Slow Dynamics of Job Flow Rates in Colombian Industry[*]

Por:
Alvaro Cháves[**],
Alejandro Mesa[***],
Fernando Mesa[****]

Keywords: *Firm Behavior and Empirical Analysis, Labor Demand, Market Structure Size Distribution of Firms, Panel Data Models, Instrumental Variables (IV) Estimation.*
Palabras clave: *Comportamiento de las empresas y análisis empírico; Demanda laboral; Distribución del tamaño y estructura de mercado; Modelos "Panel Data"; Estimación de variables instrumentales (IV).*

JEL: *D22, J23, L11, C33, C36.*

Slow Dynamics of Job Flow rates in Colombian Industry.

Baja Dinámica de las Flujos de Puestos de Trabajo en la Industria Colombiana.

Primera versión recibida el 17 de mayo de 2023; versión final aceptada el 28 de septiembre de 2023

Coyuntura Económica. Volumen LIII, diciembre de 2023, pp 29-50. Fedesarrollo, Bogotá – Colombia

Abstract

This study examines the creation and destruction of jobs in the Colombian industrial sector, at the establishment level. To achieve this purpose, the traditional academic literature on this issue is integrated with the most recent literature on the production factor shares in the product, which allows the analysis to be focused on market conditions. A close positive relationship is found between job flow rates and the labor income share in the product value, and a negative relationship with markups. The expected negative relationship between these job flow rates and the degree of concentration in the manufacturing sector markets is not obtained, given the low dynamics of changes that were registered in this sector. The above statistical relationships have strong implications for decisions in designing the labor market policies.The empirical analysis uses two econometric techniques, a static GMM and a dynamic Arellano-Bond with instrumental variables and fixed effects. Additionally, a robustness test is performed with a difference-in-differences model.

Resumen

Este estudio examina la creación y destrucción de puestos de trabajo en el sector industrial colombiano, a nivel de establecimiento. Para lograr este propósito, la literatura académica tradicional sobre este tema se integra con la literatura más reciente sobre la participación de los factores de

---

* We are grateful for the helpful comments received from the presentations at the seminars of Banco de la República, FEDESARROLLO, Universidad Nacional de Colombia, Universidad del Norte, and Asociación Colombiana de los Programas de Economía "AFADECO". The authors also wish to acknowledge the valuable comments of an anonymous reviewer, as well as those of Lucas Delgado, Ricardo Rocha, and Jaime Tenjo.

* Agradecemos los comentarios que se recibieron de las presentaciones en los seminarios del Banco de la República, FEDESARROLLO, la Universidad Nacional de Colombia, la Universidad del Norte y la Asociación Colombiana de los Programas de Economía "AFADECO". Los autores también agradecen los valiosos comentarios de un revisor anónimo, así como los de Lucas Delgado, Ricardo Rocha y Jaime Tenjo.

** Department of Economics. Escuela Colombiana de Ingeniería-Julio Garavito. alvaro.chaves@escuelaing.edu.co

*** Information Sciences Institute Emerging Markets. amesa@isimarkets.com

**** Consultor, Inteligencia Económica y Estratégica, BIOECOVAL. fernando.mesa@bioecoval.co; fmesaparra@gmail.com

producción en el valor del producto, lo que permite centrar el análisis en las condiciones del mercado. Se encuentra una estrecha relación positiva entre las tasas de flujos de puestos de trabajo y la participación de los ingresos laborales en el valor del producto; y una relación negativa con los márgenes de ganancia. La relación negativa esperada entre las tasas de flujo depuestos de trabajo y el grado de concentración en los mercados del sector manufacturero no se obtiene, dada la baja dinámica de los cambios estructurales que se registraron en este sector. Las relaciones estadísticas anteriores tienen fuertes implicaciones para las decisiones del diseño de políticas pública del mercado laboral. El análisis empírico utiliza dos técnicas econométricas, el Método Generalizado de Momentos estático y el de Arellano-Bond dinámico con variables instrumentales y efectos fijos. Además, se realiza una prueba de robustez econométrica con un modelo de diferencias en diferencias.

1. Introduction

The accepted perception of the Colombian industry is its low dynamism in job creation, which is somehow related to its limited performance in the sector and its structural conditions. The interest, especially academic, is to study the dynamics of the labor market of the Colombian industry, a medium-income economy, with a low dynamic of technological changes in its production processes, and the predominance of small productive units in the sector, if it is compared to the more advanced economies with greater industrial development (Eslava et al., 2022; Mesa and Torres, 2019).

This paper analyzes particularity the net flows of job creation and destruction in the Colombian industrial sector. The starting point to address this empirical problem is, of course, to define the concept of job creation and destruction at the industrial plant or establishment level, terms that are used interchangeably (Haltiwanger et al., 2013). An establishment is a fixed single location of business activity, which may or may not be part of a firm. We use the term net job flows to refer to the augmenting or reducing of the total number of employees in a particular plant. Then, these net flows could reflect partly the expansion or contraction of plants. This analysis highlights the role of the demand-side disturbances that induce shifts in the net job flows.

It is difficult to determine whether the large job flows primarily reflect temporary layoffs and recalls or worker turnover, as a consequence of continuous reallocation of workers at the plant level (Davis et al., 2006), an issue that is not the aim of this paper. By contrast, our analysis is the job creation minus the job destruction at the plant level; and that is net flows, according to the official statistics.

Whatever the economic situation, the notable fact is the simultaneous existence of job creation and destruction. In this way, it is important to evaluate the dynamics of the net job flows, since this indicator shows the essence of the trajectory of economic activity: the greater the dynamics of job creation and destruction, according to the concept of Shumpeterian creative destruction (Aghion et al., 2021), the greater the capacity of the productive system to adapt to new economic scenarios as well as existing technological conditions.

Currently, this problem of the creation and destruction of jobs at the establishment level has usually been addressed according to their size, age and whether or not they belong to multi-plant companies; or also with variables related to the external sector (Blanchard and Diamond, 1992; Burgess et al., 2000; Davis et al., 2006; Haltiwanger et al., 2013; Haltiwanger, 2015; Klein et al., 2003; Melo and Ballesteros, 2014; Mesa, 2012). Although it is important to address this labor market problem with the usual determinants that characterize the production units of industrial activity, it is important to introduce the market conditions in which the productive units operate.

Recently, market considerations have been incorporated into the study of the 3 labor and capital income share in the value added in the economies, issues that have a clear and close relationship to the creation and destruction of jobs. In fact, the greater the net positive flow of jobs, the greater the labor income share in the economy. Structural market conditions have been related to the markups and market concentration degrees, and these two variables are applied here to analyze net job flows (Autor et al., 2020; Dao et al., 2017; De Loecker et al., 2020; Ibarra and Ros, 2019; Grossman and Oberfield, 2022; Hubmer and Restrepo, 2021; Sangmin and Yongseok, 2020).

