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

Dinámica del Mercado Laboral en Costa Rica

Alonso Alfaro Ureña[+], Santiago Campos Rodríguez[‡], Valerie Lankester Campos[§]

Resumen

El presente documento estudia los determinantes de la demanda laboral de la economía costarricense, para lo cual se utilizan 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 nivel de 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.
Clasificación JEL.: C23, J21, J23

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Abstract

This paper studies the determinants of the labor demand in Costa Rica through 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 demand is more sensitive to changes in wages but less to changes in production than similar economies.

Key words: Labor demand, labor-output elasticity, labor-wages elasticity, job creation.
JEL codes: C23, J21, J23

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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 line of research. So far, this task had only been accomplished using aggregated data due to the lack of firm level data. Some of the pending research questions of this agenda can now be addressed thanks to the availability of the *Registro de Variables Económicas del Banco Central de Costa Rica (BCCR)* (Revec). With this database, more precise estimations are possible.

This study employs the Revec database to understand the dynamics of Costa Rica's labor demand by estimating the labor-wage and the labor-product elasticities for the economy as a whole and across industries. Reliable estimations for the aforementioned elasticities and other dynamics of labor market such as the time-adjustment of its determinants after shocks, are valuable inputs for the economic policy design.

Theefore, the purpose of this analysis is twofold. It will characterize, 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, revenues and wage shocks.

And, its results will enhance the empirical literature discussion across countries, given it is scarce on this topic for emerging economies, given the limited availability of producer microdata, as acknowledged by Hamermesh (1993).

Among the existing literature, 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 evidence between firms sales and employment which support them. Following, wages and revenues will be examined in this paper as the main determinants of labor demand.

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 the financial crisis of 2008 had on it. In this fashion, the aggregated employment behaviour was considered by economic categories of interest to unveil the industries with the highest growth and the ones that were more vulnerable to the crisis.

The document is organized as follows: Section two provides the 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 as the labor demand function. Section four, describes the database 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 for Latin American, have been limited primarily by the lack of microdata; therefore, most of the research is based on 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 industry, along with the Wholesale and Retail industry, were the largest contributors to employment growth (34.8% and 32.7% of total new employment). Meanwhile, the 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 (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 local employment has experienced an increased duality. This means, that it has polarized between traditional and less productive industries such as Agriculture, Manufacturing, Construction and Domestic Service businesses and highly productive industries including Services and high technology exports whose growth has been far higher than that of the primary activities.

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 $[-0.75, -0.15]$ interval, supporting the neoclassical theory of employment. The author also pointed 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 United States, Germany, France, Japan, Canada and United Kingdom, Symons and Layard (1984) found evidence for a positive product elasticity of the labor demand, lying within the $[0.03, 0.71]$ range. 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 in the range between $[-0.69, -0.17]$.

Research from Bencosme (2008), Melognio and Porras (2013) and Rodriguez (2013) also show relevant findings for Latin American economies. They have used diverse methodologies to estimate the labor demand for different levels of data aggregation; their results will be compared and discussed with these research's estimates. Bencosme (2008) found for Dominican Republic a labor-wage elasticity of -0.215 and labor-product elasticites of

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

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 -0.11 and -0.32 and labor-product elasticities between 0.680 and 1.09, 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 industry: 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 (2007) estimated a labor demand function with panel data by economic activity for the 2001-2004 period. With a linear state space model, he found a positive labor-wage elasticity of 0.341 (using minimum wage) and 0.547 (using private average wages), and labor-product elasticities of 0.848 and 0.849 respectively. The only

[2] Bencosme (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.

[3] They analized 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.

[4] According to the author's definition, administrative workers are involved in managerial tasks and professional workers are the qualified workers not involved in managing.

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

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 (2007) and CEPAL (2002), of the labor-wage elasticity are inconsistent with the neoclassical theory of employment and the vast majority of the empirical evidence found in the literature.

Given the regional and national context, the remarkable effort made by 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 is assumed that production is solely determined by labor and fixed capital 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 ($x = \{x_1, x_2, ..., x_n\}$) and a set of m fixed inputs ($z = \{z_1, z_2, ..., z_m\}$) 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 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):

[6] The estimations made by CEPAL (2002) for Central American countries can be found in Appendix A.

$$C = C(w, Y, K) \quad where \quad C_i > 0; \;\; i = w, Y, K \tag{3.1}$$

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:

$$L^d = \frac{\partial C(w, Y, K)}{\partial w} \tag{3.2}$$

It is important to notice that hiring 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:

$$\dot{L_t} = \gamma(L^* - L_{t-1}) \tag{3.3}$$

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 3.4 is reached:

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

$$\dot{L}_t = \gamma(G(X_t) - L_{t-1}) \tag{3.4}$$

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 3.4 can be stated as:

$$L_t = \alpha L_{t-1} + \beta X_t + \epsilon_t \tag{3.5}$$

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:

$$L_t = \alpha L_{t-1} + \sum_{m=1}^{M} \sum_{i=-\infty}^{\infty} \mu_{m,i} E_t(X_{m,t+i}) + \epsilon_t \tag{3.6}$$

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:

$$L_t = \alpha L_{t-1} + \sum_{m=1}^{M} \sum_{i=0}^{N} \mu_{m,i} X_{m,t-i} + \epsilon_t \tag{3.7}$$

where M denotes the amount of employment determinants and N their correspondent significant lags. Equation 3.8 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:

$$\mu_m^{SR} = \frac{\partial L_{i,t}}{\partial X_{i,t+i}} \tag{3.8}$$

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

$$\mu_m^{LR} = \sum_{i=0}^{\infty} \frac{\partial L_{i,t}}{\partial X_{i,t-j}} = \left(\sum_{i=0}^{N} \mu_{m,t-i} \right) \left(\frac{1}{1-\alpha} \right) \tag{3.9}$$

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.

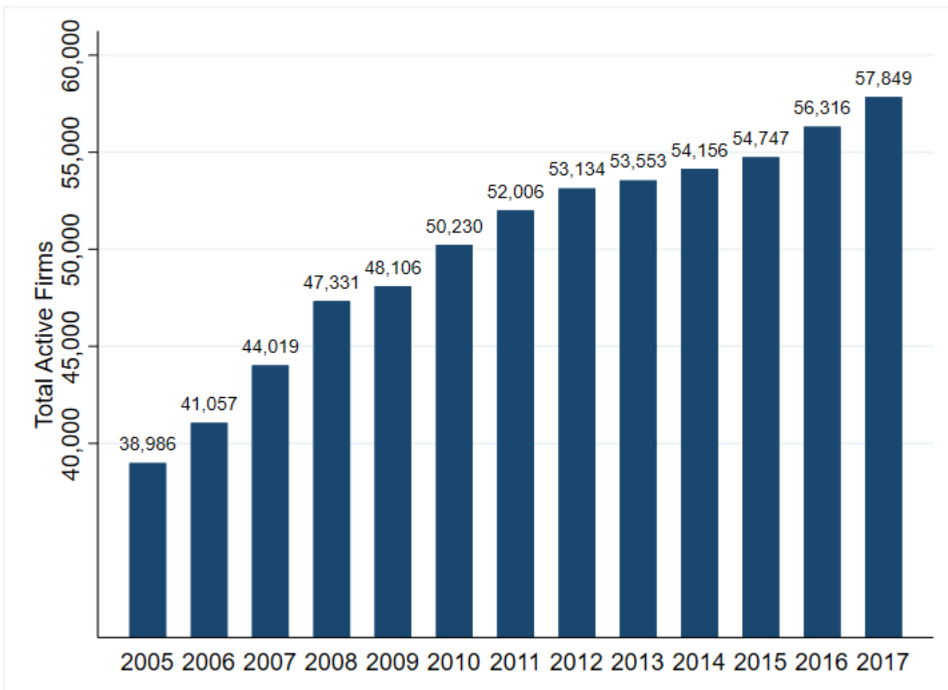
4 Data

This research makes use of the Revec database, which is constructed by the BCCR and uses inputs from several institutional sources of Costa Rica. This database contains annual data on income and expenditure per firm and data on employment averaged over the calendar year.[8] It includes formally constituted firms, including independent professionals that carry out formal economic activities. These firms inform the institutional sources of the database about their economic activity, income, expenditure, imports, exports and give other information such as the location of their establishments. Given the firm's identification number, a match is made with the employment data, resulting in a longitudinal database with the most desirable characteristics for research on Costa Rica's labor market.

[8]The processing of the data occurs at BCCR under conditions that guarantee the integrity and confidentiality of the information required for the results presented in this document.

In the aggregate, Revec has annual data, from 2005 until 2017, for 237.057 legally constituted firms.[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. Almost two thirds 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: authors.

