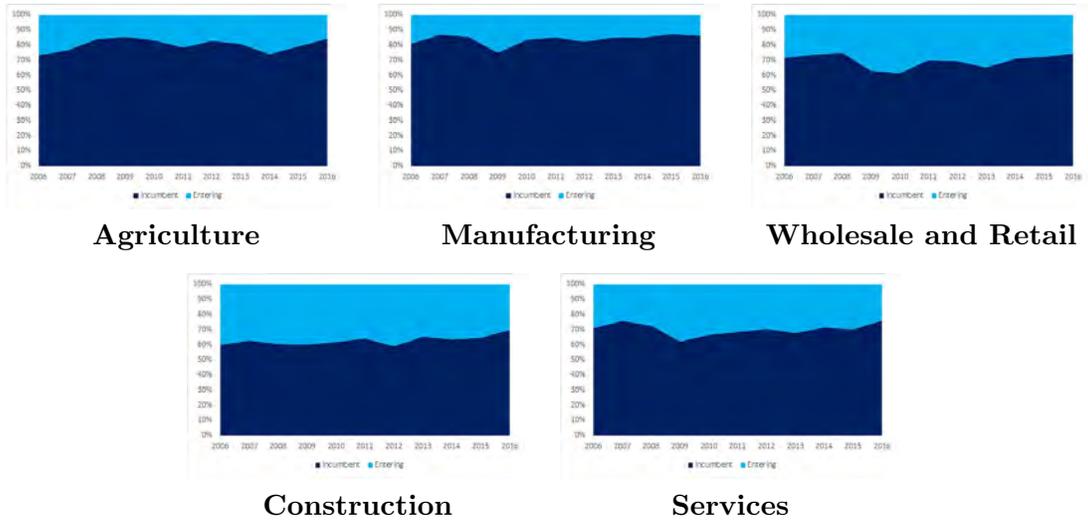
Figure F1: Industries employment mean, 2005-2017



Source: own elaboration.

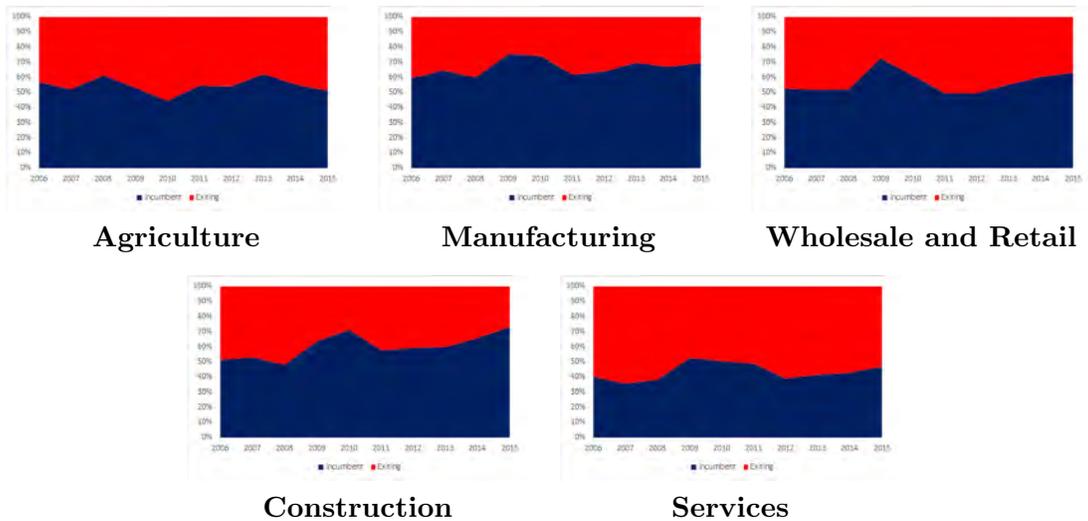
G Composition of job creation and destruction

Figure G2: Composition of job creation



Source: own elaboration.

Figure G3: Composition of job destruction



Source: own elaboration.