This connection of two streams of literature enriches the analysis of net job flows with the introduction of market conditions. Thus, the novelty of this work is to connect two analytical contributions from the literature to explain the creation and destruction of jobs in the Colombian industrial sector for the period 2001-2020 and apply more adjusted and appropriate statistical analyses to address this issue. The creative destruction of firms and jobs, related to innovation and the diffusion of knowledge as a central foundation of economic growth (Aghion, 2018; Aghion et al., 2021), allows understanding changes in net job flows under other perspectives and would subsequently contribute to the design of the Colombian industrial policy.

In this paper, there is a starting point and two fundamental hypotheses about net job flows. The starting point is to show that empirically there is a positive correlation between the net job flows, in percentage terms, and the labor share income in the total value of production, as noted above: the lower the share of the labor factor, the lower the dynamics of net job flow rates. In this way, the connection between the two strands of literature can be validated.

This first hypothesis refers to the negative relationship between the dynamic of the net job flow rates and industrial markups. The above results could be explained as follows. A fall in the capital cost relative to labor, as a consequence of the reduction in the relative price of quality-adjusted equipment, allows an increase in the capital share in total income and against labor, by increasing the job destruction more than the creation. All these effects are measured with the markups. But, naturally, these results are fulfilled if the capital-labor elasticity of substitution is greater than one (Autor et al., 2020; Dao et al., 2017; Hubmer and Restrepo, 2021).

Thus, the higher the mark-ups, the greater the capital factor share, and the decrease in the labor factor share in terms of the total production value, along with the reduction in the creation and destruction of jobs. One of the main statistical results of this paper is to show that there is a negative relationship between mark-ups and net job flow rates, given the existence of labor-capital substitution.

There are different methods for calculating markups at the establishment level, but the analytical expression used here is the one obtained by minimizing a cost function. (Autor et al., 2020; De Loecker et al., 2020). The analytical expression used is the relationship between the production value and the wages paid, multiplied by the output-labor elasticity, where this elasticity must be estimated with econometric methods.

The second hypothesis argues that a greater market concentration by the most productive, large, capital-intensive firms, and a fall in the labor income share (Aghion et al., 2021; Autor et al., 2020), should generate a lower dynamic in the net job flow rates. Although larger firms pay higher wages, the dominant factor is that of capital. Given the positive correlation between labor share and net labor flow rates, there should be a negative relationship between net job flow rates and market concentration. The Herfindahl-Hirschman Index (HHI), as a measure of the degree of market concentration, is used to verify the second hypothesis, and this index is defined as the squared sum of the total revenue shares for different industrial branches.[1]

On the other hand, the Colombian labor market, related to the formal employment used in the manufacturing sector, is characterized by high levels of non-salary costs that the employer must face. Among these costs are the minimum wage with respect to the country's productivity, contributions to health, and pension. Other costs are labor employer contributions to finance public social services, such as job training and childcare ("para-fiscales"), transportation (commuting) subsidies, and severance payments. All these labor market rigidities imply that this market is unable to adjust to the business cycle (Mondragón-Vélez et al., 2010).

The statistical source for the overall analysis is fundamentally the Colombian Annual Manufacturing Survey (AMS), collected by the Colombian Statistics Department (DANE). The survey is for plants with ten

1 Although the official industry surveys do not record all the firms, since the micro-firms are not surveyed, the information accounts for a high percentage of both sales and production, which allows us to roughly measure the degree of market concentration.

or more employees, although there are cases in which some of them registered fewer than ten when their economic and financial performance deteriorated and they still remain in the market. Furthermore, the establishments analyzed in this study are those that remain in the market for more than three years.

The two working hypotheses, the negative relationships of markup and HHI with respect to net job flow rates are verified by estimating panel data models, with fixed effects: one static according to the GMM method and another dynamic according to Arellano-Bond. The fundamental regressors of these models are the logarithm of real wages,[2] the markups and the HHI. The control variables are the capital-output ratio; the number of establishments belonging to a company; and the shares of unskilled workers and workers with temporary contracts, both with respect to the total number of employees. Given that there is an endogeneity problem between real wages and net job flow rates, both econometric models are estimated with instrumental variables.

To check the robustness of the econometric results, both models are estimated for all the establishments surveyed and then for those with less than 50 employees. Next, a quasi-experimental difference-in-differences model is estimated to test whether changes in the two fundamental variables (markups and HHI) affect net job flow rates in the industrial sector.

Empirical findings confirm that higher markups in the Colombian industry lead to a decrease in net job flow rates. This is explained because higher markups encourage establishments to intensify the use of capital against labor. This result should occur together with the substitution between capital and labor.

The effect of market concentration in Colombian industry, according to the HHI, registers the expected negative sign on net job flow rates (less creation and more destruction of job flows) in the static estimation by GMM, but not in the dynamic econometric model. In general, the results with this variable are not statistically robust, because there was not a clear process of great industrial structural changes in the analyzed period.

Due to the previous result, the quasi-experimental difference-in-differences model is applied only for the markup variable and not for the HHI. This exercise says that there is a causality relationship between markups and the net job flows, and the logarithm of the real wage parameter is greater than the panel data models estimated before

This paper is divided into four sections. The first is this introduction. The second analyzes the basic statistics of the net job flow rates and the relationships with the labor income shares, and then the markups and industrial market concentration are presented. The third is dedicated to the estimates of the econometric models that explain the net job flow rates. The last is for conclusions.

2. Empirical evidence

This section is divided into two parts. The first illustrates the creation and destruction of jobs, with some statistics related to the number of plants, and additionally shows the relationships between the net job flow rates with the labor income share with respect to the total value of production and the value-added for the Colombian industrial sector, in the period 2001-2020. The second part analyzes the trends in industrial markups and HHI, broken down into consumer, intermediate, and capital goods.

2.1. Net job flow rate statistics

Since this study deals with the creation and destruction of jobs, some basic statistics on this issue are described below. The establishment evolution and creation and destruction of jobs are illustrated in Table 1. The total

2 Real wages are obtained from the consumer price index.

establishments or plants surveyed by DANE do not exceed 10,000, being its lowest number of 6.592 in 2000 and the highest in 2010. The number of plants that did not change the number of employees was nearly 11%. Those that created jobs were, on average, slightly higher and more volatile than those that destroyed them.

Since the analysis of net job flows is in terms of growth rates, the calculation method for plant *i* and in year *t* is:

$$flows_{i,t} = \frac{L_{i,t} - L_{i,t-1}}{\frac{L_{i,t} + L_{i,t-1}}{2}}, \qquad (1)$$

where the variable L in Equation 1 is defined as the total number of employed in year t for establishment i (Haltiwanger et al., 2013).