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 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.

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

[10]The others have a legal-person identification number.

Table 1: Description of variables

Variable	Description	Detail
Employment	Headcount	Firms average headcount during a year.
Revenue	Declared income in tax form.	Annual cumulative in colones
Wages	Total labor costs	Annual cumulative in colones
Capital	Reported value of fixed assets	Total value in colones
Customs Regime	Type of regime*	Cathegorical Variable
Industry	ISIC Categorization	4-digit classification

$^*Definitive, Special or Free Zone.$
Source: authors.

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. Inferences from these estimations have limitations, as mentioned by Kuh (1959), such as 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 production, wages and 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]

$$L_{i,t} = \alpha\eta_{i,t-1} + \sigma_0 w_{(i,t)} + \sigma_1 w_{(i,t-1)} + \epsilon_0 Y_{(i,t)} + \epsilon_1 Y_{(i,t-1)} + \phi K_{(i,t)} + \lambda_t + \gamma_p + u_{it} \quad (5.1)$$

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 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 λ_t and γ_p are the temporal and geographical (over province) effects respectively. 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 differenced 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 the following characteristics:

- data with few periods but many individuals,
- a linear econometric specification,

[11] As 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.

- 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, Höffler et al. (2001) suggest that if the Difference-GMM estimator for the autorregresive parameter is less, or is 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, the classification by twenty economic categories 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 by the OECD criteria. And for the third, the firm size at birth, the Ministry of Industry, Economy and Trade's, MEIC, methodology is applied.[12]

[12] For 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 a significant shift in the composition of its economic model during the last two decades. After the crisis experienced at the beginning of 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 agricultural and manufacturing activities 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 industry, 2005 and 2017

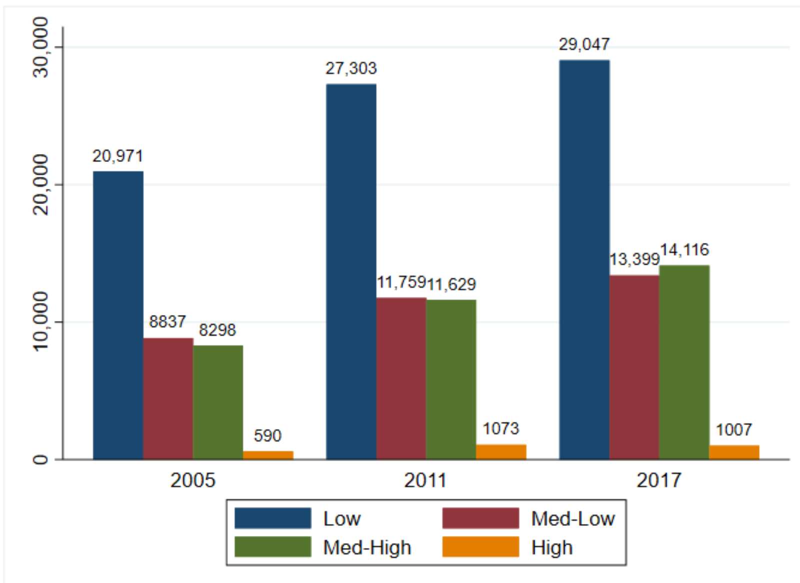
	2005	**2017**
Agriculture	10.64	6.83
Manufacturing	9.61	7.27
Wholesale and Retail	25.54	25.61
Services	54.21	60.29
Accommodation and Food Services	8.66	9.19
Professional, Scientific and Technical	7.21	8.64
Construction	6.29	5.72
Other Services	5.61	6.82
Transportation and Storage	5.30	6.09
Administrative 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: authors

Within these industries, 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: authors.

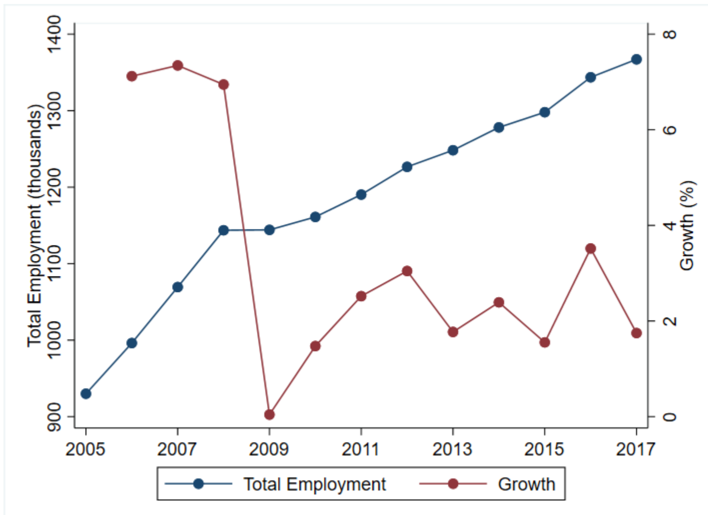
6.2 Employment analysis

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

[13] Appendix 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 by 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

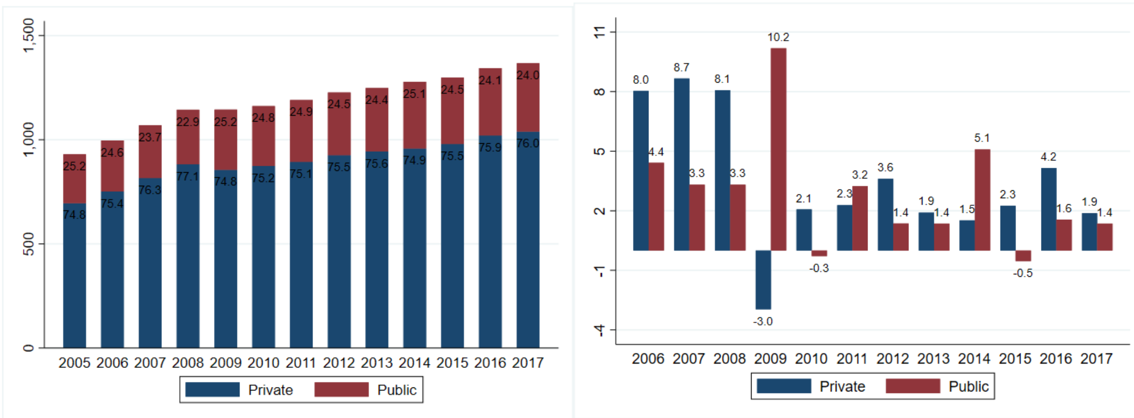


Source: authors.

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 an expansionary fiscal policy 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% while 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



Total **Annual growth (%)**

Source: authors.

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 services firm, or as independent workers of this industry, 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 Administration[14] and Wholesale and Retail, which as seen in table 3 represent 13.57% and 14.73% of total employment, in 2017, respectively[15]. Together, they account for more than a quarter of total labor, and their share has not changed significantly through time.

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

[15]Industries 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

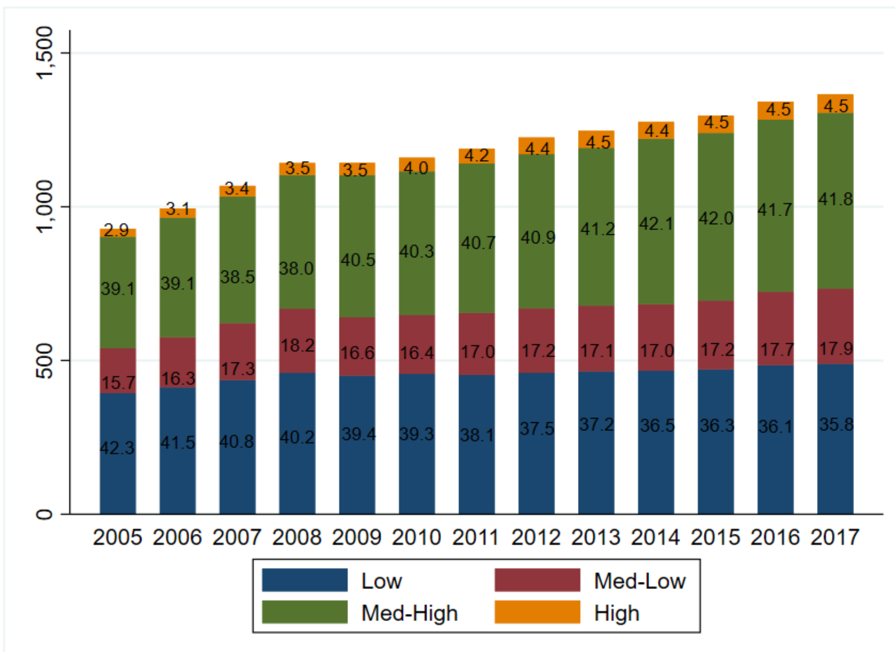
Table 3: Total employment by industry, 2005-2017 (shares in parenthesis)