H OLS, FE, Difference-GMM and Systematic-GMM estimations

Table H1: Labor demand estimations for all firms

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.859*** (0.002)	0.483*** (0.008)	0.585*** (0.091)	0.851*** (0.039)
$w_{i,t}$	-0.183*** (0.037)	-0.107** (0.044)	-0.640*** (0.249)	-0.358*** (0.126)
$w_{i,t-1}$	0.164*** (0.034)	0.131*** (0.023)	0.407** (0.192)	0.323*** (0.121)
$Y_{i,t}$	0.578*** (0.006)	0.503*** (0.007)	0.489*** (0.090)	0.435*** (0.053)
$Y_{i,t-1}$	-0.512*** (0.006)	-0.201*** (0.006)	-0.114*** (0.078)	-0.367*** (0.052)
$K_{i,t}$	0.014*** (0.001)	0.033*** (0.002)	0.057*** (0.031)	0.029** (0.012)
Constant	-0.821*** (0.054)	-	-	-
Adjusted-R^2	0.910	0.839	-	-
Hansen	-	-	0.416	0.345
AR(1)	-	-	0.000	0.000
AR(2)	-	-	0.638	0.181
Number of groups	12,846	12,846	6634	12,846
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H2: Labor demand estimations for the agricultural industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.869*** (0.008)	0.555*** (0.026)	0.510*** (0.077)	0.817*** (0.059)
$w_{i,t}$	-0.004 (0.184)	0.097 (0.153)	0.009 (0.271)	0.044 (0.290)
$w_{i,t-1}$	-0.009 (0.173)	-0.000 (0.118)	0.004 (0.257)	0.083 (0.275)
$Y_{i,t}$	0.463*** (0.028)	0.415*** (0.032)	0.183** (0.093)	0.130** (0.055)
$Y_{i,t-1}$	-0.387*** (0.027)	-0.158*** (0.024)	0.081* (0.048)	-0.028 (0.049)
$K_{i,t}$	0.011*** (0.003)	0.046*** (0.010)	0.095 (0.067)	0.020 (0.021)
Constant	-1.062*** (0.380)	-	-	-
Adjusted-R^2	0.916	0.860	-	-
Hansen	-	-	0.172	0.488
AR(1)	-	-	0.015	0.004
AR(2)	-	-	0.506	0.773
Number of groups	953	953	553	953
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H3: Labor demand estimations for the Manufacturing industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.860*** (0.007)	0.543*** (0.020)	0.737*** (0.121)	0.871*** (0.032)
$w_{i,t}$	-0.326*** (0.068)	-0.195** (0.078)	-0.749*** (0.260)	-0.510*** (0.150)
$w_{i,t-1}$	0.314*** (0.064)	0.283*** (0.049)	0.601** (0.250)	0.505*** (0.140)
$Y_{i,t}$	0.588*** (0.018)	0.524*** (0.023)	0.401*** (0.103)	0.306*** (0.064)
$Y_{i,t-1}$	-0.508*** (0.018)	-0.264*** (0.018)	-0.033 (0.107)	-0.228*** (0.064)
$K_{i,t}$	0.013*** (0.002)	0.020*** (0.004)	-0.046* (0.027)	0.005 (0.009)
Constant	-1.200*** (0.138)	- -	- -	- -
Adjusted-R^2	0.952	0.932	-	-
Hansen	-	-	0.346	0.063
AR(1)	-	-	0.003	0.000
AR(2)	-	-	0.111	0.030
Number of groups	1765	1765	1097	1765
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H4: Labor demand estimations for the Construction industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.667*** (0.015)	0.280*** (0.027)	0.153 (0.174)	0.513*** (0.114)
$w_{i,t}$	-0.382*** (0.071)	-0.411*** (0.101)	-1.320*** (0.477)	-0.949*** (0.203)
