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INCOME RISK ASYMMETRIES OVER ARGENTINA'S BUSINESS CYCLE

ASIMETRIAS EN EL RIESGO DE INGRESOS A LO LARGO DEL CICLO ECONOMICO DE ARGENTINA

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Abstract

This paper explores the aggregate income risk of formal workers in Argentina, using a longitudinal database that contains information on approximately half a million formal employees in the private sector for a span of twenty years. We estimate quantile regression models to measure the sensitivity of real wages to the business cycle along the conditional and unconditional labor earnings distribution, thus capturing the asymmetry of aggregate economic impacts on wages. The main result is that income risk decreases along the conditional and unconditional labor earnings distribution, showing that individuals located at the lower part of the distribution are more exposed to the fortunes of the aggregate economy. In addition, low-income individuals suffer a stronger fall in wages when economy declines than the increase that their experiment when business cycle is in its expansion phase, which, in a very volatile economy like Argentina, implies a deterioration over time of their remuneration.

Keywords: *Argentina, asymmetries, business cycles, collective bargaining, formal workers, income risk, unions, quantile regression.*

JEL Classification: *C13, E32, J30, J52.*

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Resumen

Este trabajo explora el riesgo agregado de ingresos de los trabajadores formales de Argentina, utilizando una base de datos longitudinal que contiene información de aproximadamente medio millón de empleados formales del sector privado para un período de veinte años. Estimamos modelos de regresión por cuantiles para medir la sensibilidad de las remuneraciones al ciclo económico a lo largo de la distribución condicional y no condicional de los salarios, capturando la asimetría de los impactos de la actividad económica en las remuneraciones. El resultado principal es que el riesgo de ingresos decrece a lo largo de la distribución condicional y no condicional de los salarios, mostrando que los individuos ubicados en la parte inferior de la distribución están más expuestos a los vaivenes de la economía agregada. Además, los individuos de bajos ingresos sufren una caída en los salarios cuando la actividad declina mayor que el incremento que experimentan cuando el ciclo económico está en su fase expansiva, lo que, en una economía muy volátil como la de Argentina, implica un deterioro de sus remuneraciones a lo largo del tiempo.

Palabras clave: *Argentina, asimetrías, ciclos económicos, negociación colectiva, trabajadores formales, riesgo de ingresos, sindicatos, regresión por cuantiles.*

Clasificación JEL: C13, E32, J30, J52.

1. INTRODUCTION

In 2020, COVID-19 pandemic and the quarantine implemented by government authorities caused a sharp fall of about ten percent in Argentine GDP, strongly affecting the labor market, not only by destroying thousands of jobs due to the bankruptcy of companies, but also by reducing wages and rewards for those who keep their jobs, beyond that in Argentina there was a ban on firing employees due to the economic downturn. Certainly, the fall in earnings hardly affected all workers with the same intensity since some lost more than others. Beyond this heterogeneity, the risk of falling wages depends on a set of factors. Some of them are specific to the workers, such as their capabilities and education, and others are external to them, such as being covered by a union collective bargaining and, particularly, the effect of the pandemic, and especially the quarantine, in the industry and the company for which they work.

In a recent study, Bell *et al.* (2020) estimated that the impact of the recession in the UK, due to COVID-19, would be, on average, much higher on the wages of young people working in smaller companies. Their empirical approach is based on the work of Guvenen *et al.* (2017) for the US economy, which, using longitudinal administrative data, estimate what they call “workers’ betas”. These estimates measure, for different population groups delimited by observable characteristics, how movements in GDP or other macroeconomic variables affect, on average, workers’ wages.

Those studies wonder, in one way or another, how labor earnings are linked, on average, to the fortunes of the aggregate economy and macroeconomic conditions, that is, they try to measure what the literature calls aggregate and systematic income risk, but also exploring whether there are asymmetries on this risk between some specific groups, delimited by observable characteristics like age, sex, industry, etc. However, the variations in labor income throughout the business cycle not only depend on observable personal and external factors, but also on a set of own and external factors, unobservable and probably not uniformly distributed, which make the impact of expansions and recessions in the mean of the labor income not representative of the changes of these throughout its conditional and unconditional distribution. Thus, there are not only asymmetries between individuals who differ in observable characteristics, but also between workers who –due to the influence of unobservable factors, which could even interact with observable factors– are located in different parts of the conditional and unconditional income distribution.

Taking in account the presence of unobservable factors mentioned above, an appropriate question for us is: how labor earnings in Argentina are systematically affected by the business cycle? More precisely, are there asymmetries in this income risk along the conditional and unconditional labor earnings distribution? That is, besides the observable characteristics of the workers, does unobservable factors play a role in explaining how the business cycle affect the wages? The answer to these questions requires the use of robust techniques that allow the possibility of estimating the impact of aggregate economic fluctuations on worker’s earnings, while controlling for other covariates.

Our data come from the Longitudinal Sample of Registered Employment (MLER, for its acronym in Spanish) of the Ministry of Labor, Employment and Social Security of Argentina, which contains historical and individual information on approximately half a million formal employees in the private sector throughout the country for a span of twenty years (1996-2015), totaling more than 1.4 million labor relations. We focus on formal workers since the amount and quality of information required to answer these questions with a reasonable degree of accuracy is not available for informal workers. Recent international literature about income risk uses longitudinal administrative data (Broer, Kramer and Mitman, 2020; Guvenen *et al*., 2017) or large survey panel datasets (Bell *et al.*, 2020), which typically only covers the formal sector of the labor market. However, informal employees are not a lesser part of Argentine labor market. On the other hand, recent literature about labor markets argues that individuals “choose” to be informal workers due to having an individual comparative advantage into the informal sector (Maloney, 1999, 2004) instead of being a strategy of last resort to escape involuntary unemployment, as the segmented or dual theory proposes (Harris and Todaro, 1970; Stiglitz, 1976). Indeed, several empirical studies show that the informal sector is not all about residual workers, but that there is an occupational decision behind formal and informal work.[1] Since ignoring this sample selection problem could bias our estimates, to explore if the validity of our results can be extended to other occupational categories, we also present our estimates using the Permanent Household Survey (EPH, for its acronym in Spanish) of the National Institute of Statistics and Censuses (INDEC, for its acronym in Spanish), which contains data about the Argentine labor market for both the formal and informal sectors.[2] However, this source of information has several disadvantages respect to MLER, that do not make it ideal for an empirical study of income risk.

The main purpose of this work is to analyze the impact of the business cycle on wages of male employees in Argentina, considering not only the observable characteristics of each worker, the company, and the economic sector where they work, but also considering that there are unobservable variables that could be heterogeneously distributed among workers, causing the business cycle to affect them differently. Hence, for measuring the effect of expansions and recessions, on the conditional and unconditional income distribution, the estimates are obtained by using quantile regression methods.

This paper contributes to the empirical literature that investigates the risk of household or individual income during the business cycle (e.g., Broer, Kramer and Mitman, 2020; Guvenen *et al.*, 2017; Parker and Vissing-Jørgensen, 2009, 2010) and the consequences on inequality of the ups and downs of the business cycle (e.g., Blanco *et al.*, 2021; Guvenen, Ozkan and Song, 2014). Our study contributes to this literature in a double sense, since it not only extends the previous analysis to an emerging economy, but also incorporating the possibility that the unobservable factors are asymmetrically distributed and, therefore, the heterogeneity of the business cycle effect along the conditional and unconditional wage distribution. Also, our paper is related to empirical studies that focus on the effect of unions and collective bargaining on wages in Argentina (e.g., Alejo and Casanova, 2016; Beccaria, Fernández and Trajtemberg, 2020; Lombardo and Martínez-Correa, 2019). In a broader view, our results could have important implications for public policy in general, since monetary or fiscal policies that stabilize business cycles would also have heterogeneous impacts across the population.

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[1] See Günther and Launov (2012) for more details.

[2] EPH is a national program carried out by INDEC in agreement with the provincial statistical institutes, whose purpose is to collect data –through a random sampling of households in a rotative panel scheme– on the demographic and socioeconomic characteristics of the Argentine population, including those linked to the labor market. Until the first semester of 2003, the survey was conducted twice a year (in May and October), but since the second semester of that year EPH became a quarterly survey. Actually, it covers thirty-one urban agglomerations which represent about 60% of the Argentine population.

The "mean" income risk estimated by Ordinary Least Squares (OLS) including individual fixed effects and using MLER data suggests, for the entire period, that an 1.0% rise of the GDP generates, on average, an 1.8% increment of wages for formal employees in the private sector in Argentina. In contrast, estimates obtained by quantile regression methods show an income risk that tends to decrease along the conditional and unconditional labor earnings distribution, highlighting the importance of looking beyond the mean to capture the asymmetry of aggregate activity impacts on wages. Although this income risk is not substantially different when comparing the effects of recessions and expansions on the conditional labor earnings distribution, if we look what happens in the unconditional distribution, poor individuals are not only more affected by business cycle expansions and contractions compared to rich employees, but they suffer a stronger fall in wages when aggregate activity declines than the increase in wages that their experiment when business cycle is in its expansion phase. When we estimate models separately by economic sector and firm size, the decreasing trend in wages' elasticity along the unconditional distribution remains for some categories and quantiles. Beyond these results, there are some interesting specificities, such as individuals that work in Construction sector are those with higher income risk, while workers' wages of large companies are less sensitive to business cycle fluctuations.

On other hand, when we estimate the models by using EPH data, we found informal workers seems to be more sensible to the business cycle than formal workers, which suggests that wage elasticities for formal employees could be considered as a lower bound for Argentine workers income risk.

The paper is organized as follows: Section 2 presents some empirical works of interest for our study. Section 3 describes the data and discusses the empirical methodology used. Section 4 presents and discusses the results, and finally Section 5 concludes.

2. RELATED EMPIRICAL STUDIES

Various studies measure the impact of the business cycle on wages using OLS and compare the results of estimates for different population groups. At this point, some of them try to build a conditional wage distribution by splitting, exogenously, the sample into decile groups. For example, Guvenen *et al.* (2017) analyze income risk for male workers in the US, by modeling the conditional expectation of wage growth rate and estimating the average effect of the product growth rate for different decile groups of individuals, which are built based on the permanent income distribution conditional to sex and age. They find that this income risk decreases until the eighth decile of permanent income distribution but increases substantially on higher quantiles, probably because the authors' database contains capital income in addition to wages, which has more importance on higher deciles, facing these income sources high risk from capital market and private business assets (Scanlon, 2020).

With a similar approach, though imposing some restrictions in the sample, Broer, Kramer and Mitman (2020) find that aggregate risk of workers' earnings in Germany decreases until second decile of the permanent income distribution, then increases smoothly until eighth decile and decreases again for higher deciles, a result quite different to the study of Guvenen *et al*. (2017). On the other hand, Parker and Vissing-Jørgensen (2009, 2010), focusing on higher wages, provide evidence for the US suggesting that wages sensitivity to aggregate fluctuations is higher on the top deciles of the distribution. However, the authors point that this elasticity pattern is valid for 1982-2006 period, since prior to 1982 they observe a decreasing pattern in income risk along the top part of distribution.

Regarding the case of Argentina, Blanco *et al*. (2021) study earnings inequality and dynamics in between 1996 and 2015, using the same database as we do. With a methodological approach similar to that of Guvenen *et al*. (2017), the authors found that, over the sample period, there was an overall increase in real wages across the entire earnings distribution for both men and women. However, the magnitude of the increase was not homogeneous since the size of the effect was monotonically decreasing along the earnings distribution.

An important feature of those studies is that they do not focus on the role of unobservable factors, which could generate income risk asymmetries across individuals that are located in different parts of the wage distribution. One typical unobservable factor is the workers' productivity, which comes from their own capacity and work effort and which in turn will be a determining factor of their job position and wage they obtain. However, even knowing the position held by the worker, if the complexity of the task that they develop in their job position –which has to do, but not strictly, with their level of formal education (Beccaria, Fernández and Trajtemberg, 2020; Paz, 2007)– is unknown, it is not possible to isolate wages differentials associated to the productivity. Also, worker's wages would be affected differently by the business cycle due to unobservable factors of the company and the economic sector, which are not fully captured by observable variables, like the type of industry and the size of the company were the individual works.