Industry	**2005**	**2011**	**2017**
Public Administration	130,036	156,972	185,576
	(13.98)	(13.19)	(13.57)
Wholesale and Retail	129,279	171,806	201,410
	(13.90)	(14.43)	(14.73)
Manufacturing	120,291	137,526	144,874
	(12.93)	(11.55)	(10.60)
Agriculture	102,235	102,943	104,402
	(10.99)	(8.65)	(7.64)
Other Services	75,406	77,685	81,294
	(8.11)	(6.53)	(5.95)
Administrative and Support Services	53,794	110,714	141,238
	(5.78)	(9.30)	(10.33)
Human Health and Social Work	51,613	70,408	81,843
	(5.55)	(5.91)	(5.99)
Accommodation and Food Services	39,312	52,481	62,560
	(4.23)	(4.41)	(4.58)
Financial Activities	37,993	47,346	55,078
	(4.09)	(3.98)	(4.03)
Education	34,464	51,253	60,834
	(3.71)	(4.31)	(4.45)
Professional, Scientific and Technical	32.112	45,142	59,053
	(3.45)	(3.79)	(4.32)
Transportation and Storage	30,516	40,373	50,309
	(3.28)	(3.39)	(3.68)
Construction	29,261	38,868	49,165
	(3.15)	(3.27)	(3.60)
Electricity and Gas	20,294	32,031	23,414
	(2.18)	(2.69)	(1.71)
Information and Communication	12,587	20,486	28,953
	(1.35)	(1.72)	(2.12)

Source: authors

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 only 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)

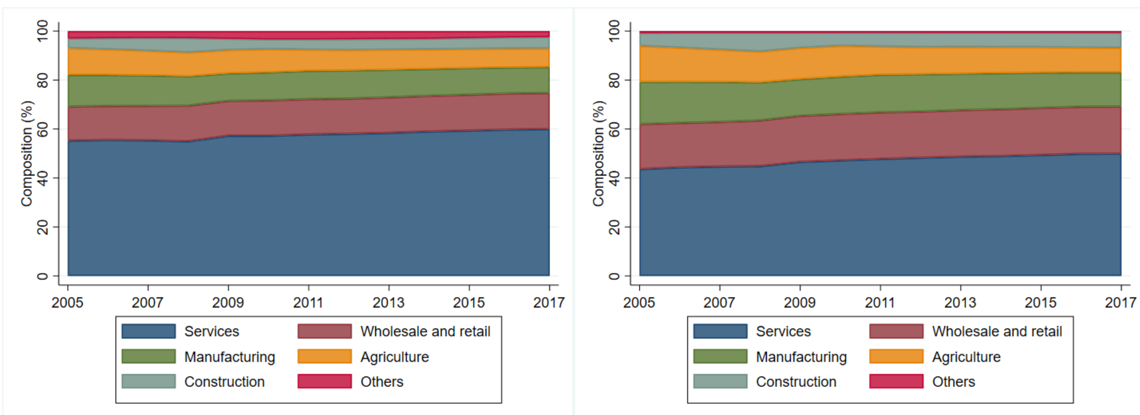


Note: labels inside bars show to the employment share of the respective category.

Source: authors.

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 diminished 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 industry that strengthened in 2009 and that has been driven specially by the private sector.

Figure 6: Employment composition by industry, 2005-2017



Total **Private**

Source: authors.

During this time, growth has been heterogeneous among industries. For the Construction industry, the financial crisis had a deep impact; before 2009 its employment grew above 20% annually, but in 2009 and 2010 it experienced substantial contractions, and despite experiencing the largest growth rates since then, they have been even less than half as before the crisis.

As shown in figure 7, employment was also lessened in industries 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

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

slightly after 2010 and had a considerable boost in 2016.

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

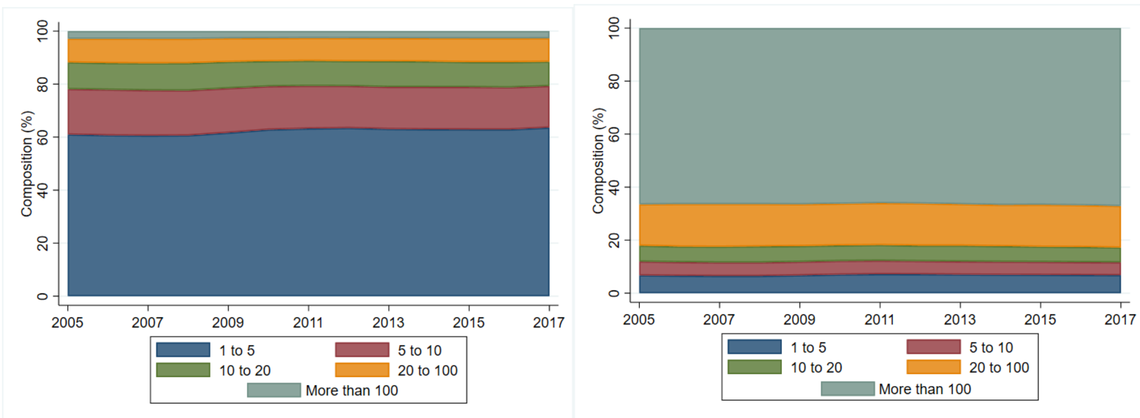
Industry **Intensity in the use of technology**

Source: authors.

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, for 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 Continious Survey (ECE) formal employment aggregates.

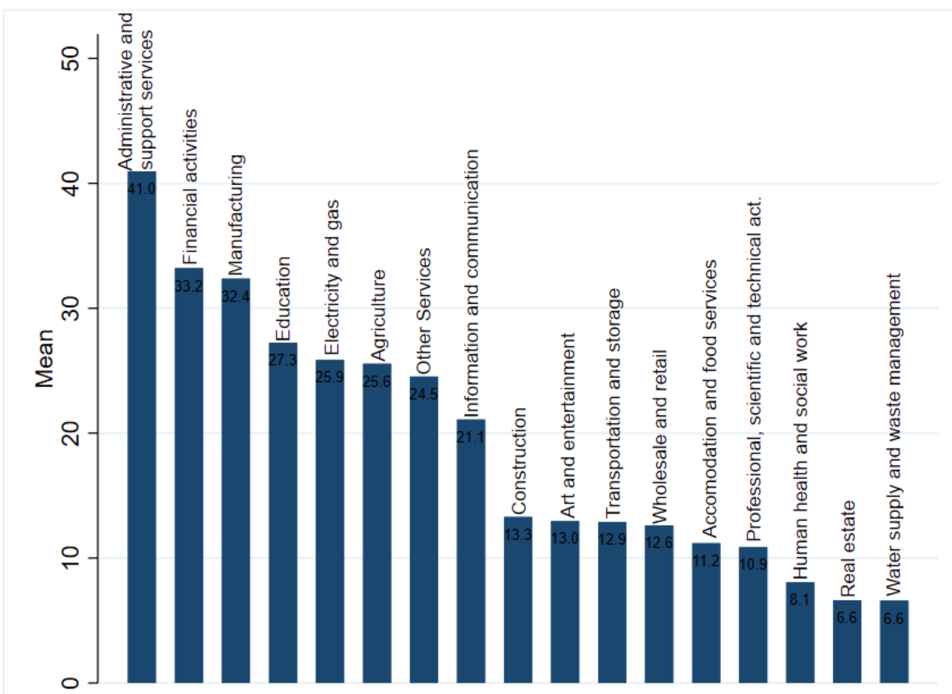
Figure 8: Firm and employment composition by headcount in the private sector, 2005-2017



Firm **Employment**

Source: authors.

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



Source: authors.