$w_{i,t-1}$	0.269*** (0.070)	0.088 (0.076)	-0.141 (0.372)	0.557** (0.220)
$Y_{i,t}$	0.591*** (0.017)	0.571*** (0.026)	0.316*** (0.121)	0.513*** (0.078)
$Y_{i,t-1}$	-0.410*** (0.019)	-0.136*** (0.025)	-0.092 (0.079)	-0.238*** (0.074)
$K_{i,t}$	0.010*** (0.004)	0.055*** (0.012)	0.034 (0.063)	-0.001 (0.028)
Constant	-1.042*** (0.242)	- -	- -	- -
Adjusted-R^2	0.743	0.619	-	-
Hansen	-	-	0.165	0.853
AR(1)	-	-	0.029	0.000
AR(2)	-	-	0.715	0.637
Number of groups	762	762	248	762
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H5: Labor demand estimations for the Wholesale and Retail industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.849*** (0.005)	0.520*** (0.013)	0.616*** (0.127)	0.958*** (0.043)
$w_{i,t}$	-0.125*** (0.046)	-0.060 (0.056)	-0.381** (0.251)	-0.287** (0.130)
$w_{i,t-1}$	0.092** (0.044)	0.097*** (0.036)	0.309** (0.169)	0.299** (0.126)
$Y_{i,t}$	0.514*** (0.012)	0.442*** (0.015)	0.407*** (0.086)	0.404*** (0.072)
$Y_{i,t-1}$	-0.448*** (0.012)	-0.212*** (0.012)	-0.184 (0.138)	-0.377*** (0.069)
$K_{i,t}$	0.016*** (0.001)	0.031*** (0.003)	0.041** (0.031)	-0.019 (0.018)
Constant	-0.644*** (0.076)	- -	- -	- -
Adjusted-R^2	0.912	0.854	-	-
Hansen	-	-	0.275	0.204
AR(1)	-	-	0.001	0.000
AR(2)	-	-	0.609	0.744
Number of groups	3511	3511	2052	3511
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H6: Labor demand estimations for the Services industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.843*** (0.005)	0.470*** (0.014)	0.485*** (0.085)	0.792*** (0.051)
$w_{i,t}$	-0.164*** (0.039)	-0.103** (0.046)	-0.194 (0.197)	-0.081 (0.097)
$w_{i,t-1}$	0.127*** (0.037)	0.111*** (0.028)	0.133 (0.100)	0.025** (0.089)
$Y_{i,t}$	0.642*** (0.010)	0.535*** (0.014)	0.289*** (0.100)	0.515*** (0.066)
$Y_{i,t-1}$	-0.545*** (0.010)	-0.247*** (0.012)	-0.087 (0.087)	-0.373*** (0.075)
$K_{i,t}$	0.005*** (0.001)	0.033*** (0.004)	0.022 (0.033)	0.017 (0.012)
Constant	-0.918*** (0.068)	- -	- -	- -
Adjusted-R^2	0.912	0.857	-	-
Hansen	-	-	0.071	0.458
AR(1)	-	-	0.001	0.000
AR(2)	-	-	0.876	0.252
Number of groups	5417	5417	2438	5417
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H7: Labor demand estimations for the Transportation and Storage industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.857*** (0.011)	0.519*** (0.025)	0.407*** (0.128)	0.855*** (0.046)
$w_{i,t}$	-0.103 (0.084)	-0.071 (0.094)	0.478 (0.250)	-0.157 (0.106)
$w_{i,t-1}$	0.084 (0.083)	0.129* (0.074)	0.443* (0.211)	0.080 (0.109)
$Y_{i,t}$	0.555*** (0.023)	0.441*** (0.026)	0.117 (0.073)	0.228*** (0.061)
$Y_{i,t-1}$	-0.482*** (0.023)	-0.205*** (0.024)	0.115 (0.086)	-0.140** (0.067)
$K_{i,t}$	0.015*** (0.003)	0.032*** (0.008)	0.047 (0.037)	-0.004 (0.013)