Particularly in Argentina, the wages of formal employees have a complex structure due to how labor relations system of the country works. There is exclusivity of wage negotiations since only unions that have union status (union uniqueness) can carry them out. In addition, these are centralized by economic activities and the labor conditions agreements can be extended to all workers, whether or not they are affiliated to the union (Trajtemberg, 2009), which in turn depends on a set of circumstances. Unions, in addition to the minimum wage institution, have a fundamental role in determining the wage structure of an economy (Alejo and Casanova, 2016; Beccaria, Fernández and Trajtemberg, 2020), including the decision to grant lump sum increments to all formal workers. In particular, the unions compress the wage differences between the employees covered by the negotiations due to the fact that they determine wages by categories of workers and not by the characteristics of each individual (Beccaria, Fernández and Trajtemberg, 2020). This union behavior is consistent with the "wage compression hypothesis", that is, unions would give an advantage to individuals who would otherwise have had lower incomes, compressing that way the income distribution (Card, 1996; Card, Lemieux and Riddell, 2004; DiNardo, Fortin and Lemieux, 1996). In the same line, the hypothesis of Freeman (1980), argues that unions can achieve wage equalization among covered workers by reducing the importance of personal characteristics in determining wages. However, Beccaria, Fernández and Trajtemberg (2020) warn that, *a priori*, it is not obvious what the effect could be on the dynamics of the income distribution, since it will depend on the strategy set by the unions during the negotiation, which can be variable over time and among economic activities. Indeed, the sectors experience different evolution in their level of activity and profitability which will influence the bargaining power of the parties and, therefore, the results in terms of the agreed wages.

Some studies analyze the effect of unions and collective bargaining on wages in Argentina. Applying decomposition methods and unconditional quantile regression, Lombardo and Martínez-Correa (2019) find that collective bargaining coverage has a stronger positive effect on lower quantiles of wage distribution in Argentina, concluding that this labor institution seems to have an equalizing effect on the income of formal workers. In other words, wages of workers that are covered by collective bargaining tend to be higher than those not covered, being this difference higher on lower quantiles. They also suggest that this decreasing effect of collective bargaining along the wage distribution could be associated with an increase in the lowest wages as a consequence of the "minimum wages of the agreement" –i.e., the first wage ranges determined in collective bargaining agreements– which would mainly benefit the less qualified workers.

With a similar approach, Alejo and Casanova (2016) suggest that, within the group of workers covered by collective bargaining, this labor institution seems to have had an equalizing effect between 2004 and 2012, by reducing the weight of some individual and job characteristics –such age, seniority and task qualification– on wages. They attribute the lesser importance of seniority and task qualification to the fact that increases in the "minimum wages of agreement" tend to benefit workers who perform tasks that require lower qualifications and those with less seniority. Since the power of the unions tends to be greater in times of expansion than in times of economic contraction, the impact of the business cycle on the wage distribution will tend to be more equalizing in times of economic expansion, decreasing the dispersion in the wage distribution (Alejo and Casanova, 2016; Etchemendy and Berins Collier, 2008; Palomino and Trajtemberg, 2012).

On the other hand, Beccaria, Fernández and Trajtemberg (2020) analyze the effect of minimum wages and collective bargaining on the reduction of the returns to schooling in Argentina, which is the main factor that explain the fall in inequality of labor income in the country since 2002 (e.g., Cruces and Gasparini, 2010; Beccaria, Maurizio and Vázquez, 2015). As the authors recognize, although their study does not find evidence of an effect of those labor institutions on the decrease of education premiums for formal employees in the private sector, this does not imply an absence of an impact on the level of wages inequality, since various studies indicate that collective bargaining is associated with smaller wage gaps.

3. DATA AND METHODOLOGY

3.1. Data

For the main estimates, we use individual data of the MLER, a wage longitudinal sample, obtained from administrative records of the Argentine Integrated Pension System (SIPA, for its acronym in Spanish) and that have been made available to the public by the Ministry of Labor, Employment and Social Security. MLER is composed of affidavits that private sector companies submit monthly to the Federal Public Revenue Administration (AFIP, for its acronym in Spanish) to determine the contributions of the social security system of their employees. The data are available on a monthly basis and include, disaggregated, all labor relations of each employee between January 1996 and December 2015, containing information on more than 500,000 workers and more than 1.4 million labor relations, covering all provinces of the country. This substantial sample size allows us to estimate, with a reasonable level of accuracy, the effects of the Argentine business cycle on real wages over the entire conditional and unconditional labor earnings distribution.

Because the source arises from the administrative records of the social security system, the sample is representative of all private formal employees in the period. This segment of the labor market represents, on average, approximately one third of total employment in the reference period. An important advantage of the record-based nature is that data contain little measurement errors, which is a common issue with survey-based microdata sets. In order to provide additional information on the labor market, the Ministry of Labor, Employment and Social Security combined the information from the affidavits of the social security system with other sources, such as AFIP Business Registry and National Administration of Social Security (ANSES, for its acronym in Spanish), proving additional data of the characteristics of employers' companies, –such as economic activity, year in which the firm started operations (in tranches), among others– and employees, such as sex and year of birth.

According to the methodological document of the MLER, the reference population is made up of the total number of registered jobs (labor relations) in the private sector declared in the SIPA, for the period 1996-2015, including all economic activities and all sizes of employer companies, covering the entire country. This population contains more than 40 million employment relationships that correspond to more than 15 million people, so the MLER, obtained by simple random sampling, has a size of 3% in relation to the population, that is, almost a million and a half records.

Employees were selected in such a way that all the worker's labor relations enter the sample. Once a person enters the panel, the individual continues in it until his exit from formal employment, therefore the panel contains the information of the entire work history of the employee.

Individual monthly wage incorporates income from all labor relations, including remuneration amounts (wage, supplementary annual wage, fees, tips, gratuities, and additional supplements that have the character of habitual and regular) and non-remuneration (e.g., indemnifications), although, unfortunately, the database does not include information on the number of hours worked. For estimates, wages are deflated and then annualized by adding the monthly values for each calendar year, to avoid intra-annual fluctuations.

As the MLER methodological document points out, a procedure was implemented in the construction of the sample to ensure the confidentiality of highest wages. This consisted in a micro-addition of wages greater than the 98th percentile per ISIC double-digit economic activity, ordering incomes from lowest to highest and averaging three continuous wages, assigning that value to the corresponding observations.

On the other hand, since in the same year a worker can have labor relations associated with different sectors of activity, for each individual we assigned the employment sector with the greatest participation in the total annual remuneration. While MLER disaggregates economic activities at four digits level using the AFIP classification based on International Standard Industrial Classification (ISIC) Revision 3 and National Classifier of Economic Activities 1997[3] (CLANAE, for its acronym in Spanish) elaborated by INDEC, for models' parsimony purposes we define the following aggregate sectors: Primary Activities[4], Trade[5], Construction, Manufacturing Industry and Private Services[6], including in the latter group employees linked to the production and distribution of electricity, gas and water services. In relation to the size and seniority of the company, the assignment of which to each individual follows the procedure detailed above, the MLER uses the following categories based on the number of employees[7] and year in which the firm started operations, respectively, in tranches: (1) up to nine employees, between ten and forty-nine employees, between fifty and two hundred employees, and more than two hundred employees; (2) prior to 2001, 2001-2005, 2006-2010, higher than 2010.

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3 See AFIP Resolution 485/99.

4 Includes the following economic activities at letter level: Agriculture, livestock, hunting and forestry; Fishing and related services; Mining and quarrying.

5 Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods.

6 Includes the following economic activities at letter level: Electricity, gas and water supply; Hotels and restaurants; Transport, storage and communications; Financial intermediation and other financial services; Real estate, renting and business activities; Education; Health and social work; Other community, social and personal service activities.

7 This variable has no monthly frequency in the database but is available for the fourth quarter of each year.

We also include dummy variables that indicate the economic region in which the individual works. Since in the same year a worker can have labor relations that take place in different provinces, each individual is assigned the province corresponding to the labor relation with the highest participation in their total annual remuneration. For models' parsimony purposes, we group the provinces into categories according to the economic regions defined by INDEC (*Cuyo*, NEA, NOA, *Pampeana* and *Patagonia*).[8]

To measure the business cycle, we use the annual series of Argentine GDP in millions of constant dollars of 2010 for the period 1996-2015, provided by the World Bank.

Finally, following Guvenen *et al.* (2014, 2017), the analysis is limited to the group of males whose age is between 26 and 65 years, in order to avoid the classic econometric complications associated with women's labor participation and focus on individuals who are most likely to belong to the workforce.

Table 1 shows the pooled information for the entire period, descriptive statistics for total annual wage (expressed in thousands of Argentine *pesos* at constant values) of employed males whose age is between twenty-six and sixty-five years, with a disaggregation by economic sector and firm size. As can be seen, Manufacturing Industry sector has the highest mean wage, followed by Private Services, Trade, Primary Activities and, finally, Construction with a mean wage of less than half that of the first sector. This order is not altered when we focus on the median wage. However, when we look at wages' differentials by percentiles, the wages in the Primary Activities sector exceed those of the rest of the sectors at the top of the distribution. Regarding to the wage dispersion, the highest standard deviations are observed in the Primary Activities and Private Services sectors, followed by Manufacturing Industry, Trade and, finally, Construction activity.

On the other hand, as expected, Table 1 shows that the mean wage increases as firm size also increases. For example, mean wages in companies with more than two hundred employees are more than double that those corresponding to smallest firms. These wage differentials tend to increase in relative terms at highest percentiles. Thus, while in the first decile there are minimal differences in wages between the first three groups of company sizes, at the top of the distribution the wages in medium-sized firms (those whose number of employees is between ten and forty-nine or between fifty and two hundred) are 76% and 133% higher, respectively, respect to those paid by smallest firms. This differential reaches 223% when we compare the largest companies with the smallest companies at the top of the distribution. Finally, respect to the wage dispersion, we also observe that standard deviation increases as firm size is higher.

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[8] *Cuyo* includes *Mendoza, San Juan* and *San Luis*; NEA includes *Corrientes, Chaco, Formosa* and *Misiones*; NOA includes *Catamarca, Jujuy, La Rioja, Salta, Santiago del Estero* and *Tucumán*; *Pampeana* includes *Ciudad Autónoma de Buenos Aires, Córdoba, Entre Ríos, La Pampa, Provincia de Buenos Aires* and *Santa Fe*; *Patagonia* includes *Chubut, Neuquén, Río Negro, Santa Cruz* and *Tierra del Fuego*.

TABLE 1

DESCRIPTIVE STATISTICS FOR TOTAL ANNUAL WAGE BY ECONOMIC SECTOR AND FIRM SIZE. MALE EMPLOYEES WHOSE AGE IS BETWEEN TWENTY-SIX AND SIXTY-FIVE YEARS. THOUSANDS OF ARGENTINE *PESOS* AT CONSTANT VALUES (AUGUST 2002 = 100)

Statistics	**Economic sector**					**Firm size**				**All male workers**
	Construction	Manufacturing Industry	Primary Activities	Private Services	Trade	Up to nine employees	Between ten and forty-nine employees	Between fifty and two hundred employees	More than two hundred employees	
Min.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max.	2,918.7	1,668.8	1,565.5	4,827.8	1,431.6	3,138.7	1,887.1	2,918.7	4,827.8	4,827.8
Mean	9.7	21.6	15.1	18.8	15.5	10.1	13.2	17.5	26.9	17.6
Std. Dev.	18.2	27.8	30.8	30.3	20.3	15.8	18.7	25.8	37.3	27.5
10th pct.	0.6	4.1	0.9	1.7	2.7	1.2	1.4	1.7	3.6	1.7
20th pct.	1.5	7.2	2.1	4.5	5.8	3.0	3.6	4.4	8.3	4.2
30th pct.	2.6	10.0	3.9	7.2	7.7	4.9	5.9	7.2	12.2	6.7
40th pct.	4.0	12.7	5.4	9.9	9.6	6.6	7.9	9.9	15.7	9.1
50th pct.	5.6	15.5	7.1	13.0	11.9	8.1	10.1	12.8	19.5	11.8
60th pct.	7.7	18.7	9.3	16.4	14.4	9.9	12.4	15.7	23.9	14.3
70th pct.	10.5	22.9	11.6	20.7	17.5	12.0	15.2	19.3	29.3	18.8
80th pct.	14.2	29.7	16.0	27.0	20.6	14.9	18.6	24.5	36.9	24.6
90th pct.	21.6	42.2	35.0	38.0	27.9	19.3	24.8	34.3	52.4	36.2
99th pct.	64.6	118.1	131.9	105.5	83.5	41.4	67.7	99.1	150.1	105.5
99.9th pct.	152.9	325.5	340.8	322.1	244.0	126.4	222.6	294.5	408.3	300.6
Obs.	214,067	479,792	202,628	777,756	295,115	374,934	403,411	346,389	570,660	1,969,358

Source: own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: missing values and zero values of wages (that represent unemployed individuals and licensed persons, respectively) are not considered for statistics computation.

3.2. Methodology

Traditional linear regression models estimated by OLS are useful for quantify the impact of a given covariate on the expectation of the response variable Y conditional to a set of explanatory variables $\mathbf{X}$. In this way, the β_j coefficient of the model can be interpreted as the effect of a unit increase in X_j regressor on $E[Y|\boldsymbol{X}]$ (the conditional expectation of the dependent variable), remaining the rest of explanatory variables constant. Also, since the Law of Iterated Expectations (LIE) allows to write the unconditional expectation of Y, $E[Y]$, as an average of the conditional expectations, the β_j coefficient can be seen as the effect of a unit increase in $E[X_j]$ on $E[Y]$. Thus, the beta coefficients from an OLS regression have a double interpretation since they are measuring impacts on the conditional and unconditional mean of a response variable.