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:

$$GJC_t = \Sigma_i^N \Delta E^{+}_{i,t} \tag{6.3.1}$$

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

$$GJD_t = \Sigma_i^N |\Delta E^{-}_{i,t}| \tag{6.3.2}$$

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

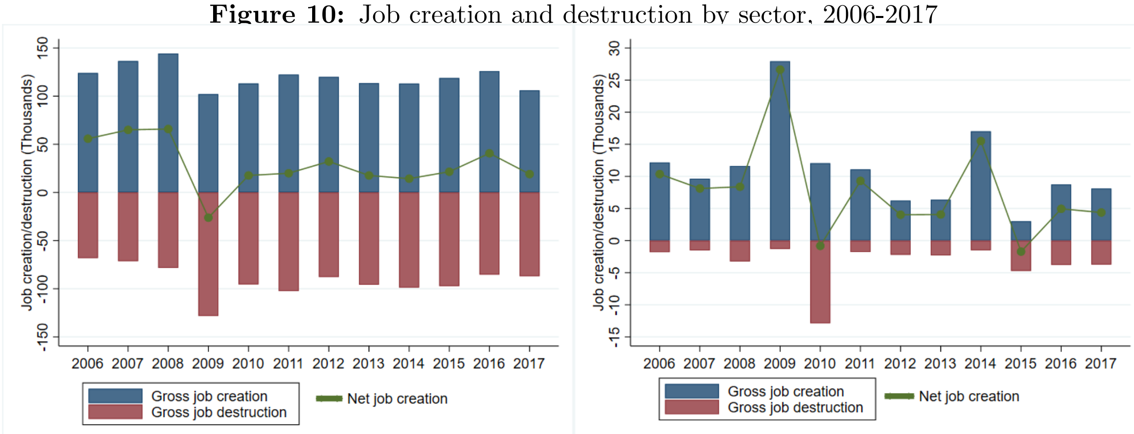
$$NJC_t = GJC_t - GJD_t \tag{6.3.3}$$

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 numbers showed in Figure 10 consider 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 necessary to extend

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



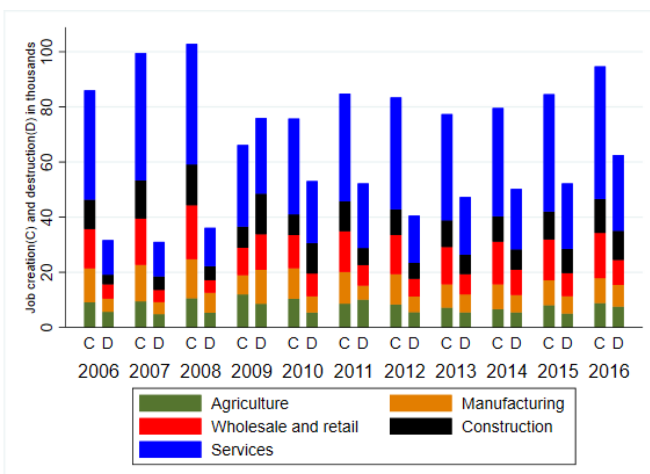
Private **Public**

Source: authors.

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 worst affected industry 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: authors.

Employment in Construction is far more volatile than any other industry. 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.

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

Job creation **Job destruction**

Source: authors.

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, in net,

[17] Refer 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 a 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.

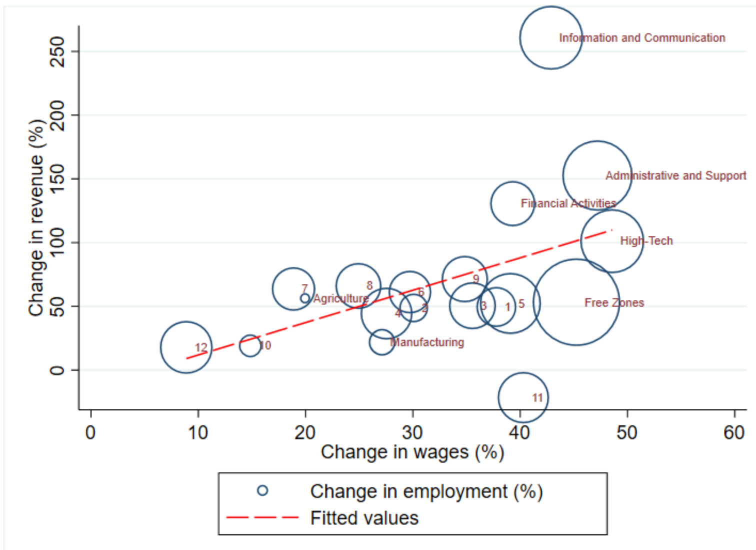
Employment growth was proportional to the intensity in the use of technology: high-tech employment grew 133%, med-high employment 85.8%, med-low 69.7% and employment in low-tech firms just 24.2%. As seen earlier in this section, and detailed in appendix C, high-technology firms include those that develop 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 rates.

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 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 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 on 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 on 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.

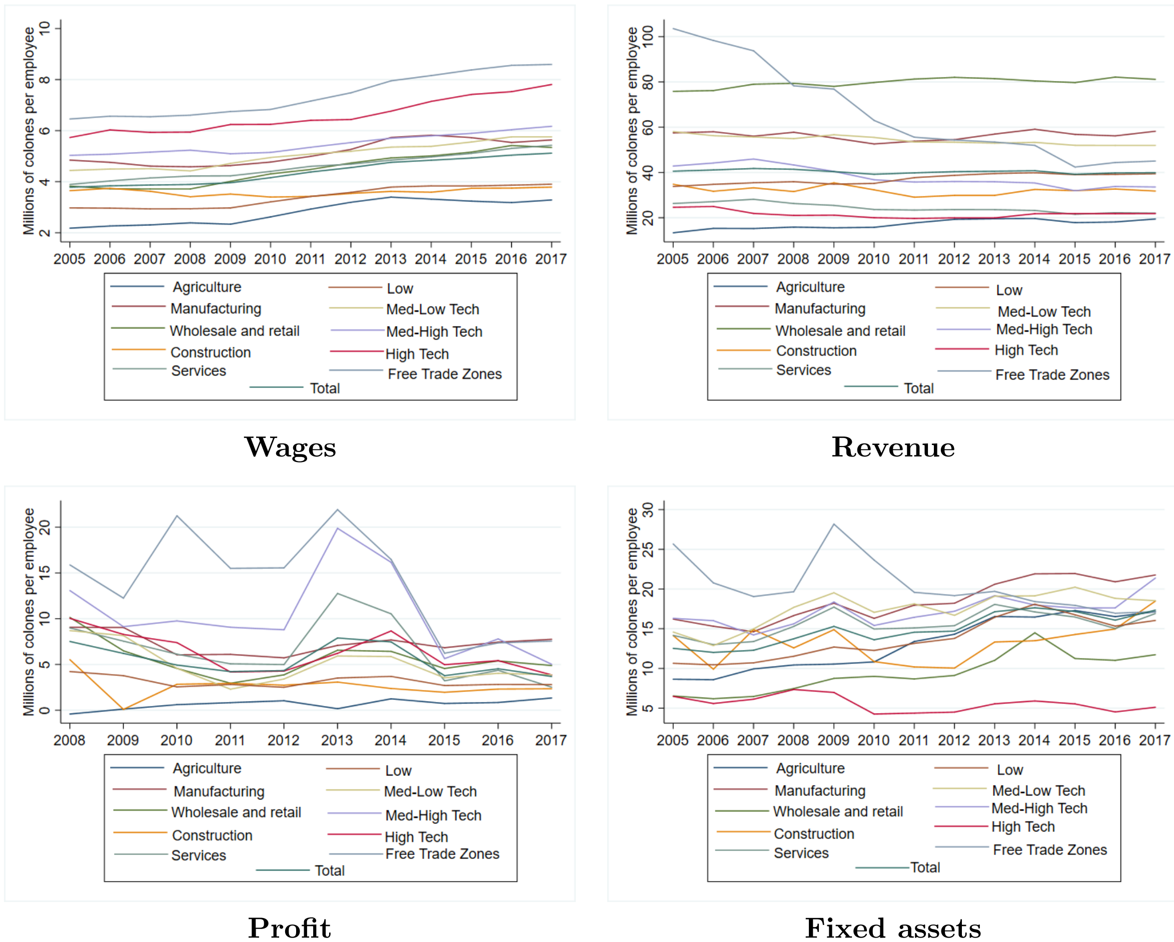
Source: authors.

Figure 14 shows wages, revenue, profit and fixed assets per employee in the private sector. It exhibits that high-tech firm's 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,

[18]Defined as total revenue minus total expenses.

fixed assets per employee are inversely proportional to the intensity in the use of technology.

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



Source: authors.

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 firm's indicators such as revenue, wages and employment growth rates, have a higher and more volatile behaviour than for 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.

[19] In 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 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 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(s) 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, there were 727,019 (78.2% of total employment) workers in 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.