Table 1:
Summary statistics: Net flows of Job Creation and Destruction: 2001-2020

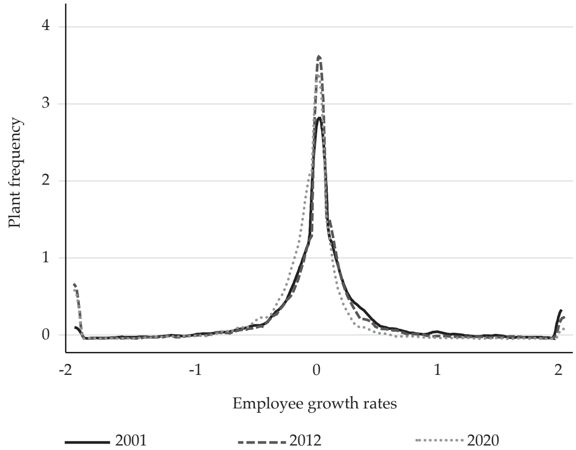
	Mean Plants	SD	Min	Max
Total plants	8.179	1.051	6.592	9.942
Plant creating jobs	3.721	651	2.201	4.989
Plant destroying jobs	3.529	590	2.623	4.418
Total jobs	653.914	65.096	518.625	725.763
In jobs	98.962	26.398	41.193	136.309
Out jobs	91.339	17.121	60.626	121.191

Source: DANE, AMS.

The total number of employed was around 654.000, reaching its highest value of 726.000 in the middle of the period (Table 1). thus, there is a higher number of jobs created than those destroyed, although also with greater volatility. The average net flow of jobs created, concerning the total employed, was 15,1%; and the net flow of destroyed jobs of 14,0%.

The growth rates of the creation and destruction of jobs in the manufacturing sector in 2001, 2012, and 2020 are presented by three kernels in Figure 1. There are two particular facts: first, the symmetry between the net flows of job creation and job destruction; and second, the high concentration around zero. These mixed results are explained by the considerable differences and uncertainties that firms have regarding the profitability of their investments, which depend on the degree of competition in the markets as well as the markup levels (Haltiwanger, 2015 and Aghion et al., 2021).

Figure 1:
Net in/out job flow rates (percentages (percentages)



Source: DANE, AMS.

The meaning of the extreme values of Figure 1 is as follows. The minus 2 is the job destruction when the plants leave the markets, and the positive 2 is the job creation when the plants enter them. This graph also shows a greater number of plants leaving than entering the markets, at least for the first two years. But it should be noted that for 2020 the establishments that enter are not taken into account, since by statistical construction those that remain for less than three years are not included.

It should be noted that the extremes to the left of the three kernels, firms leaving the market increase. On the contrary, at the extreme right, firms entering the market, are flattened. Also in 2020, during the pandemic times, the kernel shifted to the left, meaning the number of job-destroying rose.

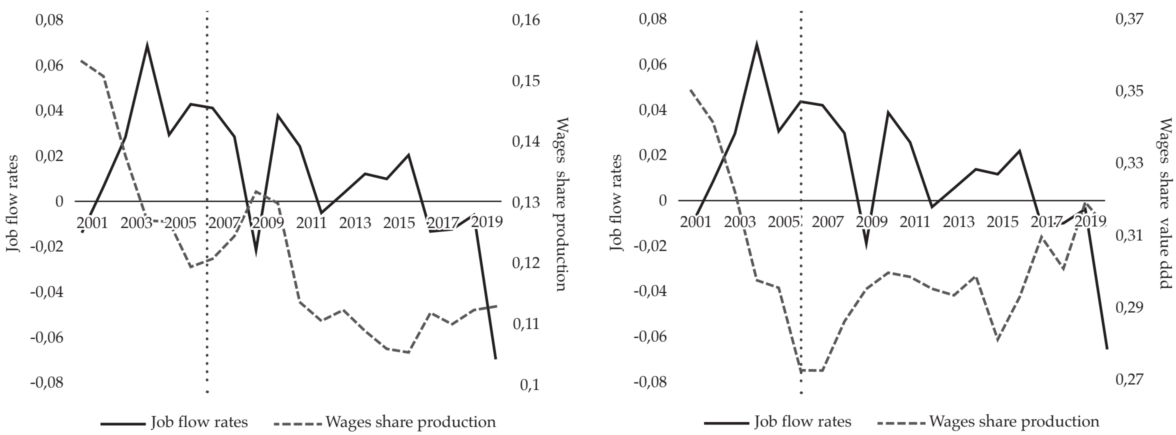
Figure 2 shows the relationship between net job flows and the labor income share in terms of the total value of production (left panel) and in terms of value-added (right panel). It is essential to note the difficulties in accurately measuring total labor remuneration in the industrial sector. Not only are all salary payments included, but also others such as insurance, and fees. There is also industrial work provided by third parties, which counts other industrial establishments. The source of all this information is provided by the AMS.

As Figure 2 shows in both panels, the job creation rates predominated over the job destruction rates in the first years of the expansive industrial cycle; but with the Venezuelan trade shock that began in 2006 and the international financial crisis that followed, the job destruction rates tended to rise more than the job creation.

The left panel of Figure 2 shows that the trend of the labor income shares in the total production value, and more related to the markup, is clearly decreasing. This fall is from nearly 15,2 in 2001 to 11,9% in 2006, and in the last years of the period that share fluctuates between 10 and 11%. In this panel, the trend of the labor income share, as well as that of net job flow rates, is decreasing.

The labor income shares in value-added in the right panel of Figure 2, which is more related to the profit rates, falls from 34% in 2001 to 26% in 2006 and 8 then recovers to reach 30% in 2020. By way of comparison with Mexico, in its private business sector, this wage share fell from 28,7% in 1990 to 22,8% in 2015, after reaching a peak of 31,8% in 1994 (Ibarra and Ros, 2019). In the Brazil case, according to the United Nations Industrial Development Organization (UNIDO) database, this labor share in the manufacturing sector increased from 33% in 2010 to 41% in 2015.

Figure 2:
Flow rates of in/out Jobs, and Wages Share in Production Value (left) and in Value-Added (right) the Manufacturing Sector.



Source: DANE, AMS.

Thus, the sharp fall in the labor share in the total production value until 2005 coincides with the recovery of industrial growth, marked by the dynamics of internal demand and the rise in international commodity prices, especially oil. That expansive phase of the industry cycle was also supported in part by Venezuelan demand for industrial goods (Carranza et al., 2018). The recovery of the labor income shares in 2006-2007 coincided, on the contrary, with the drop in manufacturing exports to the Venezuelan market, which could have been transitory given the market diversification that these types of manufacturing exported to other regions (Carranza et al., 2018), and later on with the financial crisis of 2008. In the subsequent years, with the slow and volatile recovery of growth rates in this sector, the labor share with respect to the total production values decreases, but in terms of the value-added increases.

2.2. *Markup and industrial concentration indexes*

The methodology for measuring the markup is that suggested by De Loecker et al. (2020), and is explained in Appendix A. The analytical expression is the relationship between production value and labor costs, multiplied by the output-labor elasticity

$$\mu_i = \varepsilon_i \frac{P_i Y_i}{\omega_i L_i} \quad (2)$$

being $\mu_i = \frac{P_i}{c_i}$.