While OLS's estimates can adequately measure the impact of the economy's cyclical fluctuations on the conditional and unconditional expected value of real wages, they are not necessarily informative of the effects on the entire labor earnings distribution, more precisely on their quantiles. However, there are two econometric techniques that, respectively, allow to estimate the effects of a set of regressors on different quantiles of the conditional and unconditional distribution of Y, which will be explained below.

3.1.1. Quantile regression

The first technique is simply called "quantile regression" (QR) and it was developed by the seminal work of Koenker and Bassett (1978). Regarding our topic of interest, quantile regression provides a flexible estimation framework to capture the possible heterogeneity of the business cycle's effects on the real income of employees, by allowing model any quantile of the conditional labor earnings distribution or some transformation of these. Indeed, linear QR can be seen too as a semiparametric random coefficients model with an unobservable factor, where the latter interacts with observable determinants and is associated with the order of the quantile to which the individual belongs (Arellano, 2017; Koenker, 2005).[9] In the context of our QR models, this implies that differences in unobservable variables –for example, the degree in which individuals are benefited from collective bargaining, their productivity, among others– explain the differences in the income risk across the conditional labor earnings distribution.

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[9] For example, Arellano (2017) considers the case in which wage depends on an observable factor, given by the years of education of the individual, and on an unobservable factor, given by the skill level of the person. This unobservable factor, which can be associated with the order of the quantile where the individual is located, determines the return to education, that is, the determines the coefficient of the variable "years of education".

So, we use QR models as a first approximation to explore the effects of the Argentine business cycle on different quantiles of the real wage distribution, with the following specification:

$$Q_{\tau}\left(Y_{it} \middle| \mathbf{X}_{it}\right) = \alpha(\tau) + \mathbf{X}_{it}\boldsymbol{\beta}(\tau) \qquad [1]$$

In Eq. [1], $Q_{\tau}\left(Y_{it} \middle| \mathbf{X}_{it}\right)$ is the τ-th quantile, $\tau \in (0, 1)$, of the log real wage distribution (Y_{it}) conditional to the vector of regressors ($\mathbf{X}_{it}$), where the latter is formed by log GDP (explanatory variable of interest) and a set of control variables that includes, on the one hand, age and age squared as proxy variables of experience and, on the other hand, dummy variables that indicate the economic sector, the number of employees of the firm and year in which it started operations (both variables per tranches) and the economic region. The intercept term $\alpha(\tau)$ and the vector $\boldsymbol{\beta}(\tau)$, which measures the marginal effects of the k regressors on the τ-th conditional quantile, explicitly depend on τ. The subscripts i=1, 2, …, N and t=1, 2, …, T refers to individuals and time, respectively. As usual in empirical works, the application of natural logarithm transformation on wage and GDP variables allows us to measure, for each conditional quantile, the elasticity of wages respect to product.[10] Also, with linear quantiles, we can write:

$$Y_{it} = \alpha(\tau) + \mathbf{X}_{it}\boldsymbol{\beta}(\tau) + u_{it}(\tau) \qquad Q_{\tau}\left(u_{it} \middle| \mathbf{X}_{it}\right) = 0 \qquad [2]$$

Eq. [2] shows explicitly that, in a QR framework, the error term also depends on the quantile that is modeled.

Since, we are working with panel data, it is natural to wonder if we can include fixed effects in the models to control for individual heterogeneity, but the addition of this type of effects in QR models presents some difficulties, mainly associated with the incidental parameters problem (Neyman and Scott, 1948; Lancaster, 2000). This difficulty arises mainly in short panels, given the large number of parameters to be estimated relative to the sample size. As a result, the standard QR estimator may be biased (Arellano, 2017). In addition, in contrast to mean regression models, there is no general transformation that can suitably eliminate the specific effects (Galvao and Montes-Roja, 2017). As Machado and Santos Silva (2019) point out, there is a substantial literature dealing with the challenges of QR models with individual effects[11],

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[10] Equivariance property for conditional quantiles implies that, for any monotonic transformation $h(\bullet)$, $Q_{\tau}(h(Y) \mid \mathbf{X}) = h(Q_{\tau}(Y) \mid \mathbf{X})$. Then, $Q_{\tau}(ln(Y) \mid \mathbf{X}) = ln(Q_{\tau}(Y) \mid \mathbf{X})$. Although, strictly speaking, we are modeling the conditional quantiles of log wages (or, equivalently, the log of conditional quantiles of wages), for simplicity purposes we will use the term "conditional labor earnings distribution".

[11] For example, Canay (2011), Galvao (2011), Galvao and Wang (2015), Galvao and Kato (2016), Kato, Galvao and Montes-Roja (2012), Koenker (2004), Lamarche (2010).

but the proposed methods are computationally demanding or rely on very restrictive assumptions, for example, restricting the fixed effects to be location shifters, that is, assuming individual effects that do not vary by quantile. Thus, QR models with fixed effects constitute an active research field, so we cannot talk about "optimal approach", since each proposed estimator has its own advantages and disadvantages. Instead, we estimate the QR models by pooling the annual observations of all individuals for the period 1996-2015, so the vector of pooled quantile estimators solves the following optimization problem:

$$\min_{\alpha \in \mathbb{R},\, \beta \in \mathbb{R}^k} \sum_{i=1}^{N} \sum_{t=1}^{T} c_\tau \left(Y_{it} - \alpha(\tau) - \mathbf{X}_{it}\boldsymbol{\beta}(\tau) \right) \qquad [3]$$

In Eq. [3], $c_\tau(\bullet)$ is the asymmetric absolute loss function[12] (Wooldridge, 2010), which asymmetrically penalizes positive and negative errors according to the conditional quantile which is modeled.[13] Moreover, the possible autocorrelation of observations precludes the application of the asymptotic variance formula of Koenker and Basset (1978) to compute the estimators' standard errors, since it is based on the assumption of independent observations (Abrevaya and Dahl, 2008). For this reason, standard errors are clustered by individual following Parente and Santos-Silva (2015), in order to consistently estimate the covariance matrix and perform valid statistical inference.

All the models are estimated for the quantiles 0.1, 0.2, ..., 0.9, incorporating also 0.99 and 0.999 quantiles to measure the effects of the business cycle on the top of the conditional labor earnings distribution, in the spirit of Guvenen *et al.* (2017). However, as it was pointed previously, it is important to note that we have less variability on the top of wage distribution conditional on economic activities, because the procedure applied on MLER to ensure the confidentiality of highest wages. Hence, estimates for the quantiles 0.99 and 0.999 should be interpreted with caution. In all cases, we also estimate "mean" income risk of workers by pooled OLS, to compare its results to those obtained by pooled quantile regression.

3.1.2. Unconditional quantile regression

The second technique is a method introduced by the work of Firpo, Fortin and Lemieux (2009) and it allows to estimate the effects of a set of regressors on different quantiles of the unconditional distribution of *Y*, reason why the technique is called

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[12] Let u_{it} be the error term, that is, $u_{it} = Y_{it} - \alpha(\tau) - \mathbf{X}_{it}\boldsymbol{\beta}(\tau)$. Then, the asymmetric absolute loss function is $c_\tau(u_{it}) = \left(\tau 1[u_{it} \geq 0] + (1-\tau)\, 1[u_{it} < 0]\right) |u_{it}| = (\tau - 1[u_{it} < 0])\, u_{it}$, where $1[.]$ is the indicator function, which is equal to one if the statement in brackets is true and zero otherwise.

[13] In addition, one advantage of the estimators of quantile regression models over OLS is that its estimators are robust to outliers (Wooldridge, 2010).

"unconditional quantile regression" (UQR).[14] This feature is highly appropriate for our research question since we are no longer restricted to estimate the effects of business cycle on, say, "conditional poor" or "conditional rich", via QR, but we can use UQR to estimate that impacts on the wages of individuals located at any point of the unconditional labor earnings distribution. This is very important when analyzing, for example, the effects of monetary or fiscal policy on labor income, since policy makers could be more interested in seeing how these interventions affect the wages of "poor" and "richs" without conditioning, necessarily, this population groups to a set of observable characteristics.

UQR method is based on the concept of "influence function" (IF) introduced by Hampel (1968, 1974) and, more precisely, on which Firpo, Fortin and Lemieux (2009) call "recentered influence function" (RIF). Following Rios-Avila (2020), let F_Y be the cumulative distribution function (c.d.f.) of the random variable Y, $v(F_y)$ any distributional statistic (like the mean, variance, τ-th quantile, etc.) of Y, and H_{yi} the c.d.f of a random variable with probability mass of 1 at the value y_i. The IF, denoted mathematically as $IF\{y_i, v(F_Y)\}$, is a directional derivative that shows the rate of change if the distributional statistic v caused by an infinitesimal change in F_y in the direction of H_{yi}. Intuitively, the IF can be interpreted as the influence that observation y_i has on the estimation of the distributional statistic v.[15]

Firpo, Fortin and Lemieux (2009) define the RIF as $RIF\{y_i, v(F_Y)\} = v(F_Y) + IF\{y_i, v(F_Y)\}$. Notice that the RIF is a function of the distributional statistic of interest and the value of the underlying random variable. This function can be derived analytically for the quantiles and for other distributional statistics.[16] On the other hand, since it can be shown that the unconditional expected value of the IF equals zero, it follows that $v(F_Y) = E\left[RIF\{y_i, v(F_Y)\}\right]$. Naturally, the RIF can be affected by a vector of random covariates $\mathbf{X}$. Hence, the LIE implies that $v(F_Y) = E\left[E\left[RIF\{y_i, v(F_Y)\} | \mathbf{X} = \mathbf{x}\right]\right]$ For simplicity, but without loss of generality, consider that $\mathbf{X}$ is formed by only one continuous variable X, with probability density function (p.d.f.) $f_X(x)$. The authors show that the unconditional partial effect (UPE) of a small location shift in the distribution of X on $v(F_y)$ is given by:

$$UPE = \int \frac{dE\left[RIF\{y_i, v(F_Y)\} | X = x\right]}{dx} f_X(x)\, dx \qquad [4]$$

[14] However, the method of Firpo, Fortin and Lemieux (2009) was extended to estimate the effects of the regressors on other statistics of the unconditional distribution of the response variable, like the variance, interquantile range, Atkinson index, among others.

[15] See Firpo, Fortin and Lemieux (2009), and Huber and Ronchetti (2009) for a more formal discussion.

[16] See Firpo, Fortin and Lemieux (2009) and Rios-Avila (2020) for a further discussion.

Eq. [4] shows that the partial effect on the distributional statistic of interest can be interpreted as an average derivative. As can be noted, the process requires modeling $E\left[RIF\left\{y_i, v\left(F_Y\right)\right\}|\mathbf{X}=\mathbf{x}\right]$. Firpo, Fortin and Lemieux (2009) propose to model this conditional expectation as a linear function of **X**, which can be easily estimated by OLS.[17] In the simplest case mentioned above, since this proposal implies that $\frac{dE\left[RIF\left\{y_i, v\left(F_Y\right)\right\}|X=x\right]}{dx}$ is a constant, say β, then $UPE = \beta$. Hence, the UPE can be recovered from the estimated coefficients of an OLS regression, in which the corresponding RIF is the dependent variable.

Beyond the interpretations of the marginal partial effects of an UQR model –which could be more or less useful depending on the context– for our research purpose this technique has some additional advantages over QR, related to the fact that UQR models are estimated by OLS. First, there is a computational benefit, since OLS estimation is less demanding that linear programming, especially when working with large databases such as ours. Second, we can easily introduce fixed effects in our panel data models to control for individual heterogeneity.

Our UQR models involve estimating, thorough OLS, the following type of equation:

$$RIF_{Q_\tau}(y_{it}) = \alpha_i(\tau) + \mathbf{X}_{it}\boldsymbol{\beta}(\tau) + u_{it}(\tau) \qquad [5]$$

In Eq. [5], the dependent variable corresponds to the RIF for the τ-th quantile of the unconditional log labor earnings distribution. As before, we estimate models for each one of 0.1, 0.2, …, 0.9, 0.99, and 0.999 quantiles. The set of regressors is the same that for QR models, but now we also include individual fixed effects, denoted by α_i, so estimates are not directly comparable. We use standard errors clustered by individuals for the same reasons we mentioned in Section 3.1.1. In all cases, we also estimate "mean" income risk of workers by OLS (including individual fixed effects), to compare its results to those obtained by UQR.