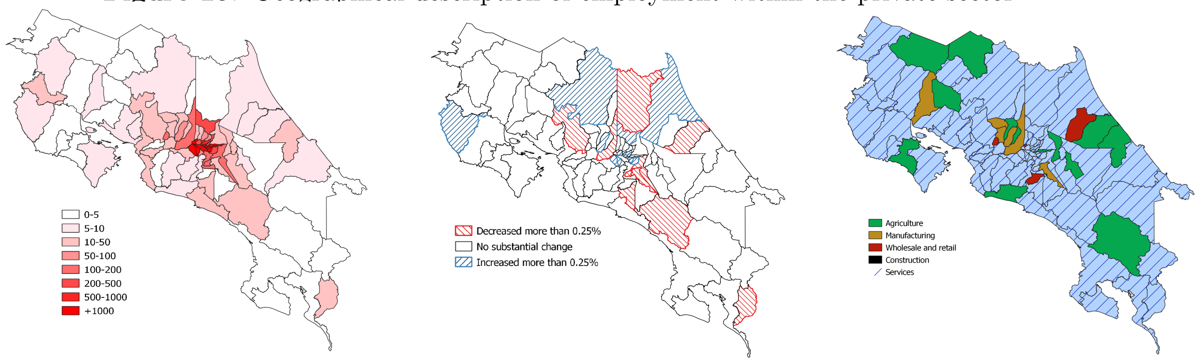
Economic activities also differ between cantons. In 2005, only 45 cantons out of 81 had services as its predominant employer. For 2017, the number had increased to 58 out of the 82[21] (or 25 out of the 31 cantons in GMA) mainly because of the change from Manufacturing and Wholesale and Retail to Services. 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%), and 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

[20] The 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 **B** **C**

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

Source: authors.

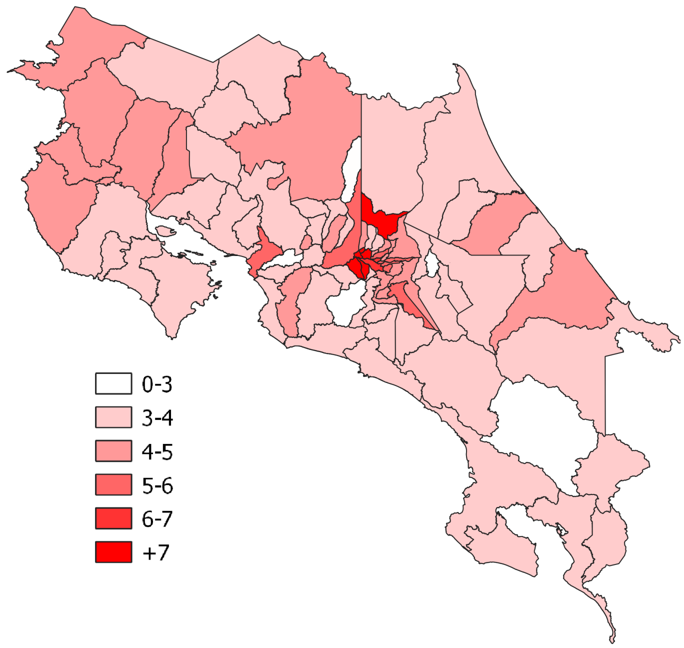
private sector), which are three times higher than the average wage of Buenos Aires and Nandayure, cantons with the lowest average wage. These two cantons have agriculture as its main activity. There is a significant difference between the wages from cantons in the GMA and the rest; it is almost double, as shown 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 the cases where employment decisions may consider other factors than market forces. The first case is public employment, which is strongly related to political outcomes, and the second, is the banking industry, where financial market imperfections given its industrial organization (as the government owns 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 in 2017 (millions of colones of 2015)



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

Source: authors.

than five because the inclusion of smaller operations such as self-employed individuals or (very) small firms 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).

For most tests, the null hypothesis of series being a unit-root process was rejected, with the exception of the Breitung test. Because this assessment and the LLC assume that all

[22] Alternative 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: authors.

The model presented in section 5 was chosen, and due to the lack of information contributed by further lags, only one lagged period was included.[25] The results of estimating the model for the specified categories, with over 500 firms, are summarized in table 5.

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 Höffler 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 autorregresive 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-order autocorrelation (but not any further) and the instruments are exogenous. Finally, in

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

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

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

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 firm's wages leads to a 0.358% decrease in the following year's 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 firm's 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 Food Services, 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 firm's 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
Transportation and Storage ⊗	0.855***	0.228***	-0.157	781
Accommodation and Food Services ⊗	0.749***	0.502***	-0.134	1124
Information and Communication ⊗	0.860***	0.371***	-0.047	545
Professional, Scientific and Technical ⊗	0.669***	0.474***	-0.326***	1044
Administrative and Support Services ⊗	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: authors

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, firms under the free trade zone regime 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 tax regime (Free Trade Zone), are shown in table 6. In general, the main differences do 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.

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 run[26]. 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, 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 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.

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

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	-
Transportation and Storage	4.4	0.607	-
Accommodation and Food Services	2.4	0.697	-
Information and Communication	4.6	0.671	-
Professional, Scientific and Technical	1.7	0.574	-0.184
Administrative and Support Services	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: authors.

8 Conclusions

This research 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 by analyzing data of more than a decade, and second, it estimates a labor demand equation where the elasticity results comply with the neoclassical theory and complements its results by estimating 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 other activities 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 financial crisis than afterwards.

In terms of firm size, employment had a quite homogeneous structure. 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 region.

When considering job rotation, it seems to be present in all of the analyzed industries, but is considerably higher in Construction, for which most of new jobs go to *newborn* firms. For Agriculture and Manufacturing, most new jobs come from incumbent firms. These firms, in general, are in industries related to more qualified jobs and 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 consider different characteristics as heterogenous results were showcased across industries.

Given the results of this research, the responsiveness of employment to changes over revenue and wages seems to be correlated to firm's size at birth in the short and long run. This characteristic 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 at birth, 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	0.436	0.960	25
			(15.20)	(6.22)		
		1991-2001	0.400	0.907	0.873	11
			(1.99)	(3.00)		
El Salvador	1.42	1994-2002	0.614	0.193	0.936	9
			(14.48)	(2.35)		
		1980-2004	0.347	0.443	0.927	25
			(6.94)	(4.57)		
Guatemala	0.86	1980-2004	0.963	0.007	0.914	25
			(14.02)	(0.06)		
		1986-2003	0.613	0.519	0.794	18
			(5.29)	(2.55)		
Honduras	1.61	1985-2004	1.187	-0.629	0.915	20
			(15.71)	(-4.40)		
		1995-2003	1.005	-0.278	0.900	9
			(14.83)	(-2.15)		
Nicaragua	0.05	1991-2004	0.660	0.082	0.865	14
			(2.26)	(0.20)		
Panama	1.08	1991-2002	0.672	0.128	0.947	12
			(3.64)	(0.35)	0.947	

Source: Guerrero (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:

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

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

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

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

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

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:

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

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 existent classifications were used. Specifically, the methodologies used to classify firms by industry, technology intensity and firm size which were followed in this research are explained as 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 rasing, 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	49-53	
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	*Code* > 49	

Source: authors.

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 criterion 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 fuel 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 prevously 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: authors based in OECD ISIC Rev.3 technology intensity definition.

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 industry i defines the formula applied to calculate the score. For the services and wholesale and retail firms the next formula applies:

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

For the information technology firms the following formula is applied:

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

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

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

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

Table C3: MEIC size classifications

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

Source: authors based on MEIC methodology.