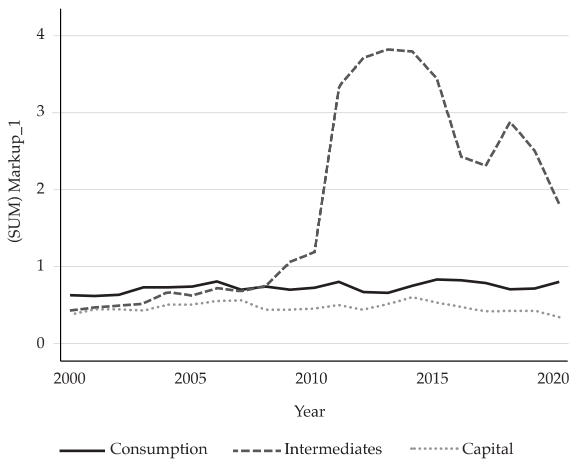
The Equation 2 is used to calculate the markups at the establishment level, and the output-labor elasticities must be estimated econometrically. This equation shows that the lower the labor share in the production value and the greater the response of output to increases in the labor factor, the greater the markups and the capital factor share in the value produced by the establishments.

The elasticity is estimated through a production function, which presents two biases, simultaneity, and selection, as were raised by Olley and Pakes (1996). Simultaneity bias arises because productivity shocks are partly known by profit maximizing firms but not in the econometric modeling. Firms then increase inputs used as a result of positive productivity shocks, but they decrease them if there is a negative one.

The selection bias is due to the correlation between negative productivity shocks and firms leaving markets. A firm with a larger capital stock is more likely to stay in the market despite a low productivity shock than a firm with a smaller capital if the former would expect higher profits in the future at the current productivity levels.

Applying the methodology and corrections recommended by the literature, as is explained in Appendix B, the elasticities are estimated and the markups are calculated. Figure 3 shows the markups by groups of goods, which are: consumption, intermediate, and capital goods.

Figure 3:
Markups for industrial activities classified according to their economic use or destination



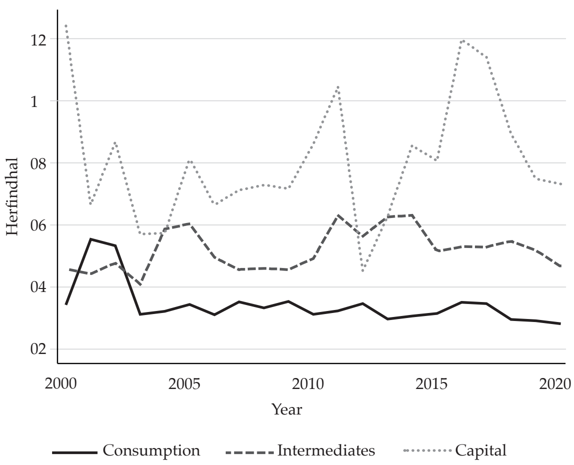
Source: DANE, AMS.

Figure 3 shows how markups jump disproportionately in the industrial activities producing intermediate after 2009, but in the last seven years of the period, they fall. The increases in markups in the consumer goods industries, by contrast, was relatively slight. The markups of the industries that produce capital goods fall in the last years of the period.

The minor changes and low markups in the first years of the period coexist with great dynamics of creation and destruction of jobs and with the loss of labor share in value-added. On the contrary, the largest changes in the markups occurred with the decrease in the creation and destruction of jobs, and with the recovery of the labor share (Figures 2 and 3).

The HHI is used as an indicator of the intensity of competition in the markets, and the size of firms in relation to others within the same industrial activity. Figure 4 shows that the industry activity of capital goods presents ups and downs in their trends, with a growing concentration between 2012 and 2016, and then falling. The consumer goods industry shows a slight downward trend, and the intermediate goods industry does so in the last years of the period.

Figure 4:
Herfindhel-Hirschman concentration index for industrial activities, according to CIIU



Source: DANE, AMS.

In summary, the cycle of the Colombian industry in the first two decades of the century is, first, of recovery of the dynamism of growth; and then between 2008 and 2009 entered into crisis. Subsequently, the sector began a recovery again, which was slow and with low dynamism; and in 2020 the pandemic occurred.

The higher industrial growth rates are correlated with declines in the labor share in the industrial value-added and increases in the net job flow rates (Figure 2), without any major changes in markups and in market concentration (Figures 3 and 4). The crisis and slow recovery phase coincide with the recovery of labor share in the value-added and the decline in net job flow rates (Figure 2), along with significant increases in the markup (Figures 3). Market concentration indexes do not show clear trends, especially capital good activities (Figures 4). Throughout the period, there is a general trend of increasing markups, but not market concentration.

3. Econometric strategy and its robustness

Here we analyze the specification of the econometric models that are estimated. The endogeneity problem that occurs with these models is discussed in Appendix C. The estimated results and the tests required when the problem of endogeneity arises are reported and analyzed. The first approach to test the robustness is carried out with a smaller number of plants, for those with less than 50 employees.

The second subsection performs another robustness test with a difference-in-differences model. This model allows for verifying the causal relationship between changes in markups and changes in the net job flow rates, and for this purpose, the existence of the parallel trend assumption is applied. It is not applied to the HHI, because no robust statistical results were found for this variable.

3.1. Econometric model

This subsection specifies the models that are estimated by two methods: a statistic panel by the Generalized Method of Moments (GMM), and another dynamic by Arellano-Bond, both with fixed effects. In addition, the endogeneity problem of 12 real wages means that the models are estimated by instrumental variables. The corresponding tests for the identification of the instrumental variables (under-identification, weak identification, and over-identification) are verified.

3.1.1. Identification analysis

The dependent variable of the model is the percentage changes in the net flows of creation and destruction of jobs, *g*, at the establishment level (Equation 1). Three types of regressors are included: relevant, control, and time. The latest takes into account the effects of the economic cycle.

The relevant regressors of the model are the logarithm of real wages (*Log.W*), the industrial markups (Markup), and the HHI (*Herfindal– Hirshman*). The control variables are the logarithm of the capital-output ratio (*log capital/output*); the relation between unskilled workers (*Unskill*), and workers with temporary contracts (*Tempo*), both related to the total employees; and the number of establishments belonging to the same firm (*Numb.Plants*).

The expected signs of the parameters for the three relevant regressors with respect to the net job flow rates must be negative. This means that increases in real wages, markups, or the degree of market concentration lead to reductions in the net flow rates of job creation and destruction.

The expected signs for the control variables are the following. The capital-output ratio parameter is negative (*logcapital/output*). The signs for the number of plants per firm (*Numb.Plants*), and the ratios of unskilled workers (*Unskill*), and temporary workers (*Tempo*) with respect to the total employees are positive. The sign of the first parameter is the well-known substitution effect due to capital factor efficiency, and the others are in line with greater labor market flexibility.

The general econometric model to estimate is:

$$g_{i,t} = \beta_0 + \beta_w \log W_{i,t} + \boldsymbol{X}'_{1,i,t}\beta_1 + \boldsymbol{X}'_{2,i,t}\beta_2 + \lambda_t + \mu_i + \epsilon_{i,t}; \quad (3)$$

where $\mathbf{X}_1$ is a matrix *nx2* with relevant regressors, and $\mathbf{X}_2$ is the other matrix nx4 with the control regressors, all of them defined back. The vectors β_1 and β_2 are the parameters of the respective matrices $\mathbf{X}_1$ and $\mathbf{X}_2$. The last three components are a vector of time dummies, λ_t; another vector of fixed effects, μ_i ; and a random error term, $\epsilon_{i,t}$.