3.1.3. Differences with other approaches and limitations

The empirical strategy used in this paper differs technically and conceptually from that adopted by the work of Guvenen *et al.* (2017) and similar studies, who model conditional expectation of wage growth rate and estimate the average effect of the product growth rate for different decile groups of individuals, which are exogenously built based on the permanent income distribution conditional to sex and age. While this strategy makes it possible to quantify the sensitivity of wages to cyclical fluctuations

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[17] However, modeling the RIF conditional expectation as a linear function of **X** should be considered as an approximation to a potentially nonlinear function, which cannot be appropriated to describe the marginal effects of the covariates (Alejo, Favata, Montes-Roja and Trombetta, 2021).

in the economy for groups of individuals who are located in different segments of the permanent income distribution (conditional on sex and age), the estimated coefficients measure average effects, and their estimators only use the information of the corresponding decile group. Thus, this method is less accurate to capture the heterogeneity of GDP impacts on wages. By contrast, quantile regression methods applied in this paper capture the effects of cyclic fluctuations on the different quantiles of the conditional and unconditional wage distribution, using the information of the entire sample in the estimates and allowing us to measure with more precision the heterogeneity of the impacts.

Although the estimated models in this study constitute a reasonable first approximation to analyze the possible heterogeneity of income sensitivity to business cycle, they are not exempt from some limitations. First, given the lack of information on hours worked, it prevents filtering the effect that the workload of the employees can have on their income. Second, given the labor market entries and exits, there is a potential selection bias, so in principle the results would be representative of the group of employees that participate in the formal labor market. This also implies that, for the individuals who leave the sample, it is not possible to know if they go into unemployment or the informal labor market.[18] Third, the models are static and do not consider the possible effects of the temporal trajectories of certain variables on real wages, such as the unemployment history of each individual. Finally, the database also does not include information about the education level of the individuals, so we cannot isolate the effect of this variable on wages, as in a standard Mincer equation. This is not a minor detail, since education affects the average level of the wages and its distribution, but the database that we are using does not capture this information.

4. RESULTS[19]

4.1. QR Models

As a first approach, we estimate a basic linear quantile regression model using the log of wages as explained variable and the log of GDP as the main covariate, pooling the information for the whole period and clustering standard errors by individual. We also control for the effects of age, economic sector, and size and seniority of the company where the worker works, as well as geographic region. As usual in the literature, we also estimate a standard regression model by OLS to compare its results with those corresponding to quantile regression models.

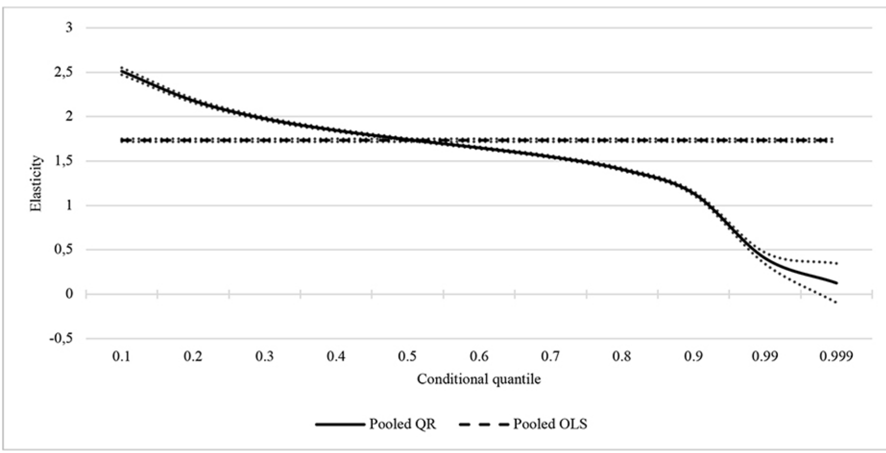
[18] As noted in the Introduction, we address the problem of informality by complementing our main estimates using EPH data.

[19] Tables with complete estimates outputs for the general QR and UQR models are shown in the Appendix. For the rest of the models, the estimates outputs are available upon request from the authors.

Figure 1 reports estimated elasticities of real wages respect to GDP for Argentina across the conditional wage distribution. As expected, these elasticities are positive but decrease monotonically as conditional quantile increases. So, while an 1.0% rise of the GDP generates, *ceteris paribus*, a 2.5% increment on the first conditional wage decile –i.e., the 0.1 quantile– this effect is reduced to 1.7% and 1.1% in the median wage and ninth decile, respectively. At the top of the conditional distribution (0.999 quantile), the elasticity is reduced to 0.1 approximately but it is not statistically significant at 5%, probably due to the high wages top coding. It is worth noting that the fall of the estimated elasticities across deciles is not homogeneous, since the fall on the coefficient is smoother until 0.6 quantile while for the rest of deciles, except for the 0.999 quantile for whom the fall slows down, is stronger. It is interesting to note that "mean" income risk estimated by pooled OLS (1.7) is very similar to conditional median's elasticity, but aside the median OLS underestimate the GDP effect on lower wages deciles and overestimate the impact in higher deciles, which illustrates the potential of quantile regression models to capture the asymmetries of the impacts of the business cycle. Also, except for the 0.999 quantile, it is important to mention the precision of quantile estimators, given the narrowness of confidence intervals.

FIGURE 1

ELASTICITIES OF REAL WAGES RESPECT TO GDP. POOLED QR



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Note: Dotted lines represent 95% confidence intervals.

The estimated elasticities show that male private employees belonging to the first segments of conditional wage distribution have a higher income risk, i.e., wages of "conditional poor" are more cyclical to aggregate economic fluctuations that "conditional rich". Besides, while elasticity reduces along the conditional distribution –more strongly for higher quantiles– only for the ninth and higher deciles the impact on the wages has the same proportional magnitude, approximately, that GDP change.

Now, an important question for us is: what factors could be explaining the decreasing pattern in income risk along the conditional labor earnings distribution in Argentina? In other words, through which channels cyclical fluctuations are transmitted heterogeneously to the wage conditional quantiles? As commented previously, since, with favorable rules in labor market, union power tends to move in the same direction as economy and employment, one possible explanation for the decreasing pattern in income risk along conditional distribution is given by the role of unions that, through collective bargaining, tends to impact more strongly on lower quantiles of wages. That is, we can interpret that the individuals whose wages correspond to the lowest quantiles are those who benefit the most from collective bargaining, either through the increase in the minimum wages of the agreement and fixed components or due to the lesser importance of individual characteristics in determining wages. However, it is important to note that, since we cannot identify which individuals are covered by collective bargaining, the asymmetric income risk that we observe in our estimates is probably simultaneously reflecting two channels through which this labor institution affects the conditional labor earnings distribution. On the one hand, the decreasing pattern on elasticities could respond to the heterogeneous effect of collective bargaining on the conditional income distribution for workers covered by this labor institution. On the other hand, the aforementioned pattern could be reflecting the wages differential between the workers that are covered by collective bargaining and those that are not covered, being this difference higher on lower quantiles. Nevertheless, Beccaria, Fernández and Trajtemberg (2020) point out that, according to estimates based on SIPA data, more than 90% of private formal employees are covered by collective bargaining. Thus, we could think that the asymmetry in income risk is mainly reflecting heterogeneities among workers covered by collective bargaining.

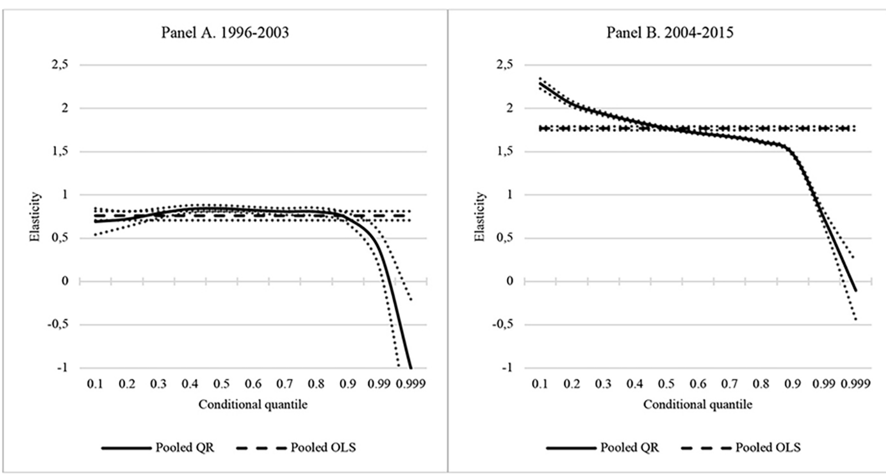
Beyond these particularities, our hypothesis is that unions can capitalize the fruits of economic growth by negotiating higher wages, with higher relative increases at the bottom of the conditional distribution. Conversely, during a recession, since unions tend to lose bargaining power, lower wages will suffer more intense wage cuts than the economic downturn and, in turn, this cut will be greater than that of workers at the top of the conditional distribution.

To explore more in detail this hypothesis, we run QR models for two separate periods, 1996-2003 and 2004-2015, which differ from each other in terms of the power and role of unions in the wage determination process. Indeed, during the 1990s, there was an individualization of labor relations, as a result of a rigid minimum wage and the absence of collective bargaining in many economic activities. In addition, price stability and increasing unemployment discouraged unions from negotiating new agreements, preferring to retain the clauses of previously negotiated collective agreements (Palomino and Trajtemberg, 2006). Conversely, during the 2000s the labor institutions of collective bargaining and minimum wage were revitalized. Particularly, in 2004 the Employment, Productivity and Minimum Wage Council was convened to resume discussions on the minimum wage after eleven years of inactivity, increasing in that way wage floors in collective bargaining. From that year, some other factors favored collective bargaining, among which we can highlight the sanction of the Labor Ordinance Law, that gives supremacy to higher-level bargaining over lower-level bargaining, the policy of periodically updating the minimum wage, and the change in the macroeconomic and institutional context (Alejo and Casanova, 2016). As a result, collective bargaining has become more widespread, extending to practically all sectors, and wages paid by firms converged to those established in collective agreements (Blanco *et al.*, 2021; Palomino and Trajtemberg, 2006).

Figure 2 show QR estimates for the periods 1996-2003 and 2004-2015. As can be seen, the results of the models for the 1996-2003 subsample –when the unions had little power in the wage determination process– show that income risk is practically the same throughout most of the conditional labor earnings distribution, except for the 0.99 and 0.999 quantiles, where the effect of business cycle strongly declines and even turns negative. In some way, we can say that “mean” elasticity estimated by OLS

FIGURE 2

ELASTICITIES OF REAL WAGES RESPECT TO GDP FOR TWO SEPARATE PERIODS (1996-2003 AND 2004-2015). POOLED QR



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

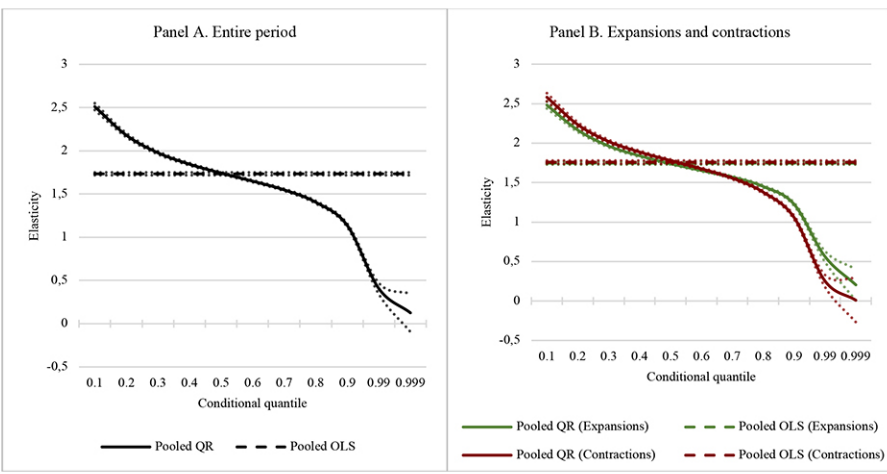
Note: Dotted lines represent 95% confidence intervals. In Panel A, the vertical axis is bounded to facilitate comparison.

(0.8) suitably sums up income risk across conditional labor earnings distribution. Also, it is interesting to note that, given the fact that elasticity for this subsample is positive but less than one, the wages of formal employees is inelastic respect to business cycle fluctuations. On the contrary, Panel B show that, using information of the period 2004-2015 for the estimates, there is an asymmetry on income risk, since elasticities of real wages respect to GDP fluctuations decrease monotonically along the conditional distribution, being this fall stronger on highest quantiles. Hence, "mean" elasticity estimated by OLS (1.8) is not sufficient to describe the income risk of formal employees, since this method underestimate business cycle effect on lower quantiles and overestimate the impact on higher quantiles; indeed, these results are very similar to those shown in Figure 1. Thus, results of Figure 2, although exploratory in nature, support our hypothesis about the role of union, and in particular of collective bargaining, in explaining the observed asymmetry on income risk of formal employees, which shows a decreasing pattern along the conditional labor earnings distribution.