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: authors

E Total employment descriptive statistics

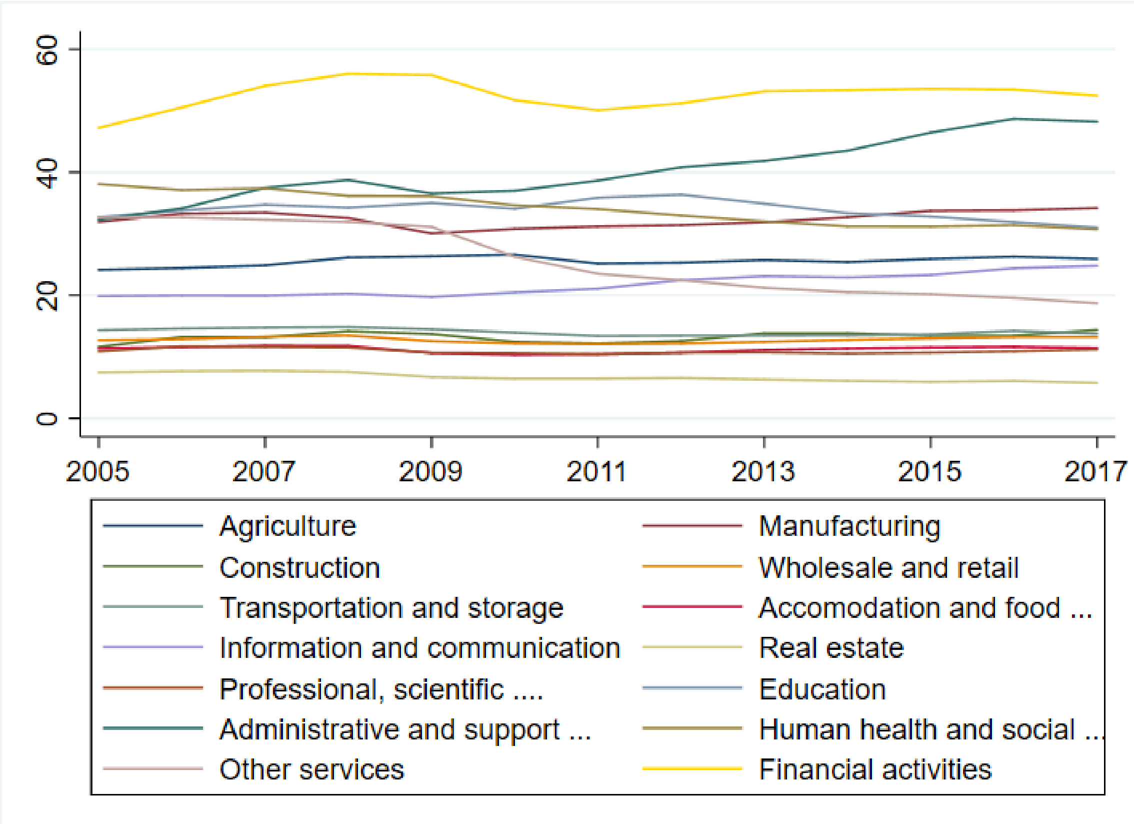
Table E1: Total employment descriptive statistics, 2005-2017

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: authors

F Average employment per industry

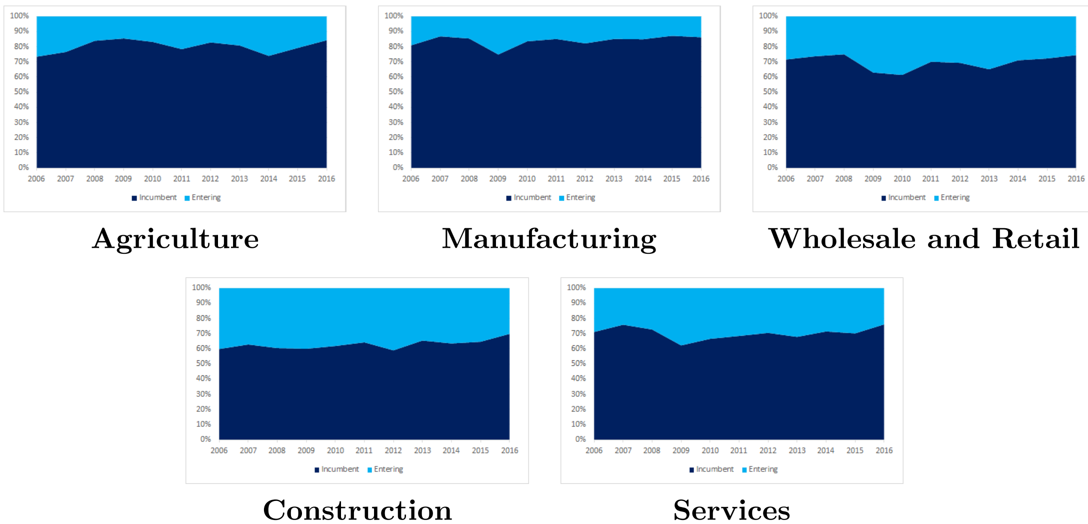
Figure F1: Average employment per industry, 2005-2017



Source: authors.

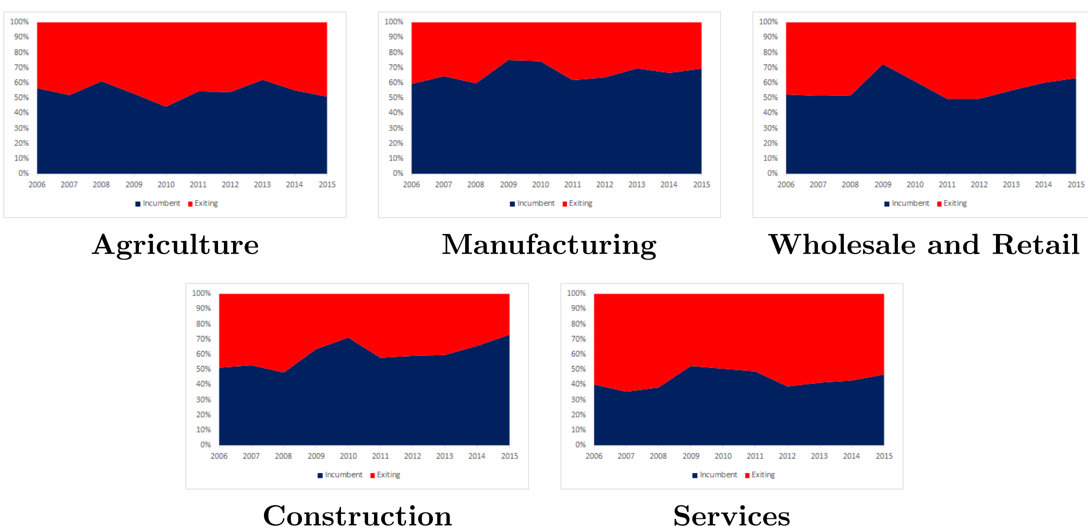
G Composition of job creation and destruction

Figure G2: Composition of job creation



Source: authors.

Figure G3: Composition of job destruction



Source: authors.

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

Table H1: Labor demand estimations for all firms

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.859***	0.483***	0.585***	0.851***
	(0.002)	(0.008)	(0.091)	(0.039)
$w_{i,t}$	-0.183***	-0.107**	-0.640***	-0.358***
	(0.037)	(0.044)	(0.249)	(0.126)
$w_{i,t-1}$	0.164***	0.131***	0.407**	0.323***
	(0.034)	(0.023)	(0.192)	(0.121)
$Y_{i,t}$	0.578***	0.503***	0.489***	0.435***
	(0.006)	(0.007)	(0.090)	(0.053)
$Y_{i,t-1}$	-0.512***	-0.201***	-0.114***	-0.367***
	(0.006)	(0.006)	(0.078)	(0.052)
$K_{i,t}$	0.014***	0.033***	0.057***	0.029**
	(0.001)	(0.002)	(0.031)	(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: authors.

Table H2: Labor demand estimations for the Agricultural industry

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.869***	0.555***	0.510***	0.817***
	(0.008)	(0.026)	(0.077)	(0.059)
$w_{i,t}$	-0.004	0.097	0.009	0.044
	(0.184)	(0.153)	(0.271)	(0.290)
$w_{i,t-1}$	-0.009	-0.000	0.004	0.083
	(0.173)	(0.118)	(0.257)	(0.275)
$Y_{i,t}$	0.463***	0.415***	0.183**	0.130**
	(0.028)	(0.032)	(0.093)	(0.055)
$Y_{i,t-1}$	-0.387***	-0.158***	0.081*	-0.028
	(0.027)	(0.024)	(0.048)	(0.049)
$K_{i,t}$	0.011***	0.046***	0.095	0.020
	(0.003)	(0.010)	(0.067)	(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: authors.

Table H3: Labor demand estimations for the Manufacturing industry

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.860***	0.543***	0.737***	0.871***
	(0.007)	(0.020)	(0.121)	(0.032)
$w_{i,t}$	-0.326***	-0.195**	-0.749***	-0.510***
	(0.068)	(0.078)	(0.260)	(0.150)
$w_{i,t-1}$	0.314***	0.283***	0.601**	0.505***
	(0.064)	(0.049)	(0.250)	(0.140)
$Y_{i,t}$	0.588***	0.524***	0.401***	0.306***
	(0.018)	(0.023)	(0.103)	(0.064)
$Y_{i,t-1}$	-0.508***	-0.264***	-0.033	-0.228***
	(0.018)	(0.018)	(0.107)	(0.064)
$K_{i,t}$	0.013***	0.020***	-0.046*	0.005
	(0.002)	(0.004)	(0.027)	(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: authors.