Estimation methods are of two types. The first is a static panel and is estimated by the GMM. The second method is a dynamic panel, which uses the Arellano-Bond technique when the dependent variable is lagged once as an additional regressor. All specifications include a time vector of dummies.

Noteworthy that the logarithm of the real wages arises as an endogeneity problem with net job flow rates in Equation 3. This econometric problem is explained rigorously in the Appendix C and is seen through a matching function. Then, this regressor must be instrumentalized, in a first-stage regression, with the labor productivity (*Labor Prod*) and the unemployment rate of the thirteen Colombian metropolitan areas (*unemployment*). The set of instrumental variables (IV) is $\boldsymbol{V}$ and is a matrix n×2. This is a full set of variables that are assumed to be exogenous, i.e., $E(Z_i u_i) = 0$ (Hayashi, 2011).

$$log.W_{i,t} = \boldsymbol{M}_{i,t},'\pi_1 + \boldsymbol{V}_{i,t}'\pi_3 + \epsilon_{i,t}; \quad (4)$$

where $\boldsymbol{M}$ is the covariate matrix, and $\boldsymbol{V}$ is the instrumental variable matrix. For the dynamic panel, both the dependent variable (the growth rate of net job flows) and the logarithm of real wages, the latter instrumentalized, are lagged for one period.

3.1.2. *Estimation*

The parameters estimated by the fixed effects panel data models are reported in Table 2, for the period 2001-2020. Column 1 is a static panel GMM and column 2 is the dynamic Arellano-Bond panel, for all plants surveyed. Columns 3 and 4 have the same econometric specifications but only for plants up to 50 employees.

Before analyzing the results of the parameters estimated by the models, it is important to show their robustness tests of them. These are the under-identification test (Anderson-Canon), the weak identification test (Cragg-Donald-Wald), and the over identification test (Sargan). All of them reject the null hypothesis in columns (1) and (3).

The high p-value in the Anderson-Canon (AC) test rejects the null hypothesis that the instrumental variables are under-identification, and there is no problem with them. The Cragg-Donald-Wald (CDW) test shows that the two instruments are not considered weak in the first stage and the two instruments (labor productivity and unemployment rate) can replace the endogenous log variable of real wages. Finally, the Sargan statistic test rejects the hypothesis that the real wage regressor is orthogonal to the error term, and therefore an IV estimation is the technique required.

The estimated results are as follows Table 2:

1. The negative signs of the instrumented logarithm of real wages are as expected in the four cases and statistically significant at one percent. The estimated values of the static panels are not different from the dynamic ones, despite the lag of this variable. It should be noted that there is a downward bias in this parameter estimated.
2. Markup signs are negative and significant at 1%. This means that increases in markups lead plants to reduce job creation and increase job destruction. If the markup increases, it indicates less dynamism in the industrial labor market and, of course, the loss of labor income share in the value produced.
3. The HHI registers a negative sign in the GMM specification, and a positive in the Arellano-Bond dynamic panel, and all of them are not statistically significant. This result, therefore, does not show that changes in the degree of the Colombian industry concentration have contributed to modifying the dynamics of the Colombian labor market.
4. Regarding the control variables, it is worth making some comments on the capital-output ratio. Its parameter is negative and statistically significant at one percent, indicating that the higher this ratio is, the less efficient the capital factor is with a negative impact on the net job flow rates. The dynamic of job creative destruction would be really low.

   The above result is an indication that the lower the capital-product ratio, or the more efficient the capital factor, the greater the dynamics of creative destruction with the corresponding reduction in the labor income share in the value produced. Those firms that introduce new capital-intensive technologies, due to their lower relative price in relation to the labor factor, would see the remuneration of capital increase in the share of the value of production (Hubmer and Restrepo, 2021).

Table 2:
Net Flows of Job-Creation and Job-Destruction Estimation

	(1) flows	(2) flows	(3) flows	(4) flows
Log. Real Wages	-0,106***	-0,110***	-0,263***	-0,214***
	(0,030)	(0,015)	(0,038)	(0,018)
Markup	-0,566***	-0,886***	-0,509***	-0,594***
	(0,027)	(0,024)	(0,034)	(0,024)
Herfindhal-Hirshman	-0,012	0,124	-0,068	0,067
	(0,063)	(0,083)	(0,077)	(0,101)
Log capital/output	-0,151***	-0,276***	-0,097***	-0,150***
	(0,003)	(0,002)	(0,003)	(0,003)
Break Tend	-0,202***	-0,092***	-0,106***	-0,151***
	(0,007)	(0,004)	(0,010)	(0,006)
Tempo	0,079***	0,213***	0,029***	0,134***
	(0,006)	(0,007)	(0,007)	(0,008)
Numb. Plants	-0,000	0,013***	-0,002	0,014***
	(0,001)	(0,002)	(0,001)	(0,002)
Unskill	0,082***	0,135***	0,145***	0,240***
	(0,010)	(0,012)	(0,010)	(0,013)
Flow rates (Lag)		-0,233***		-0,091***
		(0,002)		(0,003)
Labour Productivity		0,000***		-0,000
		(0,000)		(0,000)
Unemployment		-0,006***		-0,009***
		(0,001)		(0,001)
Log Real Wages (Lag)		-0,026**		0,339***
		(0,011)		(0,016)
Observations	151.912	138.302	95.524	81.646
Period	2001-20	2001-20	2001-20	2001-20
Method	GMM	Ar Bond	GMM	Ar Bond
Time FE	Yes	Yes	Yes	Yes
Test	IV		IV	
Anderson	2.256,73		8.177,24	
CDW	2.293,48		9.039,59	
SW	12,03		2.978,02	
Sargan	0,00		0,00	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Net job flow rates
Data source: Estimations using DANE, AMS.

5. The parameters obtained from unskilled workers and those with temporary contracts, in relation to the total employed, indicate that these factors introduce greater dynamism into the labor market, and allow greater creative destruction of jobs. Regarding the number of plants per firm, the estimated parameters are not significant and show that this variable has no effect on the net job flow rates.

   A difference found is in the estimated parameter for the logarithm of real wages between the total of plants surveyed and those that hire up to 50 employees. It is greater for smaller plants and in the dynamic panel the lag has a positive sign. This means that variations of ten points in the logarithm of real wages have a greater impact on small plants than on large ones, and adjustments are faster. In relation to the estimated parameter for the markup, this is lower for the smallest ones.

   The estimated parameter of the lag of the dependent variable, the net job flow rates, is significantly reduced for small plants. This result is consistent with the above; that is, small plants adjust faster than large ones.