Constant	-0.965*** (0.199)	-	-	-
Adjusted-R^2	0.924	0.870	-	-
Hansen	-	-	0.167	0.098
AR(1)	-	-	0.071	0.001
AR(2)	-	-	0.765	0.867
Number of groups	781	781	547	781
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H8: Labor demand estimations for the Accommodation and Food Services industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.685*** (0.023)	0.348*** (0.053)	0.268 (0.184)	0.749*** (0.069)
$w_{i,t}$	0.070 (0.073)	0.087 (0.080)	-0.404* (0.163)	-0.134 (0.077)
$w_{i,t-1}$	-0.022 (0.069)	0.020 (0.064)	0.289** (0.144)	0.094 (0.148)
$Y_{i,t}$	0.638*** (0.020)	0.573*** (0.035)	0.537*** (0.107)	0.502*** (0.078)
$Y_{i,t-1}$	-0.422*** (0.024)	-0.175*** (0.039)	-0.064 (0.160)	-0.327*** (0.084)
$K_{i,t}$	0.013*** (0.002)	0.015*** (0.006)	-0.006 (0.063)	0.022** (0.012)
Constant	-4.161*** (0.383)	-	-	-
Adjusted-R^2	0.908	0.859	-	-
Hansen	-	-	0.277	0.459
AR(1)	-	-	0.071	0.000
AR(2)	-	-	0.870	0.793
Number of groups	1124	1124	458	1124
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H9: Labor demand estimations for the Information and Communication industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.781*** (0.016)	0.445*** (0.032)	0.301*** (0.148)	0.860*** (0.059)
$w_{i,t}$	-0.009 (0.161)	0.074 (0.169)	-0.126 (0.243)	-0.047 (0.145)
$w_{i,t-1}$	-0.004 (0.151)	-0.038 (0.107)	-0.034 (0.171)	-0.009 (0.151)
$Y_{i,t}$	0.672*** (0.027)	0.564*** (0.041)	0.320*** (0.094)	0.371*** (0.086)
$Y_{i,t-1}$	-0.551*** (0.027)	-0.104 (0.032)	-0.106** (0.079)	-0.277*** (0.095)
$K_{i,t}$	0.013** (0.005)	0.043*** (0.0122)	0.033 (0.027)	0.004 (0.026)
Constant	-1.728*** (0.256)	-	-	-
Adjusted-R^2	0.891	0.834	-	-
Hansen	-	-	0.508	0.343
AR(1)	-	-	0.197	0.014
AR(2)	-	-	0.594	0.527
Number of groups	545	545	199	545
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H10: Labor demand estimations for the Professional, Scientific and Technical industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.761*** (0.012)	0.435*** (0.025)	0.224** (0.103)	0.669*** (0.102)
$w_{i,t}$	-0.276*** (0.055)	-0.196*** (0.058)	-0.664*** (0.173)	-0.326** (0.082)
$w_{i,t-1}$	0.471*** (0.020)	0.168*** (0.040)	0.210 (0.168)	0.265 (0.168)
$Y_{i,t}$	0.614*** (0.020)	0.537*** (0.027)	0.451*** (0.093)	0.474*** (0.079)
$Y_{i,t-1}$	-0.471*** (0.020)	-0.219*** (0.019)	-0.059 (0.088)	-0.281*** (0.088)
$K_{i,t}$	0.013*** (0.003)	0.044*** (0.058)	0.047 (0.034)	0.021 (0.020)
Constant	-1.690*** (0.151)	-	-	-
Adjusted-R^2	0.880	0.824	-	-
Hansen	-	-	0.408	0.242
AR(1)	-	-	0.072	0.000
AR(2)	-	-	0.546	0.341
Number of groups	1044	1044	475	1044
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H11: Labor demand estimations for the Administrative and Support Services