Table H4: Labor demand estimations for the Construction industry

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.667***	0.280***	0.153	0.513***
	(0.015)	(0.027)	(0.174)	(0.114)
$w_{i,t}$	-0.382***	-0.411***	-1.320***	-0.949***
	(0.071)	(0.101)	(0.477)	(0.203)
$w_{i,t-1}$	0.269***	0.088	-0.141	0.557**
	(0.070)	(0.076)	(0.372)	(0.220)
$Y_{i,t}$	0.591***	0.571***	0.316***	0.513***
	(0.017)	(0.026)	(0.121)	(0.078)
$Y_{i,t-1}$	-0.410***	-0.136***	-0.092	-0.238***
	(0.019)	(0.025)	(0.079)	(0.074)
$K_{i,t}$	0.010***	0.055***	0.034	-0.001
	(0.004)	(0.012)	(0.063)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.849***	0.520***	0.616***	0.958***
	(0.005)	(0.013)	(0.127)	(0.043)
$w_{i,t}$	-0.125***	-0.060	-0.381**	-0.287**
	(0.046)	(0.056)	(0.251)	(0.130)
$w_{i,t-1}$	0.092**	0.097***	0.309**	0.299**
	(0.044)	(0.036)	(0.169)	(0.126)
$Y_{i,t}$	0.514***	0.442***	0.407***	0.404***
	(0.012)	(0.015)	(0.086)	(0.072)
$Y_{i,t-1}$	-0.448***	-0.212***	-0.184	-0.377***
	(0.012)	(0.012)	(0.138)	(0.069)
$K_{i,t}$	0.016***	0.031***	0.041**	-0.019
	(0.001)	(0.003)	(0.031)	(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: authors.

Table H6: Labor demand estimations for the Services industry

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.843***	0.470***	0.485***	0.792***
	(0.005)	(0.014)	(0.085)	(0.051)
$w_{i,t}$	-0.164***	-0.103**	-0.194	-0.081
	(0.039)	(0.046)	(0.197)	(0.097)
$w_{i,t-1}$	0.127***	0.111***	0.133	0.025**
	(0.037)	(0.028)	(0.100)	(0.089)
$Y_{i,t}$	0.642***	0.535***	0.289***	0.515***
	(0.010)	(0.014)	(0.100)	(0.066)
$Y_{i,t-1}$	-0.545***	-0.247***	-0.087	-0.373***
	(0.010)	(0.012)	(0.087)	(0.075)
$K_{i,t}$	0.005***	0.033***	0.022	0.017
	(0.001)	(0.004)	(0.033)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.857***	0.519***	0.407***	0.855***
	(0.011)	(0.025)	(0.128)	(0.046)
$w_{i,t}$	-0.103	-0.071	0.478	-0.157
	(0.084)	(0.094)	(0.250)	(0.106)
$w_{i,t-1}$	0.084	0.129*	0.443*	0.080
	(0.083)	(0.074)	(0.211)	(0.109)
$Y_{i,t}$	0.555***	0.441***	0.117	0.228***
	(0.023)	(0.026)	(0.073)	(0.061)
$Y_{i,t-1}$	-0.482***	-0.205***	0.115	-0.140**
	(0.023)	(0.024)	(0.086)	(0.067)
$K_{i,t}$	0.015***	0.032***	0.047	-0.004
	(0.003)	(0.008)	(0.037)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.685***	0.348***	0.268	0.749***
	(0.023)	(0.053)	(0.184)	(0.069)
$w_{i,t}$	0.070	0.087	-0.404*	-0.134
	(0.073)	(0.080)	(0.163)	(0.077)
$w_{i,t-1}$	-0.022	0.020	0.289**	0.094
	(0.069)	(0.064)	(0.144)	(0.148)
$Y_{i,t}$	0.638***	0.573***	0.537***	0.502***
	(0.020)	(0.035)	(0.107)	(0.078)
$Y_{i,t-1}$	-0.422***	-0.175***	-0.064	-0.327***
	(0.024)	(0.039)	(0.160)	(0.084)
$K_{i,t}$	0.013***	0.015***	-0.006	0.022**
	(0.002)	(0.006)	(0.063)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.781***	0.445***	0.301***	0.860***
	(0.016)	(0.032)	(0.148)	(0.059)
$w_{i,t}$	-0.009	0.074	-0.126	-0.047
	(0.161)	(0.169)	(0.243)	(0.145)
$w_{i,t-1}$	-0.004	-0.038	-0.034	-0.009
	(0.151)	(0.107)	(0.171)	(0.151)
$Y_{i,t}$	0.672***	0.564***	0.320***	0.371***
	(0.027)	(0.041)	(0.094)	(0.086)
$Y_{i,t-1}$	-0.551***	-0.104	-0.106**	-0.277***
	(0.027)	(0.032)	(0.079)	(0.095)
$K_{i,t}$	0.013**	0.043***	0.033	0.004
	(0.005)	(0.0122)	(0.027)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.761***	0.435***	0.224**	0.669***
	(0.012)	(0.025)	(0.103)	(0.102)
$w_{i,t}$	-0.276***	-0.196***	-0.664***	-0.326**
	(0.055)	(0.058)	(0.173)	(0.082)
$w_{i,t-1}$	0.471***	0.168***	0.210	0.265
	(0.020)	(0.040)	(0.168)	(0.168)
$Y_{i,t}$	0.614***	0.537***	0.451***	0.474***
	(0.020)	(0.027)	(0.093)	(0.079)
$Y_{i,t-1}$	-0.471***	-0.219***	-0.059	-0.281***
	(0.020)	(0.019)	(0.088)	(0.088)
$K_{i,t}$	0.013***	0.044***	0.047	0.021
	(0.003)	(0.058)	(0.034)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.884***	0.460***	0.291***	0.841***
	(0.008)	(0.034)	(0.137)	(0.062)
$w_{i,t}$	-0.300***	-0.231**	-0.578***	-0.308***
	(0.088)	(0.103)	(0.148)	(0.189)
$w_{i,t-1}$	0.252***	0.140**	-0.073	0.264***
	(0.083)	(0.066)	(0.168)	(0.169)
$Y_{i,t}$	0.758***	0.663***	0.574***	0.687***
	(0.021)	(0.032)	(0.148)	(0.119)
$Y_{i,t-1}$	-0.682***	-0.313***	-0.081	-0.540***
	(0.021)	(0.033)	(0.073)	(0.116)
$K_{i,t}$	0.004	0.048***	0.010	-0.038
	(0.003)	(0.011)	(0.036)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.863***	0.515***	0.478***	0.800***
	(0.004)	(0.014)	(0.125)	(0.041)
$w_{i,t}$	-0.073	-0.005	-0.226	-0.149
	(0.071)	(0.076)	(0.311)	(0.178)
$w_{i,t-1}$	0.058	0.074*	0.074	0.234
	(0.065)	(0.043)	(0.206)	(0.162)
$Y_{i,t}$	0.540***	0.472***	0.462***	0.256***
	(0.011)	(0.015)	(0.109)	(0.074)
$Y_{i,t-1}$	-0.476***	-0.220***	-0.025	-0.179***
	(0.010)	(0.012)	(0.109)	(0.073)
$K_{i,t}$	0.018***	0.028***	0.015	0.021
	(0.001)	(0.003)	(0.036)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.846***	0.456***	0.546***	0.788***
	(0.005)	(0.014)	(0.117)	(0.044)
$w_{i,t}$	-0.282***	-0.205***	-0.972***	-0.604***
	(0.041)	(0.049)	(0.366)	(0.177)
$w_{i,t-1}$	0.236***	0.185***	0.657**	0.504***
	(0.041)	(0.040)	(0.259)	(0.172)
$Y_{i,t}$	0.563***	0.493***	0.477***	0.496***
	(0.010)	(0.014)	(0.124)	(0.069)
$Y_{i,t-1}$	-0.492***	-0.206***	-0.182**	-0.383***
	(0.011)	(0.013)	(0.092)	(0.072)
$K_{i,t}$	0.014***	0.042***	0.049	0.022
	(0.002)	(0.004)	(0.038)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.830***	0.451***	0.230*	0.652***
	(0.006)	(0.017)	(0.135)	(0.098)
$w_{i,t}$	-0.232***	-0.141**	-0.553*	-0.368***
	(0.057)	(0.063)	(0.247)	(0.122)
$w_{i,t-1}$	0.176***	0.125***	0.026	0.214*
	(0.053)	(0.035)	(0.026)	(0.116)
$Y_{i,t}$	0.643***	0.555***	0.474***	0.507***
	(0.013)	(0.017)	(0.110)	(0.083)
$Y_{i,t-1}$	-0.544***	-0.249***	-0.064	-0.272***
	(0.013)	(0.014)	(0.083)	(0.086)
$K_{i,t}$	0.009***	0.028***	0.027	0.026
	(0.002)	(0.004)	(0.033)	(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: authors.