3.2. *Robustness check*

This subsection presents the robustness test of the statistical causal relationship between changes in the markup trend (3) and net job flow rates (2). The same exercise is not carried out for the HHI, since there are no significant changes in the behavior of this series, and the estimated parameters confirm that the impact of the HHI is ambiguous on the labor market.

Therefore, a quasi-experimental differences-in-differences model is estimated to verify that changes in markup trends affect the net flows of job creation and destruction. For this analysis, two groups are defined, one that is the object of the treatment (which is affected by the trade break with Venezuela and the international financial crisis), and another is the control group that helps to measure the effectiveness of the treatment.

The treatment is a binary variable, which results from the interaction between two dummies. The first dummy (*time1*) is constructed when the net job flow trend change due to the collapse of trade with Venezuela in 2006 and 2007, and the subsequent negative effects of the international financial crisis on the Colombian economy (Figure 2). Since significant trend changes in markups started in 2008, this dummy is one since that year.

The second interaction dummy is one when the markup is greater than its mean at the establishment level, and zero otherwise (*dMarkup*). Then the treatment variable (treatment) is the product of these two dummy variables. Thus the binary treatment variable (treatment) of the differences-in-differences model, for the markup case, is one for those years where the level of the markup is greater than its mean, and after 2008. That is

$$treatment_{i,t} = time1_{i,t} * dMarkup_{i,t.}$$

The differences-differences model to be estimated, with fixed effects, is written as (Angrist and Pischke, 2009)

$$g_{i,t} = \alpha_0 + \beta_0 * treatment_{i,t} + \sum_{j=1}^{6} \beta_{-j} * treatment_{i,t-j} + \sum_{j=1}^{6} \beta_{+j} * treatment_{i,t+j} + \gamma \boldsymbol{X} + \mu_i + \eta_t . \quad (5)$$

Where $\boldsymbol{X}$ is a matrix of covariates, which are: the logarithm of instrumented real wages, the markups, and the Herfindhal-Hirschman indices. Additionally, the control variables are the same: the logarithm of the capital-output ratio, and the relationships between temporary and unskilled workers with respect to the total employed. The γ is the vector of estimation coefficients. Additionally, μ_i represents plant fixed effects, and η_t is the random effects.

Table 3:
Impact of the falling demand on the net flow of job rates

	Flows-Markup (2008)
Treatment-6	0,011*
	(0,005)
Treatment-5	0,003
	(0,005)
Treatment-4	-0,005
	(0,005)
Treatment-3	- 0,005
	(0,005)
Treatment-2	0,003
	(0,005)
Treatment-1	-0,006
	(0,005)
Binary treatment variable	-0,071***
	(0,006)
Treatment+1	0,039***
	(0,007)
Treatment+2	0,025***
	(0,006)
Treatment+3	0,026***
	(0,007)
Treatment+4	-0,000
	(0,008)
Treatment+5	0,010
	(0,009)
Treatment+6	0,026*
	(0,010)
Real Wages (log)	-1,102***
	(0,333)
Markup	-1,335***
	(0 ,320)
Herfindhal	0 ,636***
	(0 ,175)
Observations	151.925
Period	2001-2020
Test	Parallel – trend passed

Data source: Estimations using DANE, AMS.

In order to test the parallel trend assumption in this differences-in-differences model, the treatment dummy is lagged and led to six periods. Their conforming parameters are βs, with the subscript plus j for the leading, and with the subscript minus j for the lagging. The parallel trend means that if the treatment had not been carried out, without the commercial shock or financial crises, the markup and the net job flow rate trends would have been the same.[3]

Therefore, the null hypothesis to verify the parallel trend assumption is

$$H_0: \beta_{+1} = \beta_{+2} = \beta_{+3} = \beta_{+4} = \beta_{+5} = \beta_{+6} = 0,$$

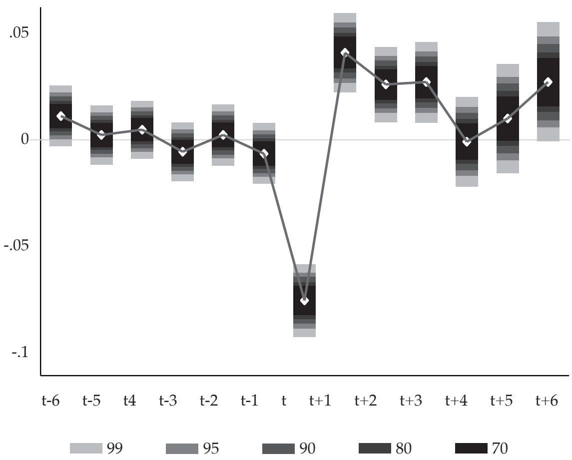
which must not be rejected and therefore accept the parallel trend assumption. As long as it is assumed that there are not "anticipation effects", it means that in the years before the treatment, both the treated and the control group of plants have the same trend, and the difference between them in the years after the treatment is strictly due to treatment.

The estimation of the differences-in-differences model for the markup is reported in Table 3. The dummy variable *treatment* in terms of the markups is negative and statistically significant (at 1%) on the net job flow rates (-0,071). This means that increases in markups, caused by trade breaks and international trade, come along with less creation and destruction of jobs. In this model, the effects of the markup (-1,335) and the logarithms of the real wages (-1,102) are bigger. The concentration index presents a positive sign (0,636), although statistically significant, the positive sign is not as expected (Table 4). The other control variables parameters are not reported in the table, with the purpose of reducing the number of lines.

3 According to Cerulli and Ventura (2019) the leading coefficients measure the treatment impacts in periods prior to their occurrence, while the lagged coefficients measure the impact of the treatment in later periods. In fact, when a lag is introduced in the treatment variable, it shifts forward one period, so that the $treatment_{i,t-1}$ refers to time t. Similarly, the $treatment_{i,t+1}$ shifts backward corresponding to time t.

This assumption of the parallel trend is verified by the leading coefficients since the null hypothesis ($\beta_{+j}s = 0$) is not rejected. In fact, the untreated plants, those with below-average markups after 2008, are assumed to provide the appropriate counterfactual trend for treated plants, i.e., plants with above-average indices. In this sense, the two groups would have had parallel trends.

Figure 5:
The pre and post-treatment pattern for the relation between treatment and the net job flows



Finally, the pattern of the leading coefficients and the treatment coefficient are illustrated in Figure 5. The robustness test of the parallel trend assumption allows verifying the causality in the Granger (1969) spirit. According to Cerulli and Ventura (2019), the differences-in-differences model, conditional on all regressors and with fixed effects, the $treatment_{it}$ causes changes in the net job flow rates (g_{it}) according to the Equation 5.

4. Concluding remarks

A relevant empirical fact of the labor market in the Colombian industrial sector is its loss of dynamism when it is measured with the growth rates of net job flows. This empirical result is a clear sign of the low technological updating of the productive system and an environment of low market competition. Therefore, there are increases in the plant markups and losses in the labor income share in the value produced.

A strong negative relationship was statistically found between the plant markups and the net job flow rates, and this result allows us to understand the internal adjustments of industrial plants in the economic cycle. In this way, the greater the markups, the less the creation than the destruction of jobs in the manufacturing sector. In addition, there is a causal relationship between the markups and the net job flow rates, which should occur through the intermediation of the technologies that are implemented.