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.884*** (0.008)	0.460*** (0.034)	0.291*** (0.137)	0.841*** (0.062)
$w_{i,t}$	-0.300*** (0.088)	-0.231** (0.103)	-0.578*** (0.148)	-0.308*** (0.189)
$w_{i,t-1}$	0.252*** (0.083)	0.140** (0.066)	-0.073 (0.168)	0.264*** (0.169)
$Y_{i,t}$	0.758*** (0.021)	0.663*** (0.032)	0.574*** (0.148)	0.687*** (0.119)
$Y_{i,t-1}$	-0.682*** (0.021)	-0.313*** (0.033)	-0.081 (0.073)	-0.540*** (0.116)
$K_{i,t}$	0.004 (0.003)	0.048*** (0.011)	0.010 (0.036)	-0.038 (0.027)
Constant	-0.381*** (0.159)	- -	- -	- -
Adjusted-R^2	0.931	0.857	-	-
Hansen	-	-	0.414	0.281
AR(1)	-	-	0.089	0.019
AR(2)	-	-	0.574	0.431
Number of groups	1018	1018	458	1018
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H12: Labor demand estimations for firms with low intensity in the use of technology

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.863*** (0.004)	0.515*** (0.014)	0.478*** (0.125)	0.800*** (0.041)
$w_{i,t}$	-0.073 (0.071)	-0.005 (0.076)	-0.226 (0.311)	-0.149 (0.178)
$w_{i,t-1}$	0.058 (0.065)	0.074* (0.043)	0.074 (0.206)	0.234 (0.162)
$Y_{i,t}$	0.540*** (0.011)	0.472*** (0.015)	0.462*** (0.109)	0.256*** (0.074)
$Y_{i,t-1}$	-0.476*** (0.010)	-0.220*** (0.012)	-0.025 (0.109)	-0.179*** (0.073)
$K_{i,t}$	0.018*** (0.001)	0.028*** (0.003)	0.015 (0.036)	0.021 (0.013)
Constant	-0.935*** (0.134)	- -	- -	- -
Adjusted-R^2	0.922	0.867	-	-
Hansen	-	-	0.098	0.131
AR(1)	-	-	0.001	0.000
AR(2)	-	-	0.890	0.425
Number of groups	5875	5875	3151	5875
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H13: Labor demand estimations for firms with medium-low intensity in the use of technology

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.846*** (0.005)	0.456*** (0.014)	0.546*** (0.117)	0.788*** (0.044)
$w_{i,t}$	-0.282*** (0.041)	-0.205*** (0.049)	-0.972*** (0.366)	-0.604*** (0.177)
$w_{i,t-1}$	0.236*** (0.041)	0.185*** (0.040)	0.657** (0.259)	0.504*** (0.172)
$Y_{i,t}$	0.563*** (0.010)	0.493*** (0.014)	0.477*** (0.124)	0.496*** (0.069)
$Y_{i,t-1}$	-0.492*** (0.011)	-0.206*** (0.013)	-0.182** (0.092)	-0.383*** (0.072)
$K_{i,t}$	0.014*** (0.002)	0.042*** (0.004)	0.049 (0.038)	0.022 (0.021)
Constant	-0.446*** (0.071)	- -	- -	- -
Adjusted-R^2	0.887	0.787	-	-
Hansen	-	-	0.163	0.349
AR(1)	-	-	0.000	0.000
AR(2)	-	-	0.202	0.221
Number of groups	3648	3648	1930	3648
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H14: Labor demand estimations for firms with medium-high intensity in the use of technology

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.830*** (0.006)	0.451*** (0.017)	0.230* (0.135)	0.652*** (0.098)
$w_{i,t}$	-0.232*** (0.057)	-0.141** (0.063)	-0.553* (0.247)	-0.368*** (0.122)
$w_{i,t-1}$	0.176*** (0.053)	0.125*** (0.035)	0.026 (0.026)	0.214* (0.116)
$Y_{i,t}$	0.643*** (0.013)	0.555*** (0.017)	0.474*** (0.110)	0.507*** (0.083)
$Y_{i,t-1}$	-0.544*** (0.013)	-0.249*** (0.014)	-0.064 (0.083)	-0.272*** (0.086)
$K_{i,t}$	0.009*** (0.002)	0.028*** (0.004)	0.027 (0.033)	0.026 (0.021)
Constant	-0.712*** (0.097)	- -	- -	- -
Adjusted-R^2	0.910	0.855	-	-
Hansen	-	-	0.040	0.299
AR(1)	-	-	0.035	0.000
AR(2)	-	-	0.364	0.126
Number of groups	2792	2792	1295	2792
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H15: Labor demand estimations for firms with high intensity in the use of technology