Finally, since the relationship between wages and aggregate economy could differ according to the different phases of the business cycle (Guvenen, Ozkan and Song, 2014), we estimate QR models by pooling respectively the periods of annual expansion and contraction of GDP, on the other hand (Figure 3). It is important to note that the decreasing pattern in estimated elasticity across the conditional wage

FIGURE 3

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY BUSINESS CYCLE PHASES. POOLED QR



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Note: Dotted lines represent 95% confidence intervals.

distribution remains when we model separately periods of expansion and recession in economy's production. While the effect of GDP on real wages in a recession is slightly higher for the first six deciles compared to expansions, this relationship is reversed for higher quantiles, but the differences are not substantial, except at the top of the distribution. Hence, these estimates suggest that, in general terms, there are not big differences in wages risk comparing the different phases of business cycle. Also, is interesting to note that "mean" elasticities estimated by OLS are practically identical in expansions and recessions, but in both cases underestimate elasticity in lower deciles and overestimate in higher deciles.

Given these results, the decrease in the elasticity of wages as we move away from the lowest deciles has two main implications for the inequality in the conditional wage distribution in Argentina. First, in periods of economic expansion one may expect that GDP increase produces an equalizing effect in income distribution, since lower deciles growth rates are higher. Second, and inversely, estimates suggest that recessions have a unequalizing effect on earnings distribution, since conditional poor may be more affected –in proportional and negative terms– than conditional rich. Hence, within-group income inequality may be affected differently depending on business cycle phase.

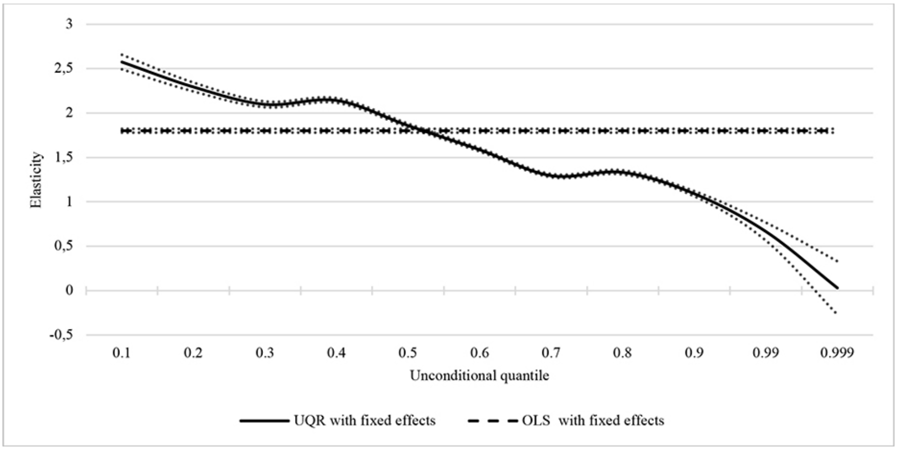
4.2. UQR Models

In this section we show the estimation results for UQR models. As a first approach, we replicate the general model shown in Figure 1 of the Section 4.1. As can be seen in Figure 4, the estimated elasticities are positive as expected and, in general terms, show a decreasing pattern along the unconditional labor earnings distribution. For example, and while an 1.0% rise of the GDP generates a 2.6% increment on the 0.1 unconditional quantile of wages, this effect is reduced to 1.9% and 1.1% in the median wage and ninth decile, respectively. At the top of the distribution, the elasticity is practically equal to zero and it is not statistically significant at 5%. Although QR and UQR estimates are not strictly comparable, it can be observed that elasticities estimated by the latter method show a similar magnitude to its conditional counterpart, but with the difference that UQR estimates slightly increases at some quantiles of the distribution. Anyway, beyond the technical issues of comparability, an important point is that the conclusions about the income risk that we derived for the conditional labor earnings distribution are the same when we look the unconditional distribution. In other words, now we can say that not only the conditional poor are more exposed to aggregate economic fluctuations that conditional rich, but the individuals with lower wages have a higher income risk than their rich counterpart, regardless of their observable characteristics.

In Figure 5 we repeat our exercise of estimate models for the periods 1996-2003 and 2004-2015, to explore if our hypothesis about unions and income risk is consistent when we look at unconditional labor earnings distribution. Panel A show that in the

FIGURE 4

ELASTICITIES OF REAL WAGES RESPECT TO GDP.
UQR WITH INDIVIDUAL FIXED EFFECTS



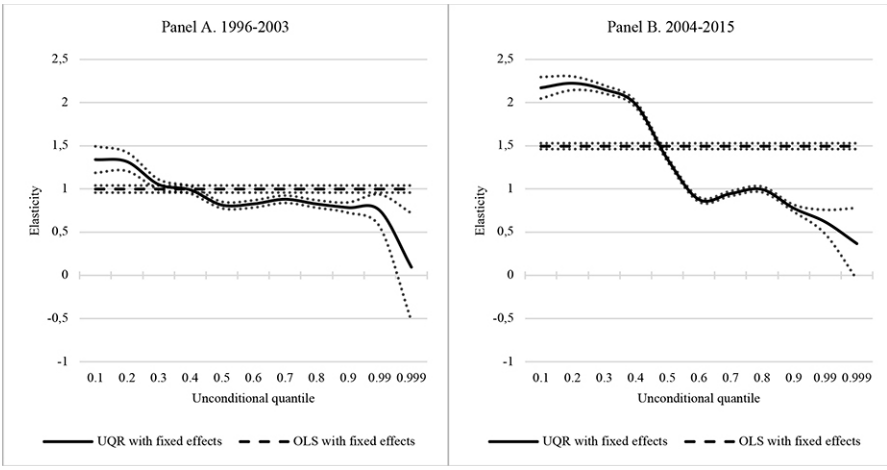
Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

period 1996-2003 the income risk is homogeneous along quantiles, except at the bottom and top of the distribution. On the contrary, Panel B (period 2004-2015) show estimated elasticities that tend to decrease along the unconditional labor earnings distribution, with slight increases at some deciles. Hence, these results seem to validate our hypothesis that unions have in important role in explaining the observed asymmetry on income risk.

On the other hand, Figure 6 shows UQR estimates by business cycle phases. As can be seen, results for contraction phase subsample exhibit, in general terms, a decreasing pattern on income risk along unconditional labor earnings distribution, in a similar way that elasticities estimated for the entire period. Regarding the results for expansions periods, it can be observed that while income risk tends to decline from the fourth decile onwards, estimates does not seem to show a clear pattern on the first three deciles of the distribution. Comparing both "curves", elasticity of real wages respect to GDP tends to be higher in recessions compared to expansion phases for the first three deciles of the unconditional distribution, while this relationship is reversed for higher quantiles. These results are similar to those obtained for the QR models, but with more notable differences. One potential implication of our UQR estimates is that poor are not only more affected by business cycle fluctuations compared to their rich counterparts, but they suffer a stronger fall in wages when aggregate activity declines than the increase in wages that their experiment when business cycle is in its

FIGURE 5

ELASTICITIES OF REAL WAGES RESPECT TO GDP FOR TWO SEPARATE PERIODS (1996-2003 AND 2004-2015). UQR WITH INDIVIDUAL FIXED EFFECTS



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

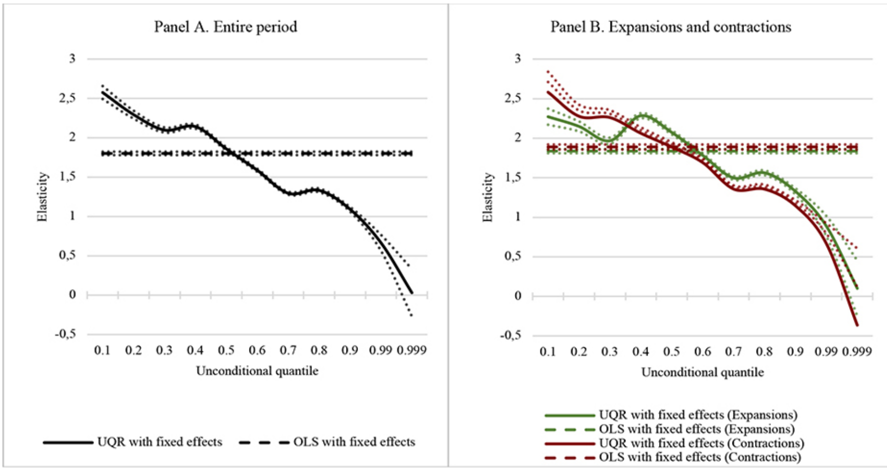
expansion phase. Another consequence is that expansions (contractions) of business cycle is expected to have an equalizing (unequalizing) effect on unconditional income distribution, a conclusion similar to that obtained from the results of QR models.

Since MLER database only covers private formal employees, our estimates could present a selection bias if workers "choose" to work in the informal sector. Hence, it is necessary to check if our income risk results are also valid when we incorporate information about other groups, such as informal employees, self-employed individuals, and workers from the public sector. This can be done, although with several limitations, by using EPH, which contains data about the Argentine labor market including both formal and informal private employees, as well as covering other occupational categories. However, it is important to note that this source of information has various disadvantages respect to MLER, that do not make it ideal for an empirical study of income risk. First, although we can virtually cover the same period (1996-2015) [20], INDEC implemented several changes in the data collection in the second half of 2003, moving from a biannual to a quarterly survey, which makes it difficult to compare the variables over time. In addition, EPH data from 2006 onwards should be treated with caution, due to the administrative irregularities that affected the validity of INDEC's

[20] EPH data from the third quarter of 2007, and from the third and fourth quarters of 2015 are not available.

FIGURE 6

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY BUSINESS CYCLE PHASES.
UQR WITH INDIVIDUAL FIXED EFFECTS



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Note: Dotted lines represent 95% confidence intervals.

statistical information.[21] Second, EPH uses a rotative panel scheme for the data collection, which actually allows to track the same household for one and a half years only.[22] So, we cannot include individual fixed effects in our models. Additionally, since EPH does not provide information about the workers for every month each year, to annualize the labor earnings we must assume that the worker was employed during the whole year.[23] Third, the survey only covers urban agglomerations, which actually represents about 60% of the Argentine population. Finally, the information collected by EPH is declared, so it is likely that it contains more measurement errors than an administrative database.

Beyond the limitations of EPH, this source of information could be useful for the validation of our previous empirical results. To maximize comparability, we construct

[21] See Decree 55/2016: https://www.argentina.gob.ar/normativa/nacional/decreto-55-2016-257615/texto.

[22] Since it is possible for us to observe the same individual with the same observable characteristics (dependent and independent variables of our models) within the same year, we eliminated "duplicated" observations from the sample in order to mitigate possible biases due to the presence of repeated individuals in a given year.

[23] Also, it is important to note that declared labor earnings collected by EPH are net income.

similar variables to those used in our previous UQR models[24], and we use standard errors clustered by individual. Also, we estimate separate models for the periods 1996-2003 and 2004-2015, due to changes in the data collection (e.g., survey frequency).

Panels A and B of Figure 7 shows income risk estimates[25] for formal and informal workers[26], including employees and self-employed workers in private and public sectors, using EPH data. All those elasticities are statistically different from zero, except at the top quantiles for the period 2004-2015. For almost all quantiles and regardless the period, wage elasticity for informal workers is higher than for formal workers. Since informal workers comprise not only non-registered employees but also self-employed workers that perform non-professional tasks in their jobs, the former results imply that lower quality jobs are more exposed to the business cycle, especially at the lower part of labor earnings distribution. However, there are some differences between formal and informal workers in the shape of the income risk pattern for the first period. Indeed, while informal individuals exhibit a wage elasticity that tends to decrease, income risk for formal workers is virtually constant along the unconditional distribution. On the contrary, for the period 2004-2015, both groups have an income risk that decreases along the distribution. All in all, these results suggest that low-income informal workers always have a higher income risk than their wealthy counterparts.

In Panels C and D of Figure 7 we show income risk estimates –also using EPH data– for formal employees in the private sector, since this group resembles the population covered by MLER database. In general terms, these income risk patterns along the unconditional distribution mimic the shape of our previous results from Figure 4. That is, for the period 1996-2003, we observe an income risk that does not exhibit major changes along the distribution, although now it oscillates around a higher average. On the other hand, estimates for the period 2004-2015 show a decreasing pattern as in Figure 4, but with a slightly different convexity at the middle of the distribution.

In sum, using EPH, our results do not change the conclusions that we obtained with MLER database, but they provide valuable information about the informal sector. Indeed, this segment of the Argentine labor market seems to be more sensible to the business cycle than the formal sector. Moreover, informal workers at the lower part

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[24] Harmonization of variables between EPH and MLER was not complete. On the one hand, although using EPH we can measure firm size through the number of employees in tranches, we had to construct different categories from those of the MLER database: up to twenty-five employees, between twenty-six and one hundred employees, between one hundred and one and five hundred employees, and more than five hundred employees. On the other hand, EPH does not collect information about the year in which the firm started operations, so we cannot include this information as a control variable in the models.