On the other hand, a greater or lesser market concentration (HHI) should instead manifest itself in the creative destruction of jobs, but in the Colombian case, this result does not occur. This result is due to the fact that the Colombian industrial sector has not registered significant structural changes in the last two decades.

The negative sign of the capital-output ratio parameter on the net job flow rates implies that the reduction of this ratio, or the increase in the capital factor efficiency, accelerates the dynamics of creative destruction of firms and jobs. The introduction of new technologies would allow certain productive tasks to be automated, which naturally displaces workers. This topic would give rise to starting a specific study on the effects of new investments in technologies in the industrial labor market.

The phenomenon of creativity and the destruction of jobs has close implications for the design of labor policy. The destruction and creation of jobs clearly require the flexibility of this market to facilitate the readjustment of firms to the new dynamics generated by technological changes.

Aggressive public policies should also be offered for the retraining of workers who lose their jobs and also offer qualified workers to the changing productive system. In fact, the training system with new skills for workers who lose their jobs must be accompanied by government support for education and research. In general, the system must be based on quality education, promote innovation, and the application of new technologies in the productive system. To be effective in these policies, the government must be immune to the political pressure of the rent-seeking agents and possess a competent and honest bureaucracy.

4. References

Aghion, P. (2018). Innovation and growth from a schumpeterian perspective. Revue d'économie politique (5), 693–711.

Aghion, P., C. Antonin, and S. Bunel (2021). The power of creative destruction: economic upheaval and the wealth of nations. Harvard University Press.

Angrist, J. D. and J.-S. Pischke (2009). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The fall of the labor share and the rise of superstar firms. The Quarterly Journal of Economics 135 (2), 645–709.

Azkarate-Askasua, M. and M. Zerecero (2020). The aggregate effects of labor market concentration. Unpublished Working Paper.

Belzil, C. (2000). Job creation and job destruction, worker reallocation, and wages. Journal of Labor Economics 18 (2), 183–203.

Blanchard, O. J. and P. A. Diamond (1992). The flow approach to labor markets. The American Economic Review 82 (2), 354-359.

Burgess, S., J. Lane, and D. Stevens (2000). Job flows, worker flows, and churning. Journal of labor economics 18 (3), 473–502.

Carranza, J. E., J. A. B. Rojas, C. Casas, A. X. González-Ramirez, S. Moreno-Burbano, F. Arias-Rodríguez, J. S. Vélez-Velásquez, et al. (2018). La industria colombiana en el siglo xxi. Revista ESPE-Ensayos sobre Política Económica, 1–69.

Cerulli, G. and M. Ventura (2019). Estimation of pre- and posttreatment average treatment effects with binary time-varying treatment using stata. The Stata Journal 19, 551–565.

Dao, M. C., M. Das, Z. Koczan, and W. Lian (2017). Understanding the downward trend in labor income shares. World Economic Outlook April 2017: Gaining Momentum, 121–71.

Davis, S. J., R. J. Faberman, and J. Haltiwanger (2006). The flow approach to labor markets: New data sources and micro-macro links. Journal of Economic Perspectives 20 (3), 3–26.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeconomic implications. The Quarterly Journal of Economics 135 (2), 561–644.

Eslava, M., J. Haltiwanger, and A. Pinzón (2022). Job creation in Colombia versus ´ the USA:'up-or-out dynamics' meet 'the life cycle of plants'. Economica 89 (355), 511–539.

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

Grossman, G. M. and E. Oberfield (2022). The elusive explanation for the declining labor share. Annual Review of Economics 14, 93–124.

Haltiwanger, J. (2015). Job creation, job destruction, and productivity growth: The role of young businesses. Annual Reviews 7 (1), 341–358.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013). Who creates jobs? small versus large versus young. Review of Economics and Statistics 95 (2), 347–361.

Hayashi, F. (2011). Econometrics. Princeton University Press.

Hubmer, J. and P. Restrepo (2021). Not a typical firm: The joint dynamics of firms, labor shares, and capital–labor substitution. Technical report, National Bureau of Economic Research.

Ibarra, C. A. and J. Ros (2019). The decline of the labor income shares in México, 1990–2015. World Development 122, 570–584.

Klein, M. W., S. Schuh, and R. K. Triest (2003). Job creation, job destruction, and the real exchange rate. Journal of International Economics 59 (2), 239–265.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. The Review of Economic Studies 70 (2), 317–341.

Melo, L. and C. Ballesteros (2014). Impacto de los factores externos sobre la creación y destrucción de empleo en el sector manufacturero colombiano. Lecturas de Economía (81), 155–186.

Mesa, F. (2012). International trade and unemployment in less developed countries. Theoretical Economics Letters 2 (5), 545-556.

Mesa, F. and R. Torres (2019). Pymes manufactureras exportadoras en Colombia: un análisis de su actividad real. Lecturas de economía 45 (90), 127–157.

Mondragón-Vélez, C., X. Peña, D. Wills, and A. Kugler (2010). Labor market rigidities and informality in Colombia [with comment]. Economía 11 (1), 65–101.

Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry, 64. Econometrica 64, 1263–1297.

Petrin, A., B. P. Poi, and J. Levinsohn (2004). Production function estimation in stata using inputs to control for unobservables. The Stata Journal 4 (2), 113–123.

Pissarides, C. A. (2000). Equilibrium unemployment theory. MIT press.

Sangmin, A. and S. Yongseok (2020). Why is the labor share declining? Federal Reserve Bank of St. Louis Review 102, 413–28.

Appendices

A. The analytical expression for calculating the markup

Although there are different alternatives to measure markups, the expression used in this paper is obtained by minimizing the firm's costs (De Loecker et al., 2020). The analytical expression is obtained as follows.

Consider the following Cobb-Douglas production function (Autor et al., 2020)

$$Y_i = z_i \, L_i^{\alpha_L} \; K_i^{1-\alpha} \quad ; \quad (6)$$

where Y_i is the production, L_i the labor, K_i the capital, and z_i is Hicks-neutral efficiency in firm i. Autor et al. (2020) assume that z_i is a random process and represents heterogeneous firms, where the more productive firm presents higher z_i . Factor markets are assumed to be competitive (with wage as ω and cost of capital ϱ) but the product markets could be imperfect.[4]

The Lagrangian objective function associated with the firm's cost minimization is

$$L_i = \; \omega \, L_i + \; \rho \, K_i - \; \lambda\big(Yi \; - \; \overline{Y}_i\big). \quad (7)$$

$\bar{Y}$ is a scalar and λ is the Lagrange multiplier. The minimization with respect to L_i is:

$$0 \; = \; \omega \; - \; \lambda\left(\; \frac{\partial Y_i}{\partial L_i}\right). \quad (8)$$

Then

$$\frac{\omega}{\lambda} = \; \frac{\partial Y_i}{\partial L_i}, \quad (9)$$

and if both sides of the equation are multiplied by $\frac{L_i}{Y_i}$, the right-hand side of the equation is the labor-output elasticity (ε).

$$\varepsilon_i = \; \frac{\omega}{c_i} * \; \frac{L_i}{Y_i}. \quad (10)$$

Where λ is the marginal cost (c_i). Using P_i in Equation 10, we have

$$\varepsilon_i = \frac{\omega}{c_i \, \frac{P_i}{P_i}} * \frac{L_i}{Y_i} \; . \quad (11)$$

4 Azkarate-Askasua and Zerecero (2020) analyze the effects of the labor market power of employers and unions on welfare and the set wage rate.