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.863*** (0.011)	0.493*** (0.030)	0.311** (0.127)	0.840*** (0.073)
$w_{i,t}$	-0.370*** (0.075)	-0.374*** (0.086)	-0.484* (0.276)	-0.537*** (0.229)
$w_{i,t-1}$	0.324*** (0.075)	0.216*** (0.071)	0.305 (0.309)	0.434*** (0.226)
$Y_{i,t}$	0.700*** (0.026)	0.629*** (0.042)	0.526*** (0.111)	0.766*** (0.133)
$Y_{i,t-1}$	-0.609*** (0.025)	-0.296*** (0.030)	-0.013 (0.132)	-0.630*** (0.120)
$K_{i,t}$	0.001 (0.003)	0.046*** (0.071)	0.053*** (0.053)	-0.015 (0.016)
Constant	-0.572*** (0.137)	-	-	-
Adjusted-R^2	0.938	0.895	-	-
Hansen	-	-	0.208	0.181
AR(1)	-	-	0.252	0.000
AR(2)	-	-	0.225	0.417
Number of groups	531	531	258	531
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H16: Labor demand estimations for micro firms at birth

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.655*** (0.009)	0.356*** (0.013)	0.365*** (0.109)	0.726*** (0.082)
$w_{i,t}$	-0.279*** (0.035)	-0.088*** (0.026)	-0.214 (0.229)	-0.185 (0.127)
$w_{i,t-1}$	0.215*** (0.035)	0.110*** (0.018)	0.233 (0.149)	0.221* (0.119)
$Y_{i,t}$	0.538*** (0.011)	0.498*** (0.018)	0.313*** (0.073)	0.361*** (0.063)
$Y_{i,t-1}$	-0.417*** (0.011)	-0.165*** (0.013)	-0.013 (0.057)	-0.251*** (0.072)
$K_{i,t}$	0.012*** (0.002)	0.028*** (0.003)	-0.003 (0.040)	0.024 (0.021)
Constant	-0.716*** (0.137)	-	-	-
Adjusted-R^2	0.735	0.550	-	-
Hansen	-	-	0.620	0.279
AR(1)	-	-	0.018	0.001
AR(2)	-	-	0.921	0.260
Number of groups	2158	2158	813	2158
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H17: Labor demand estimations for small-sized firms at birth

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.819*** (0.005)	0.482*** (0.011)	0.637*** (0.113)	0.806*** (0.067)
$w_{i,t}$	-0.058** (0.029)	0.008 (0.034)	-0.382 (0.316)	-0.169 (0.128)
$w_{i,t-1}$	0.038 (0.028)	0.041 (0.025)	0.234 (0.154)	0.180 (0.120)
$Y_{i,t}$	0.510*** (0.009)	0.447*** (0.012)	0.425*** (0.094)	0.384*** (0.060)
$Y_{i,t-1}$	-0.446*** (0.009)	-0.199*** (0.009)	-0.193* (0.115)	-0.307*** (0.064)
$K_{i,t}$	0.012*** (0.001)	0.025*** (0.003)	0.029 (0.037)	0.016 (0.015)
Constant	-0.667*** (0.137)	- -	- -	- -
Adjusted-R^2	0.788	0.653	-	-
Hansen	-	-	0.365	0.519
AR(1)	-	-	0.000	0.000
AR(2)	-	-	0.722	0.659
Number of groups	5473	5473	2608	5473
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H18: Labor demand estimations for medium-sized firms at birth

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.873*** (0.006)	0.528*** (0.018)	0.489*** (0.133)	0.897*** (0.037)
$w_{i,t}$	-0.194*** (0.069)	-0.130 (0.079)	-0.221 (0.309)	-0.195*** (0.156)
$w_{i,t-1}$	0.196*** (0.065)	0.174*** (0.048)	-0.041*** (0.164)	0.110 (0.149)
$Y_{i,t}$	0.566*** (0.013)	0.494*** (0.016)	0.494*** (0.113)	0.399*** (0.079)
$Y_{i,t-1}$	-0.522*** (0.013)	-0.253*** (0.016)	-0.282*** (0.089)	-0.358*** (0.077)
$K_{i,t}$	0.014*** (0.002)	0.037*** (0.004)	0.043 (0.031)	0.037** (0.018)
Constant	-0.784*** (0.109)	- -	- -	- -
Adjusted-R^2	0.811	0.677	-	-
Hansen	-	-	0.055	0.098
AR(1)	-	-	0.000	0.000
AR(2)	-	-	0.250	0.625
Number of groups	3148	3148	1752	3148
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H19: Labor demand estimations for large firms at birth