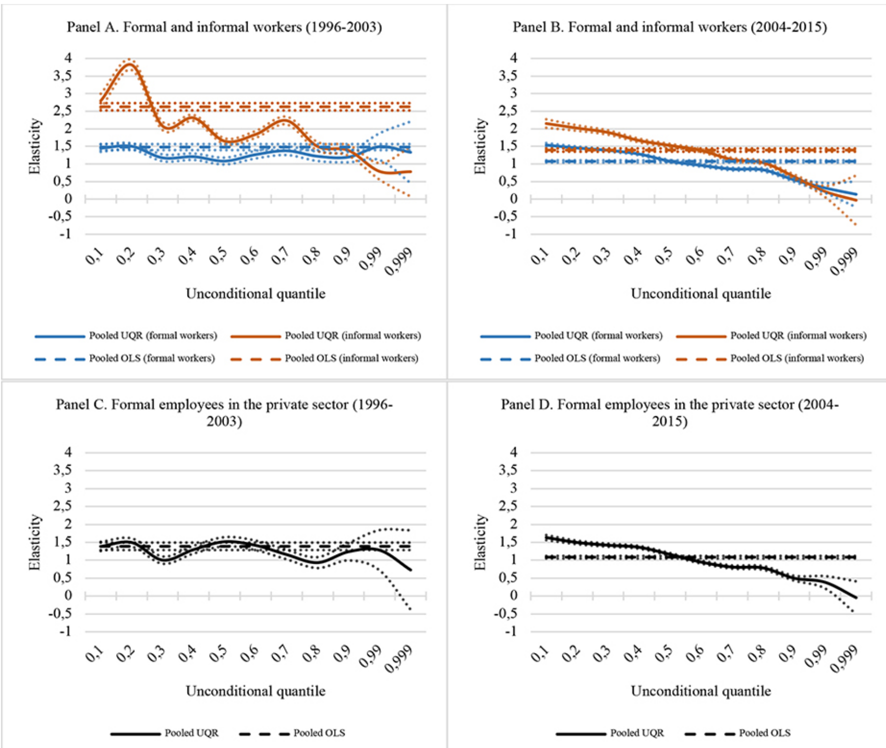
[25] Tables with complete estimates outputs are available upon request from the authors.

[26] To classify individuals into formal and informal workers we apply two criteria. For employees, we consider them to be formal workers if they declare to have pension discount in their jobs. For self-employed individuals, we follow Salvia (2002) and consider them to be formal workers if they realize professional tasks in their jobs.

of the distribution have a higher income risk than their wealthy counterparts, which highlights the income volatility that these workers experience along the business cycle. Our results as a whole suggest that wage elasticities for formal employees could be considered as a lower bound for the Argentine workers income risk.

FIGURE 7

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY OCCUPATIONAL CATEGORY. POOLED UQR



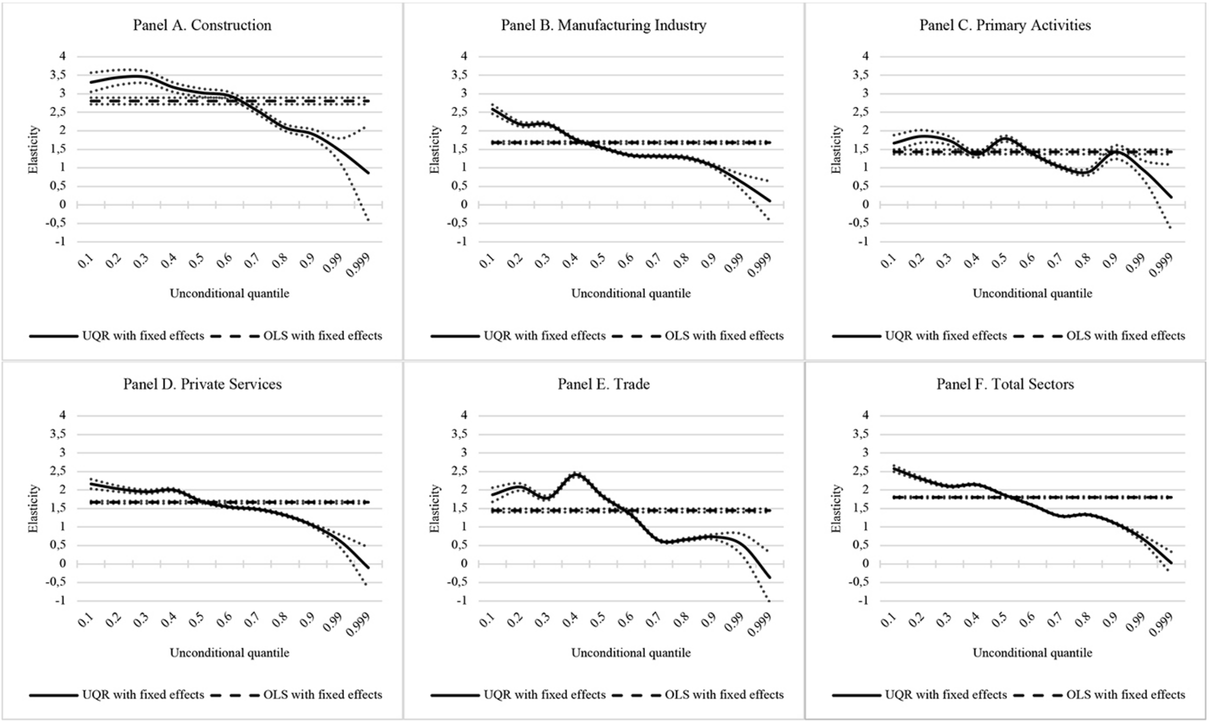
Source: Own elaboration based on data from INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

4.2.1. *Estimation results by economic sector and firm size*

Since the results of collective bargaining may differ between industries and companies (Beccaria, Fernández and Trajtemberg, 2020), in this section we disaggregate the UQR estimates by economic sector and firm size to explore the potential differences in income risk.

FIGURE 8

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY ECONOMIC SECTOR.
UQR WITH INDIVIDUAL FIXED EFFECTS



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

In the first place, it is important to note that income risk tends to reduce along unconditional distribution in Construction, Manufacturing Industry, and Private Services sectors (Figure 8). Instead, income risk for Primary Activities workers seems to be relatively homogeneous, but with oscillations, along the distribution, while Trade sector does not seem to show a clear pattern on elasticities. Besides these differences, it is clear that OLS estimates do not capture the heterogeneity business cycle impacts in most economic sectors.

Secondly, for all quantiles, the magnitude of elasticities for Construction activity is higher respect to all other sectors, reaching values near three up to the median, indicating that the percentage changes on wages triple the percentage changes on GDP in this part of the unconditional distribution. This higher income risk in Construction sector is also reflected in a higher "mean" elasticity (2.8) estimated by OLS. These results are consistent with the well-known fact that, Construction is an activity very sensitive to economic fluctuations. Indeed, Guvenen *et al.* (2017) suggest that men employed in Construction have higher income risk respect to other sectors, at least in the middle of permanent income distribution. Third, it is interesting to note that UQR and OLS estimates for Manufacturing Industry and Private Services are similar to each other, indicating that workers in those sectors face similar income risk. Finally, it can be observed that, from the sixth decile onwards, elasticities for Trade are less than for the other sectors.

Previous results suggest the existence of heterogeneities in income risk for the aggregate economic sectors, which is consistent with the fact that unions of different economic activities do not have the same bargaining power, consequently affecting the results of collective agreements and income risk in each sector. On the other hand, if the asymmetries in the elasticities explained by the effect of being covered by collective bargaining are of little importance within the group of formal employees, the heterogeneity that we observe with the general UQR model could be explained, in part, by differences in the bargaining power within sectors. In other words, income risk could differ among the different economic activities that make up an aggregate sector. To explore this hypothesis, for illustrative purposes only, in Figure 9 we show UQR estimates for each of the economic activities –at letter level of ISIC Revision 3– of Private Services, since it is a sector that groups activities very different between them.[27]

First, in general terms, it can be observed that the most notable differences between economic activities of Private Services occur in the lower and upper deciles. Thus, at the bottom of the distribution, Real estate, renting and business activities; and Transport, storage and communications have the highest income risk, while Education; Electricity, gas and water supply; and Financial intermediation have the lowest elasticities. Instead, at the top of the distribution, Health and social work

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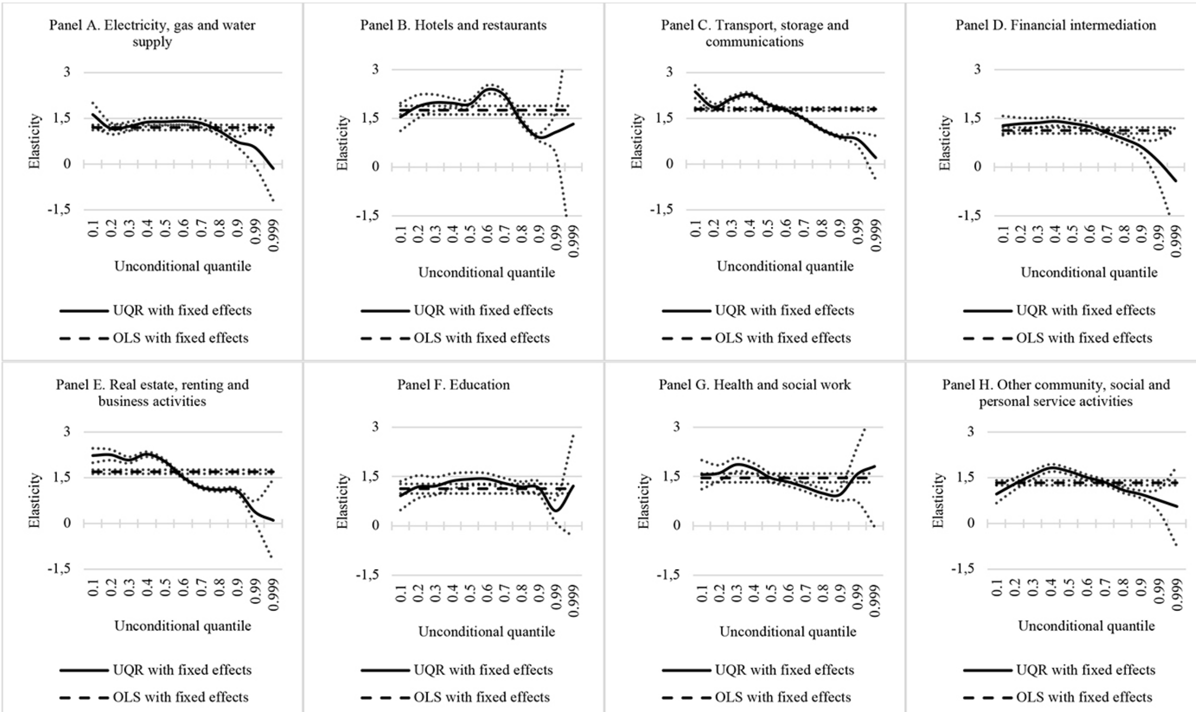
[27] Naturally, we could repeat this exercise for the other aggregate sectors, but a higher level of disaggregation it is outside the scope of this paper.

FIGURE 9

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY ECONOMIC ACTIVITIES OF PRIVATE SERVICES.
UQR WITH INDIVIDUAL FIXED EFFECTS

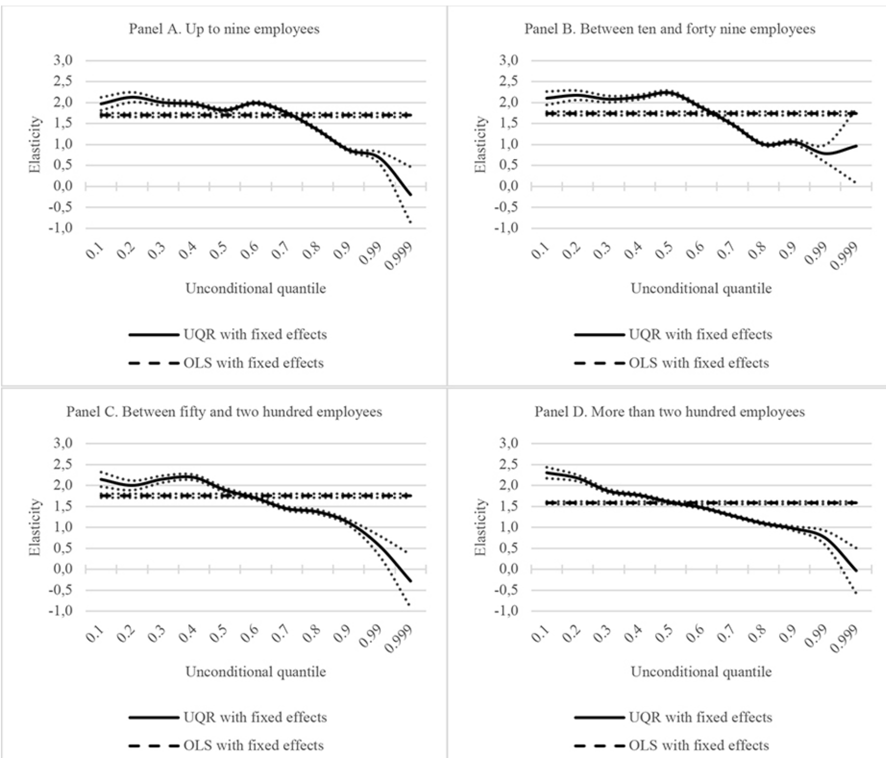


Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals. The vertical axis of the graphs is bounded to facilitate their visualization.

exhibits the highest income risk. Second, there are economic activities like Financial intermediation; Real estate, renting and business activities; and Transport, storage and communication services, with income risk profiles that tend to decrease along the distribution, while others do not show a clear pattern, such as Hotels and restaurants; and Health and social work. Finally, it is interesting to note that Education shows an income risk that is relatively homogeneous along the distribution, while Financial intermediation is the economic activity that exhibits the lowest elasticities, except at the bottom of wage distribution. This disaggregation of the estimates is illustrative of how income risk varies, in patterns and levels, between the different economic activities, clearly showing the heterogeneities that are hidden if we focus only on the aggregate sectors.