Rearranging the equation, we get

$$\mu_i = \varepsilon_i \frac{P_i Y_i}{\omega_i L_i}. \quad (12)$$

being $\mu_i = \dfrac{P_i}{ci}$

Equation 12 is used to calculate the markups at the establishment level, and the output-labor elasticities must be estimated.

B. Elasticity production factor estimation

There is the methodology presented by Olley and Pakes (1996) to estimate the output-labor elasticity, correcting simultaneity and selection biases. The review carried out by Levinsohn and Petrin (2003), is the one used here.

These last authors introduce an estimator that uses intermediate inputs (like energy consumption) as proxies for unobservable shocks. They argue that this proxy responds more smoothly and with a lower adjustment cost to productivity shocks than the investment variable used by Olley and Pakes (1996). This approach was programmed in Stata by Petrin et al. (2004).

The Levinsohn and Petrin (2003) production technology, written in logarithms, is:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \psi_t + \eta_t, \quad (13)$$

where the variables are: y_t the firm production value; l_t the labor inputs; and k_t the capital as a state variable. The error has two components: one is the productivity shock ψ_t, known by firms that maximize their profits and correlate with the intermediate inputs and the capital stock. The other error is the random term η_t that is not correlated with the input choice.

Levinsohn and Petrin (2003) define a expression Φ_t written in terms of the capital stock (k_t), the intermediate inputs (m_t), and the productivity shock. This expression is:

$$\Phi_t(m_t, k_t) = \beta_0 + \beta_k k_t + \beta_m m_t + \psi_t(m_t, k_t).$$

Therefore, the Equation 13 is expressed as

$$y_t = \beta_1 l_t + \Phi_t(m_t, k_t) + \eta_t \quad (14)$$

where the Φ_t function includes the parameter β_0. This is the first stage of the process, where β_1 is estimated by assuming that $\Phi_t(m_t, k_t)$ is a third-order polynomial approximation in terms of k_t and m_t

$$\Phi_t(m_t, k_t) = \sum_{i=0}^{3}\sum_{j=0}^{3-j} \delta_{ij} k_t^i m_t^j$$

so that is obtained the fitting $\hat{y}_t$ in Equation 14.

In the second stage of the process, the β_k parameter is estimated. Initially, the Φ_t is fitted as

$$\widehat{\Phi_t} = \hat{y}_t - \hat{\beta}_l \, l_t$$

At this stage, the values for ψ_t are predicted for each period, given an initial tentative value of β^*_k. This is

$$\psi_t = \widehat{\Phi_t} - \beta_k^* k_t \, .$$

Finally, optimal β^*_k is obtained by minimizing a quadratic function of the random errors of the Petrin et al. (2004) production function:

$$\min_{\beta_k^*} = (\hat{y}_t - \hat{\beta}_l \, l_t - \beta_k^* t k_t - \hat{\psi}_t)^2 \quad (15)$$

being $\hat{\psi}_t$ an autoregressive process, defined as

$$\hat{\psi}_t = E[\hat{\psi}_t / \hat{\psi}_{t-1}]$$

and where $\hat{y}_t$, in the equation 15, is replaced from Equation 14.

The labor-output elasticities are reported in Table 2. Their values are between 0,57 and 0,64, higher for capital goods and lower for intermediate goods. These elasticities are used to calculate the markup rates.

Table 4:
Production-Factor Elasticities

	(1) log value-added	(2) log value-added	(3) log value-added
Log inputs	0,277***	0,249***	0,273***
	(0,008)	(0,017)	(0,020)
Log energy	0,061***	0,057***	0,061***
	(0,008)	(0,009)	(0,014)
Log employed	0,627***	0,566***	0,638***
	(0,011)	(0,018)	(0,029)
log real capita	0,254***	0,433***	0,150
	(0,052)	(0,112)	(0,136)
Observations	58.345	53.700	13.808

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Log Value-added
Columns: (1) Non-dyrables and durables; (2) Intermediate goods; (3) Capital goods.
Data source: Estimations using AMS - DANE.

C. Note on the endogeneity problem between the net job flow rates of and real wages

To explain the existence of endogeneity in labor market theory, in the flow approach, let us define ω_{it} as real wages, in period t for plant i. This "low approach" is based on three building blocks (Blanchard and Diamond 1992, and Pissarides 2000). The first two blocks specify the labor demand in terms of the net flow rates of destruction, d, and creation, c, of jobs. These are:

$$d_{i,t} = d(\omega_{i,t}, \theta_d) + \epsilon_{i,t}; \quad d_\omega \geq 0. \quad (16)$$

$$c_{i,t} = c(\omega_{i,t}, \theta_c) + v_{i,t}; \; c_\omega \leq 0. \quad (17)$$

The θ in equations 16 and 17 reflects many factors, like aggregate demand variables, foreign competition, and changes in technology (productivity). The error term in job destruction is ϵ_{it} and in job creation is $v_{it.}$ The subscripts ω in d and in c are partial derivatives with respect to ω.

The third block specifies the process of job creation and destruction rates explained through a matching function "m", which depends on the existence of vacancies offered by firms (v_t) along with workers looking for work (u_t). This function is given as

$$h_t = m(v_t, u_t); \quad m_v > 0; \quad m_u > 0; \quad (18)$$

where h denotes hires and the subscripts u and ν in m refer to the first derivative of the matching function.

Thus, the determination of the real salary (ω_t) and the net job flow rates depend simultaneously on labor market conditions, such as the difficulty for firms to hire or fire workers; and for workers, the probability of finding a job if they are unemployed Belzil (2000). So the wage rate equation (ω) is

$$\omega_{i,t} = \omega(v_t, u_t) + \vartheta_t \,;\; \omega_v > 0;\; \omega_u < 0. \quad (19)$$

The error term in the above equation is ϑ_t.

The important point is that c and d are correlated to ω through the matching function, and thus the random term in Equation 19 is correlated with the random terms of Equations 16 and 17. So that

$$\vartheta_t = \vartheta(\epsilon_t, v_t);\; E[\omega\, \epsilon] \neq 0, and \;\; E[\omega\, v] \neq 0$$

The expected values of the wages multiplied by the error terms in equations 16 and 17 are different from zero since the two variables are correlated, and the OLS assumptions do not hold. Therefore, the sensitivity of net job flows and real wages are related to the conditions of the business cycle (Belzil, 2000 and Hayashi, 2011), and the econometric exercise implies an endogeneity problem.