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.930*** (0.005)	0.588*** (0.029)	0.515*** (0.126)	0.924*** (0.040)
$w_{i,t}$	-0.308 (0.204)	-0.228 (0.213)	-0.429 (0.460)	-0.569** (0.315)
$w_{i,t-1}$	0.292 (0.196)	0.212 (0.142)	0.601** (0.300)	0.376*** (0.096)
$Y_{i,t}$	0.655*** (0.020)	0.587*** (0.024)	0.455*** (0.123)	0.462*** (0.037)
$Y_{i,t-1}$	-0.614*** (0.020)	-0.328*** (0.025)	0.011 (0.125)	-0.443*** (0.083)
$K_{i,t}$	0.009*** (0.002)	0.047*** (0.006)	0.065** (0.027)	0.004 (0.013)
Constant	-0.526*** (0.181)	-	-	-
Adjusted-R^2	0.925	0.846	-	-
Hansen	-	-	0.179	0.518
AR(1)	-	-	0.022	0.021
AR(2)	-	-	0.643	0.441
Number of groups	2066	2066	1461	2066
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

Table H20: Labor demand estimations for free trade zones

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sis
$L_{i,t-1}$	0.906*** (0.012)	0.406*** (0.035)	0.139 (0.168)	0.905*** (0.036)
$w_{i,t}$	-0.721*** (0.209)	-0.639** (0.306)	-1.075*** (0.401)	-1.004*** (0.316)
$w_{i,t-1}$	0.737*** (0.194)	0.361** (0.166)	0.106 (0.349)	0.966*** (0.336)
$Y_{i,t}$	0.685*** (0.033)	0.544*** (0.042)	0.512*** (0.149)	0.332*** (0.112)
$Y_{i,t-1}$	-0.641*** (0.033)	-0.243*** (0.038)	0.086 (0.121)	-0.306*** (0.105)
$K_{i,t}$	0.010* (0.006)	0.087*** (0.028)	0.198*** (0.076)	0.034 (0.025)
Constant	-0.948*** (0.312)	-	-	-
Adjusted-R^2	0.948	0.885	-	-
Hansen	-	-	0.128	0.267
AR(1)	-	-	0.249	0.029
AR(2)	-	-	0.316	0.393
Number of groups	303	303	153	303
Number of instruments	-	-	81	180

Notes: * significant at the 10% level, ** significant at the 5% level and *** significant at the 1 level. Standard errors in parenthesis. Source: own estimations.

I Alternate estimations

Table I1: Alternate results

Category	Estimated Coefficient			GMM Estimator	Groups
	$\eta_{i,t-1}$	ϵ_0	σ_0		
All firms					
All firms	0.680***	0.415***	-0.293*	<i>First-Difference</i>	8613
Industry categories					
Agriculture	0.838***	0.160***	0.049	<i>System</i>	1465
Manufacturing	0.721***	0.323***	-0.040	<i>First-Difference</i>	1333
Construction	0.378***	0.523***	-0.479***	<i>System</i>	1136
Wholesale and retail	0.542***	0.335***	0.075	<i>First-Difference</i>	2717
Transportation and storage	0.866***	0.342***	-0.329***	<i>System</i>	1178
Accommodation and food services	0.770***	0.345***	0.020	<i>System</i>	1750
Information and communication	0.757***	0.467***	-0.079	<i>System</i>	729
Professional, scientific and technical act.	0.586***	0.473***	-0.030	<i>System</i>	1597
Administrative and support services	0.880***	0.489***	-0.303***	<i>System</i>	1393
Technology intensiveness categories					
Low	0.700***	0.314***	-0.108	<i>First-Difference</i>	4227
Medium-Low	0.672***	0.413***	-0.548***	<i>System</i>	5345
Medium-High	0.642***	0.428***	-0.263***	<i>System</i>	4127
High	0.813***	0.706***	-0.434***	<i>System</i>	646
Firm size at birth categories					
Micro firms	0.510***	0.209***	-0.093	<i>First-Difference</i>	1799
Small firms	0.652***	0.346***	0.012	<i>First-Difference</i>	3529
Medium firms	0.527***	0.328***	-0.218***	<i>First-Difference</i>	1817
Large firms	0.958***	0.418***	-0.380***	<i>System</i>	2108
Free trade zones					
Free zones	0.905***	0.332***	-0.840***	<i>System</i>	310

Source: own estimations.