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

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.863***	0.493***	0.311**	0.840***
	(0.011)	(0.030)	(0.127)	(0.073)
$w_{i,t}$	-0.370***	-0.374***	-0.484*	-0.537***
	(0.075)	(0.086)	(0.276)	(0.229)
$w_{i,t-1}$	0.324***	0.216***	0.305	0.434***
	(0.075)	(0.071)	(0.309)	(0.226)
$Y_{i,t}$	0.700***	0.629***	0.526***	0.766***
	(0.026)	(0.042)	(0.111)	(0.133)
$Y_{i,t-1}$	-0.609***	-0.296***	-0.013	-0.630***
	(0.025)	(0.030)	(0.132)	(0.120)
$K_{i,t}$	0.001	0.046***	0.053***	-0.015
	(0.003)	(0.071)	(0.053)	(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: authors.

Table H16: Labor demand estimations for micro firms at birth

Variable	**OLS**	**Fixed effects**	**MGM-Dif**	**MGM-Sys**
$L_{i,t-1}$	0.655***	0.356***	0.365***	0.726***
	(0.009)	(0.013)	(0.109)	(0.082)
$w_{i,t}$	-0.279***	-0.088***	-0.214	-0.185
	(0.035)	(0.026)	(0.229)	(0.127)
$w_{i,t-1}$	0.215***	0.110***	0.233	0.221*
	(0.035)	(0.018)	(0.149)	(0.119)
$Y_{i,t}$	0.538***	0.498***	0.313***	0.361***
	(0.011)	(0.018)	(0.073)	(0.063)
$Y_{i,t-1}$	-0.417***	-0.165***	-0.013	-0.251***
	(0.011)	(0.013)	(0.057)	(0.072)
$K_{i,t}$	0.012***	0.028***	-0.003	0.024
	(0.002)	(0.003)	(0.040)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.819***	0.482***	0.637***	0.806***
	(0.005)	(0.011)	(0.113)	(0.067)
$w_{i,t}$	-0.058**	0.008	-0.382	-0.169
	(0.029)	(0.034)	(0.316)	(0.128)
$w_{i,t-1}$	0.038	0.041	0.234	0.180
	(0.028)	(0.025)	(0.154)	(0.120)
$Y_{i,t}$	0.510***	0.447***	0.425***	0.384***
	(0.009)	(0.012)	(0.094)	(0.060)
$Y_{i,t-1}$	-0.446***	-0.199***	-0.193*	-0.307***
	(0.009)	(0.009)	(0.115)	(0.064)
$K_{i,t}$	0.012***	0.025***	0.029	0.016
	(0.001)	(0.003)	(0.037)	(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: authors.

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

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.873***	0.528***	0.489***	0.897***
	(0.006)	(0.018)	(0.133)	(0.037)
$w_{i,t}$	-0.194***	-0.130	-0.221	-0.195***
	(0.069)	(0.079)	(0.309)	(0.156)
$w_{i,t-1}$	0.196***	0.174***	-0.041***	0.110
	(0.065)	(0.048)	(0.164)	(0.149)
$Y_{i,t}$	0.566***	0.494***	0.494***	0.399***
	(0.013)	(0.016)	(0.113)	(0.079)
$Y_{i,t-1}$	-0.522***	-0.253***	-0.282***	-0.358***
	(0.013)	(0.016)	(0.089)	(0.077)
$K_{i,t}$	0.014***	0.037***	0.043	0.037**
	(0.002)	(0.004)	(0.031)	(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: authors.

Table H19: Labor demand estimations for large firms at birth

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.930***	0.588***	0.515***	0.924***
	(0.005)	(0.029)	(0.126)	(0.040)
$w_{i,t}$	-0.308	-0.228	-0.429	-0.569**
	(0.204)	(0.213)	(0.460)	(0.315)
$w_{i,t-1}$	0.292	0.212	0.601**	0.376***
	(0.196)	(0.142)	(0.300)	(0.096)
$Y_{i,t}$	0.655***	0.587***	0.455***	0.462***
	(0.020)	(0.024)	(0.123)	(0.037)
$Y_{i,t-1}$	-0.614***	-0.328***	0.011	-0.443***
	(0.020)	(0.025)	(0.125)	(0.083)
$K_{i,t}$	0.009***	0.047***	0.065**	0.004
	(0.002)	(0.006)	(0.027)	(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: authors.

Table H20: Labor demand estimations for free trade zone regime

Variable	OLS	Fixed effects	MGM-Dif	MGM-Sys
$L_{i,t-1}$	0.906***	0.406***	0.139	0.905***
	(0.012)	(0.035)	(0.168)	(0.036)
$w_{i,t}$	-0.721***	-0.639**	-1.075***	-1.004***
	(0.209)	(0.306)	(0.401)	(0.316)
$w_{i,t-1}$	0.737***	0.361**	0.106	0.966***
	(0.194)	(0.166)	(0.349)	(0.336)
$Y_{i,t}$	0.685***	0.544***	0.512***	0.332***
	(0.033)	(0.042)	(0.149)	(0.112)
$Y_{i,t-1}$	-0.641***	-0.243***	0.086	-0.306***
	(0.033)	(0.038)	(0.121)	(0.105)
$K_{i,t}$	0.010*	0.087***	0.198***	0.034
	(0.006)	(0.028)	(0.076)	(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: authors.

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*	*First-Difference*	8613
Industry categories					
Agriculture	0.838***	0.160***	0.049	*System*	1465
Manufacturing	0.721***	0.323***	-0.040	*First-Difference*	1333
Construction	0.378***	0.523***	-0.479***	*System*	1136
Wholesale and Retail	0.542***	0.335***	0.075	*First-Difference*	2717
Transportation and Storage	0.866***	0.342***	-0.329***	*System*	1178
Accommodation and Food Services	0.770***	0.345***	0.020	*System*	1750
Information and Communication	0.757***	0.467***	-0.079	*System*	729
Professional, Scientific and Technical act.	0.586***	0.473***	-0.030	*System*	1597
Administrative and Support Services	0.880***	0.489***	-0.303***	*System*	1393
Technology intensiveness categories					
Low	0.700***	0.314***	-0.108	*First-Difference*	4227
Medium-Low	0.672***	0.413***	-0.548***	*System*	5345
Medium-High	0.642***	0.428***	-0.263***	*System*	4127
High	0.813***	0.706***	-0.434***	*System*	646
Firm size at birth categories					
Micro firms	0.510***	0.209***	-0.093	*First-Difference*	1799
Small firms	0.652***	0.346***	0.012	*First-Difference*	3529
Medium firms	0.527***	0.328***	-0.218***	*First-Difference*	1817
Large firms	0.958***	0.418***	-0.380***	*System*	2108
Free trade zones					
Free zones	0.905***	0.332***	-0.840***	*System*	310

Source: authors.
Note: the sample included firms with a median employment grater than 5.

J Okun's Law

Several studies have tested the empirical observation of Okun (1963), who established a short run inverse relationship between unemployment and production. Guerrero (2007) test this relationship for the Central American region with country-level data for the eighties, nineties and early two 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 and trend product growth rates dyt_t, i.e.:

$$u_t = \alpha_0 + \alpha_1 dy_t + e_t \tag{10.6.1}$$

$$u_t = \beta_0 + \beta_1 (dy_t - d_y t_t) + e_t \tag{10.6.2}$$

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 (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 has an impact of $-0,257\%$ over the 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.

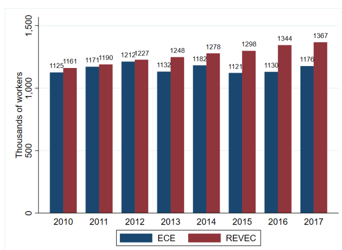
Table J1: Okun's law estimations

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
	$R^2 = 0,026$	

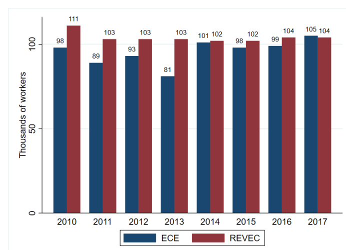
Source: authors.

K Revec and Continuous Employment Survey comparison

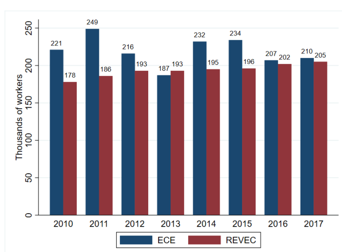
Figure K4: Yearly Employment (2010-2017)



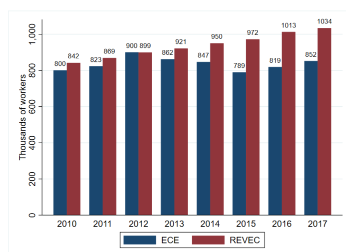
Total employment



Primary Sector



Secondary Sector



Tertiary Sector

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: authors.