FIGURE 10

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY FIRM SIZE.
UQR WITH INDIVIDUAL FIXED EFFECTS



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

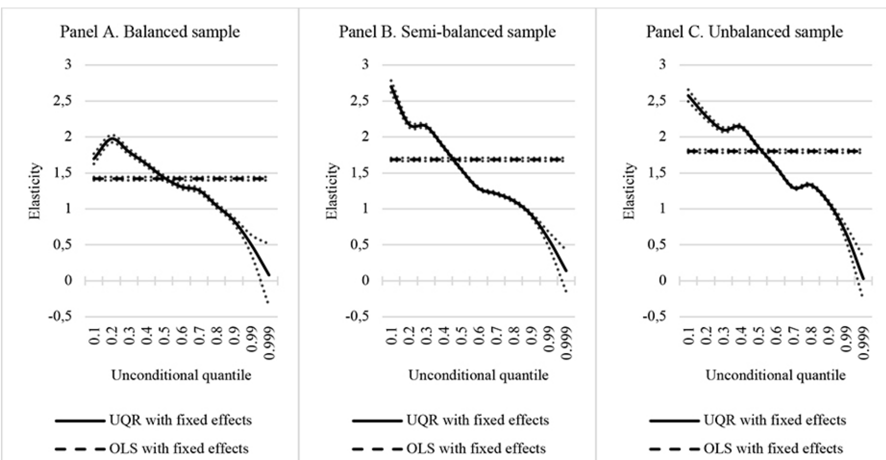
Figure 10 shows estimated income risk by firm size. In the first place, it can be observed that income risk for individuals that work in large companies clearly decreases along the unconditional labor earnings distribution, but this pattern is not replicated for firms with less employees. Indeed, for companies' categories shown in Panels A, B, and, to a lesser extent, C, impact of business cycle on labor income is relatively homogeneous for lower quantiles. Instead, this income risk decreases in higher quantiles for Panels A and C, while it tends to stabilize in companies with between ten and forty-nine employees (Panel B), after declining in the intermediate deciles. Beyond these differences in the pattern of elasticities, between the third and seventh decile the income risk for firms with more than two hundred employees is lower than for smaller companies. In part, this result is consistent with those obtained by Bell *et al.* (2020) and Guvenen *et al.* (2017) for UK and US economies, respectively, who find that workers of larger firms face a lower income risk, although the latter work measures firm size through earnings percentile.

4.2.2. *Some robustness checks*

As previously discussed, when an individual leaves the MLER database, we do not know when someone moves to unemployment or to the informal labor market.

FIGURE 11

ELASTICITIES OF REAL WAGES RESPECT TO GDP BY SAMPLE BALANCE.
UQR WITH INDIVIDUAL FIXED EFFECTS



Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.
Note: Dotted lines represent 95% confidence intervals.

In either case, for many employees the sequence of observations of their income is not complete, affecting the panel balance and, if entries and exits are non-random, our results. A more detailed study of this potential sample selection bias is outside the scope of this work, but, in this section, we exogenously balance workers income by imposing some restrictions on the sample to check if our UQR estimates change substantially. In this sense, we compare our previous results with those that are obtained by restricting the number of missing values on the income history of each worker. Particularly, we estimate our general UQR models using information from a "semi-balanced" sample (limiting the missing values on each income history to ten at most) and from a "balanced" sample (not admitting any missing values). These results are shown in Figure 11. It is important to note that restrictions on labor income history of employees does not affect our conclusion that income risk tends to decrease along the unconditional labor earnings distribution. However, we can observe some differences on the level of estimates curves. Indeed, for most quantiles, the elasticities of the unbalanced case are the highest. Until the median, income risk resulting from the balanced sample is lower compared with other cases, while from the sixth decile onwards these elasticities are similar to those corresponding to the semi-balanced case.

5. CONCLUDING REMARKS

Income risk analysis using QR and UQR models allows to measure the sensitivity of wages respect to the business cycle along the whole conditional and unconditional labor earnings distribution, capturing the asymmetry of the impacts and providing valuable information about unobservable factors that could be interacting with the variable of interest. Applying these methods, in this paper we focused on income risk of private formal male employess of Argentina, taking advantage of a large longitudinal administrative database (MLER) with information for approximately half a million private formal employees for a span of twenty years (1996-2015), which allowed us to estimate income risk for different quantiles of conditional and unconditional labor earnings distribution with a reasonable level of accuracy.

Using this database, pooled OLS estimates for entire period show that an 1.0% rise of the GDP generates, on average, an 1.7% increment of wages, *ceteris paribus,* while this effect increases slightly to 1.8% if individual fixed effects are included in the model. However, QR results show an income risk that decreases monotonically along the conditional labor earnings distribution, highlighting the importance of looking beyond the mean to capture the heterogeneity of GDP impacts on real wages of formal employees. Indeed, these results can be extrapolated to the unconditional labor earnings distribution, since the decreasing pattern in elasticities remains, in general terms, when we estimate UQR models. Hence, our results suggest that poor workers are more affected by aggregate economic fluctuations than their wealthy counterparts, regardless of their observable characteristics.

This income risk is not substantially different when comparing recessions with expansions of the economy for QR models, although if we look at what happens in the unconditional distribution, poor individuals are not only more affected by business cycle expansions and contractions compared to rich employees, but they suffer a stronger fall in wages when aggregate activity declines than the increase in wages that their experiment when the business cycle is in its expansion phase. In a very volatile economy like Argentina, this implies a deterioration over time of the wages for low-income workers. On the other hand, when we estimate UQR models separately by economic sector and firm size, the decreasing trend in wages' elasticity remains for some categories and quantiles. There are also some specificities, since, for example, individuals that work in Construction sector are those with higher income risk, while workers' wages of large companies are less sensitive to business cycle fluctuations. In addition, that decreasing pattern in income risk remains when we apply some robustness checks to our UQR models, related to the balance of the panel.

The interpretation of the income risk of private formal employees in Argentina must consider the labor relations system of the country. Hence, one hypothesis is that the asymmetry of GDP impact on wages could respond to the bargaining power of unions –which varies throughout the business cycle– and to the structure of wage agreements, with fixed components and minimum wages –which also vary due to economic fluctuations– that benefit in a greater proportion the employees with less seniority and with less qualified job positions. These workers are likely to be located in the lowest segments of the conditional and unconditional labor earnings distribution and our estimates suggest that they are the most benefited by GDP expansions. Inversely, their wages tend to reduce in greater magnitude in periods of economic recession, compared to individuals with higher wages. This hypothesis is supported by an exploratory analysis, consisting of estimating QR and UQR models for two separate periods, which differ from each other in terms of the power and role of unions in the wage determination process. In this sense, we found that when the unions had little bargaining power, the asymmetry in income risk practically disappears, since estimated elasticities are the same throughout most of the conditional and unconditional labor earnings distribution.

The previous point leads us to rethink the effectiveness of the Argentine wage system, and of the unions particularly, in the management of income risk: although the poorest workers benefit the most in the expansive phases of the cycle, in recessions they suffer a major drop in wages.

When we incorporate information about other occupational categories by using EPH data, the results we get do not change our previous main conclusions, but they provide valuable information about the informal sector of the Argentine labor market. Indeed, informal workers seems to be more sensible to the business cycle than formal workers. Moreover, income volatility is higher for low-income informal workers when we compare them with their wealthy counterparts. Hence, these complementary results suggest that wage elasticities for formal employees could be considered as a lower bound for Argentine workers income risk.

Finally, it is important to note that this study contributes to the literature of income risk by extending previous empirical works to an emerging economy and incorporating the possibility that the unobservable factors are asymmetrically distributed and, therefore, the heterogeneity of the business cycle effect along the conditional and unconditional wage distribution, which could have important implications for public policy in general. Likewise, some other questions emerge that can be addressed by future research lines, related to how business cycle fluctuations affect other features of the labor earnings distribution in Argentina (variance, asymmetry, among others), which are also an important part of the concept of income risk.

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APPENDIX

TABLE A.1
QR ESTIMATES OF INCOME RISK FOR PRIVATE FORMAL EMPLOYEES IN ARGENTINA. MALES WHOSE AGE IS BETWEEN TWENTY-SIX AND SIXTY-FIVE YEARS

Dependent variable	**Log (Wage)**											
Estimator	**Pooled quantile**											**Pooled OLS**
Conditional quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99	0.999	-
Interest variable												
Log (GDP)	**2.511*****	**2.180*****	**1.977*****	**1.845*****	**1.742*****	**1.649*****	**1.548*****	**1.405*****	**1.136*****	**0.406*****	**0.126**	**1.734*****
	(0.0198)	(0.0119)	(0.00884)	(0.00723)	(0.00628)	(0.00599)	(0.00631)	(0.00770)	(0.0112)	(0.0323)	(0.113)	(0.00810)
Control variables												
Age	0.125***	0.0910***	0.0755***	0.0690***	0.0632***	0.0593***	0.0583***	0.0615***	0.0754***	0.139***	0.206***	0.0845***
	(0.00301)	(0.00176)	(0.00136)	(0.00111)	(0.000969)	(0.000950)	(0.000986)	(0.00114)	(0.00162)	(0.00540)	(0.0144)	(0.00129)
Age-squared	-0.00119***	-0.000869***	-0.000717***	-0.000655***	-0.000597***	-0.000554***	-0.000538***	-0.000566***	-0.000697***	-0.00129***	-0.00191***	-0.000801***
	(3.56e-05)	(2.04e-05)	(1.58e-05)	(1.29e-05)	(1.12e-05)	(1.11e-05)	(1.16e-05)	(1.35e-05)	(1.90e-05)	(6.67e-05)	(0.000169)	(1.52e-05)
Trade Sector	1.099***	0.854***	0.572***	0.412***	0.341***	0.300***	0.266***	0.225***	0.161***	-0.0136	-0.239***	0.479***
	(0.0181)	(0.0148)	(0.0126)	(0.00789)	(0.00669)	(0.00594)	(0.00624)	(0.00721)	(0.0116)	(0.0342)	(0.0766)	(0.00855)
Construction Sector	-0.456***	-0.550***	-0.595***	-0.545***	-0.468***	-0.404***	-0.353***	-0.319***	-0.334***	-0.508***	-0.534***	-0.447***
	(0.0176)	(0.0158)	(0.0142)	(0.0100)	(0.00852)	(0.00791)	(0.00810)	(0.00885)	(0.0121)	(0.0315)	(0.0770)	(0.00957)
Manufacturing Industry Sector	1.255***	0.906***	0.604***	0.441***	0.369***	0.330***	0.298***	0.253***	0.174***	-0.0840**	-0.287***	0.541***
	(0.0166)	(0.0145)	(0.0125)	(0.00782)	(0.00669)	(0.00611)	(0.00658)	(0.00773)	(0.0122)	(0.0341)	(0.0727)	(0.00849)
Private Services Sector	0.421***	0.436***	0.321***	0.275***	0.272***	0.274***	0.273***	0.263***	0.225***	0.0963***	0.0165	0.280***
	(0.0171)	(0.0149)	(0.0128)	(0.00817)	(0.00688)	(0.00614)	(0.00650)	(0.00735)	(0.0113)	(0.0318)	(0.0788)	(0.00848)
Firms whose number of employees is between fifty and two hundred	-0.483***	-0.383***	-0.353***	-0.350***	-0.356***	-0.350***	-0.345***	-0.354***	-0.380***	-0.352***	-0.295***	-0.381***
	(0.0113)	(0.00649)	(0.00521)	(0.00468)	(0.00441)	(0.00452)	(0.00467)	(0.00539)	(0.00763)	(0.0207)	(0.0551)	(0.00516)
Firms whose number of employees is between ten and forty-nine	-0.635***	-0.552***	-0.511***	-0.520***	-0.544***	-0.568***	-0.595***	-0.629***	-0.679***	-0.696***	-0.531***	-0.591***
	(0.0108)	(0.00657)	(0.00521)	(0.00457)	(0.00414)	(0.00413)	(0.00452)	(0.00539)	(0.00770)	(0.0210)	(0.0618)	(0.00514)