Note: the sample considered firms with a median employment greater than 5.

J Okun's Law

Several studies have tested the empirical observation of Okun (1963), whom established a short run inverse relationship between unemployment and production. Guerrero de Lizardi (2007) test this relationship for the Central American region with country-level data for the eighties, nineties and early thousands. Congruent with the classical aggregated supply and demand model, he found that for the Costa Rican economy, a one percent increase in production decreases unemployment in a 0,25%. In this fashion he estimates coefficients of -0,020 for El Salvador, -0,714 for Guatemala, -0,384 for Nicaragua, -0,171 for Panamá and 0,048 for Honduras. This estimations usually have a low goodness of fit but generally give a good insight of the relationship between this macro variables.

In order to update this empirical approximations for Costa Rica, two specifications proposed by Okun (1963) are used. The first lineal equation expresses unemployment natural rate as a function of the real production growth rate, while the latter establishes the same unemployment rate u_t as a function of the difference of real production growth dy_t y del trend production growth $dy_t t_t$, i.e.:

$$u_t = \alpha_0 + \alpha_1 dy_t + e_t \quad (10.6.1)$$

$$u_t = \beta_0 + \beta_1(dy_t - d_y t_t) + e_t \quad (10.6.2)$$

For this exercises, the BCCR quarterly series of of real product were used. Through the Hodrick-Prescott filter (with =1800) the trend GDP was estimated. Finally the International Labor Organization (ILO) was the source for the Costa Rican unemployment rate.

Results for both regressions are shown in table J1. Both estimators are close to the ones reckoned by Guerrero de Lizardi (2007) and share some properties, like a low goodness of fit and negative estimated coefficients. Results imply that, under the first approach, a one percent increase in GDP decreases a -0,257% unemployment rate. Under the second approach, a 1% deviation of the production growth from its trend decreases a 0,140% the unemployment rate. However, this estimations lack of statistical significance.

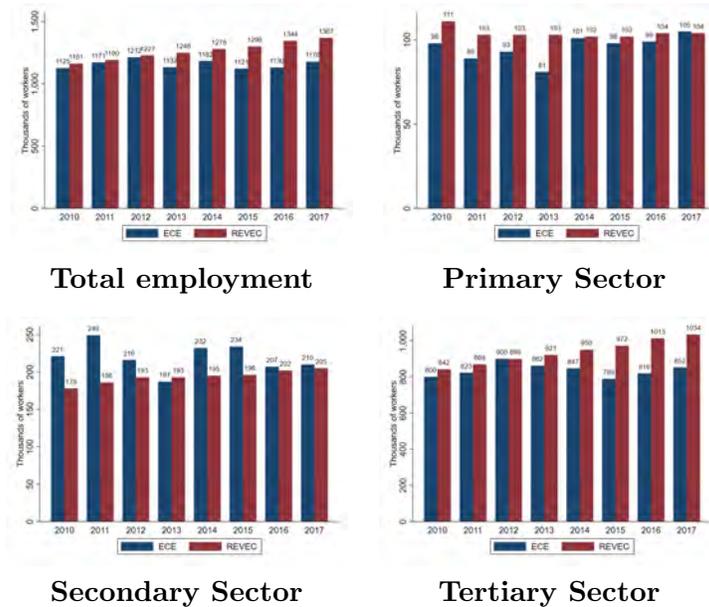
Table J1: Okun's law estimations

Coefficient	Estimation	Standard error
α_0	9,112	1,176
α_1	-0,257	0,242
$R^2 = 0,101$		
β_0	8,069	0,592
β_1	-0,140	0,268
$R^2 = 0,026$		

Source: own estimations.

K REVEC and Continuous Employment Survey comparison

Figure K4: Composition of job creation



Notes: The Continuous Employment Survey (ECE since its acronym in Spanish) is a quarterly inquiry. Graphs compare ECE data from the third quarter of each year to the yearly REVEC data.
Source: own elaboration.