(Table continues on next page)

Firms whose number of employees is less than ten	-0.791***	-0.745***	-0.695***	-0.694***	-0.718***	-0.749***	-0.789***	-0.854***	-0.972***	-1.159***	-0.956***	-0.795***
	(0.0116)	(0.00740)	(0.00619)	(0.00518)	(0.00463)	(0.00450)	(0.00473)	(0.00548)	(0.00748)	(0.0201)	(0.0790)	(0.00558)
Firms whose activity began between 2001 and 2005	-0.461***	-0.360***	-0.303***	-0.262***	-0.210***	-0.170***	-0.143***	-0.121***	-0.0939***	-0.0266	-0.0838	-0.264***
	(0.0120)	(0.00858)	(0.00652)	(0.00543)	(0.00481)	(0.00428)	(0.00435)	(0.00478)	(0.00656)	(0.0192)	(0.0535)	(0.00576)
Firms whose activity began between 2006 and 2010	-0.815***	-0.635***	-0.503***	-0.415***	-0.323***	-0.244***	-0.184***	-0.134***	-0.0774***	-0.00117	-0.0149	-0.410***
	(0.0141)	(0.00970)	(0.00771)	(0.00670)	(0.00584)	(0.00520)	(0.00483)	(0.00510)	(0.00711)	(0.0195)	(0.0691)	(0.00659)
Firms whose activity began after 2010	-1.362***	-1.096***	-0.886***	-0.702***	-0.558***	-0.434***	-0.339***	-0.255***	-0.173***	-0.0641***	-0.156**	-0.725***
	(0.0237)	(0.0163)	(0.0131)	(0.0101)	(0.00884)	(0.00808)	(0.00722)	(0.00690)	(0.00895)	(0.0224)	(0.0695)	(0.0106)
Región NEA	0.228***	0.0571***	-0.0325**	-0.0593***	-0.0704***	-0.0732***	-0.0843***	-0.105***	-0.148***	-0.233***	-0.265**	0.00817
	(0.0249)	(0.0195)	(0.0157)	(0.0124)	(0.0111)	(0.00971)	(0.00960)	(0.0101)	(0.0128)	(0.0280)	(0.120)	(0.0121)
Región NOA	0.169***	-0.0430**	-0.139***	-0.161***	-0.155***	-0.142***	-0.134***	-0.143***	-0.180***	-0.254***	-0.356***	-0.0846***
	(0.0229)	(0.0181)	(0.0150)	(0.0119)	(0.0103)	(0.00943)	(0.00925)	(0.00944)	(0.0122)	(0.0252)	(0.0697)	(0.0113)
Región Pampeana	0.604***	0.441***	0.326***	0.267***	0.234***	0.212***	0.197***	0.187***	0.195***	0.313***	0.528***	0.323***
	(0.0201)	(0.0150)	(0.0115)	(0.00851)	(0.00746)	(0.00645)	(0.00663)	(0.00743)	(0.0101)	(0.0203)	(0.0674)	(0.00890)
Región Patagonia	0.775***	0.580***	0.477***	0.436***	0.444***	0.487***	0.556***	0.628***	0.657***	0.517***	0.398***	0.612***
	(0.0253)	(0.0190)	(0.0153)	(0.0122)	(0.0116)	(0.0115)	(0.0127)	(0.0129)	(0.0153)	(0.0256)	(0.0679)	(0.0126)
Constant	-27.83***	-21.87***	-18.30***	-16.09***	-14.40***	-12.93***	-11.45***	-9.460***	-5.955***	2.961***	5.732***	-15.12***
	(0.260)	(0.156)	(0.116)	(0.0939)	(0.0811)	(0.0772)	(0.0813)	(0.0986)	(0.144)	(0.441)	(1.461)	(0.105)
R-squared	**0.197**	**0.205**	**0.209**	**0.211**	**0.209**	**0.206**	**0.202**	**0.195**	**0.184**	**0.144**	**0.100**	**0.214**
Observations	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**

Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Note: Standard errors clustered by individual in brackets. *10% significance level **5% significance level ***1% significance level. All control variables, except "age" and "age-squared", are dummy variables. Base categories are: "Primary Activities Sector"; "Firms whose number of employees is more than two hundred"; "Firms whose activity began before 2001"; "*Región Cuyo*".

TABLE A.2

UQR ESTIMATES OF INCOME RISK FOR PRIVATE FORMAL EMPLOYEES IN ARGENTINA.
MALES WHOSE AGE IS BETWEEN TWENTY-SIX AND SIXTY-FIVE YEARS

Dependent variable	**Log (Wage)**											
Estimator	**UQR FE**											**OLS FE**
Unconditional quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99	0.999	-
Interest variable												
Log (GDP)	**2.575*****	**2.294*****	**2.098*****	**2.142*****	**1.859*****	**1.587*****	**1.295*****	**1.332*****	**1.092*****	**0.666*****	**0.0306**	**1.801*****
	(0.0417)	(0.0255)	(0.0165)	(0.0135)	(0.0111)	(0.0102)	(0.00966)	(0.0120)	(0.0149)	(0.0515)	(0.153)	(0.0109)
Control variables												
Age	0.0913***	0.0875***	0.0681***	0.0665***	0.0695***	0.0794***	0.0750***	0.0804***	0.0772***	0.0842***	0.0402**	0.0738***
	(0.00403)	(0.00265)	(0.00192)	(0.00170)	(0.00147)	(0.00139)	(0.00135)	(0.00174)	(0.00228)	(0.00776)	(0.0185)	(0.00130)
Age-squared	-0.00136***	-0.00115***	-0.000791***	-0.000690***	-0.000659***	-0.000706***	-0.000620***	-0.000648***	-0.000594***	-0.000501***	0.000145	-0.000796***
	(4.40e-05)	(2.94e-05)	(2.20e-05)	(1.98e-05)	(1.71e-05)	(1.63e-05)	(1.59e-05)	(2.06e-05)	(2.70e-05)	(9.23e-05)	(0.000230)	(1.47e-05)
Trade Sector	0.881***	0.449***	0.243***	0.132***	0.0820***	0.0231***	-0.0571***	-0.151***	-0.202***	-0.216***	-0.0839	0.178***
	(0.0465)	(0.0259)	(0.0156)	(0.0122)	(0.00969)	(0.00876)	(0.00813)	(0.00986)	(0.0129)	(0.0455)	(0.118)	(0.0128)
Construction Sector	-0.0203	-0.284***	-0.236***	-0.194***	-0.142***	-0.136***	-0.129***	-0.170***	-0.210***	-0.201***	-0.0155	-0.143***
	(0.0491)	(0.0265)	(0.0152)	(0.0115)	(0.00897)	(0.00802)	(0.00746)	(0.00921)	(0.0121)	(0.0420)	(0.105)	(0.0129)
Manufacturing Industry Sector	0.991***	0.542***	0.315***	0.239***	0.189***	0.135***	0.0726***	0.0169*	-0.0752***	-0.186***	-0.0538	0.297***
	(0.0451)	(0.0250)	(0.0150)	(0.0116)	(0.00920)	(0.00836)	(0.00782)	(0.00958)	(0.0125)	(0.0475)	(0.119)	(0.0122)
Private Services Sector	0.289***	0.0410*	-0.0300**	-0.0563***	-0.0421***	-0.0636***	-0.0851***	-0.142***	-0.213***	-0.260***	-0.0707	-0.0410***
	(0.0432)	(0.0237)	(0.0141)	(0.0108)	(0.00850)	(0.00769)	(0.00715)	(0.00885)	(0.0119)	(0.0450)	(0.121)	(0.0117)
Firms whose number of employees is between fifty and two hundred	-0.310***	-0.262***	-0.197***	-0.179***	-0.155***	-0.152***	-0.162***	-0.198***	-0.184***	-0.120***	-0.00268	-0.200***
	(0.0153)	(0.00929)	(0.00611)	(0.00521)	(0.00445)	(0.00419)	(0.00409)	(0.00517)	(0.00653)	(0.0245)	(0.0569)	(0.00475)
Firms whose number of employees is between ten and forty-nine	-0.702***	-0.580***	-0.425***	-0.381***	-0.321***	-0.287***	-0.272***	-0.290***	-0.230***	-0.124***	0.00195	-0.382***
	(0.0193)	(0.0114)	(0.00721)	(0.00596)	(0.00502)	(0.00470)	(0.00447)	(0.00548)	(0.00675)	(0.0232)	(0.0532)	(0.00572)

(Table continues on next page)

Firms whose number of employees is less than ten	-1.121***	-0.929***	-0.687***	-0.618***	-0.494***	-0.412***	-0.343***	-0.327***	-0.248***	-0.125***	-0.00333	-0.568***
	(0.0241)	(0.0141)	(0.00874)	(0.00712)	(0.00590)	(0.00540)	(0.00498)	(0.00597)	(0.00700)	(0.0234)	(0.0578)	(0.00701)
Firms whose activity began between 2001 and 2005	0.133***	0.0745***	0.0323***	-0.0149**	-0.0953***	-0.157***	-0.181***	-0.211***	-0.204***	-0.229***	-0.248***	-0.0773***
	(0.0221)	(0.0130)	(0.00829)	(0.00677)	(0.00551)	(0.00496)	(0.00454)	(0.00538)	(0.00612)	(0.0191)	(0.0441)	(0.00634)
Firms whose activity began between 2006 and 2010	0.104***	0.0932***	0.00989	-0.0528***	-0.107***	-0.174***	-0.216***	-0.268***	-0.257***	-0.322***	-0.281***	-0.117***
	(0.0237)	(0.0140)	(0.00874)	(0.00728)	(0.00609)	(0.00551)	(0.00498)	(0.00581)	(0.00695)	(0.0210)	(0.0618)	(0.00705)
Firms whose activity began after 2010	-0.210***	-0.116***	-0.121***	-0.168***	-0.179***	-0.197***	-0.265***	-0.348***	-0.358***	-0.469***	-0.466***	-0.277***
	(0.0346)	(0.0193)	(0.0119)	(0.00966)	(0.00808)	(0.00750)	(0.00659)	(0.00713)	(0.00813)	(0.0236)	(0.0657)	(0.0108)
Región NEA	0.112	-0.0984	-0.127***	-0.109***	-0.0573**	-0.0410*	-0.00426	0.0171	0.0724**	0.107	0.0591	-0.000902
	(0.126)	(0.0684)	(0.0406)	(0.0324)	(0.0264)	(0.0246)	(0.0231)	(0.0287)	(0.0359)	(0.111)	(0.104)	(0.0347)
Región NOA	0.281**	0.00435	-0.0526	-0.0611**	-0.0362*	-0.0205	-0.00830	-0.00772	0.0330	0.0235	0.0225	0.0325
	(0.114)	(0.0580)	(0.0330)	(0.0257)	(0.0207)	(0.0194)	(0.0183)	(0.0233)	(0.0298)	(0.0996)	(0.0952)	(0.0305)
Región Pampeana	0.330***	0.182***	0.109***	0.0801***	0.0787***	0.0721***	0.0831***	0.0826***	0.101***	0.0524	0.0576	0.115***
	(0.0861)	(0.0459)	(0.0271)	(0.0215)	(0.0178)	(0.0171)	(0.0163)	(0.0210)	(0.0279)	(0.0990)	(0.114)	(0.0246)
Región Patagonia	0.944***	0.473***	0.273***	0.223***	0.202***	0.213***	0.231***	0.271***	0.358***	0.131	0.179	0.402***
	(0.101)	(0.0544)	(0.0323)	(0.0259)	(0.0215)	(0.0205)	(0.0200)	(0.0262)	(0.0372)	(0.150)	(0.242)	(0.0286)
Constant	-27.20***	-22.50***	-19.28***	-19.60***	-15.92***	-12.50***	-8.513***	-8.822***	-5.318***	0.832	10.46***	-15.41***
	(0.507)	(0.310)	(0.201)	(0.167)	(0.137)	(0.126)	(0.121)	(0.153)	(0.192)	(0.661)	(1.895)	(0.134)
R-squared	**0.507**	**0.566**	**0.603**	**0.638**	**0.661**	**0.671**	**0.674**	**0.668**	**0.639**	**0.572**	**0.470**	**0.151**
Observations	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**	**1,656,617**

Source: Own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Note: Standard errors clustered by individual in brackets. *10% significance level **5% significance level ***1% significance level. All control variables, except "age" and "age-squared", are dummy variables. Base categories are: "Primary Activities Sector"; "Firms whose number of employees is more than two hundred"; "Firms whose activity began before 2001"; "*Región Cuyo*".