Asymmetries in aggregate income risk over the business cycle: evidence from administrative data of Argentina

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Abstract

This paper explores the aggregate and systematic income risk of formal workers in Argentina, using an extensive longitudinal database that contains information on approximately half a million formal employees in the private sector throughout the country for a span of twenty years (1996-2015). We estimate quantile regression models to measure the sensitivity of remunerations to business cycle along the conditional and unconditional distribution of salaries, thus capturing the asymmetry of economic activity impacts on workers' remunerations. The main result is that income risk decreases along the conditional and unconditional distribution of salaries, showing that individuals located at the lower part of the distribution are more exposed to the fortunes of the aggregate economy. One important factor that probably explains this asymmetry is given by the role of the unions. On the other hand, unconditional poor individuals are not only more affected by business cycle fluctuations, but they suffer a stronger fall in wages when activity declines than the increase that their experiment when business cycle is in its expansion phase. We also detect some interesting specificities, since individuals that work in Construction sector face a higher income risk, while workers' remunerations of large companies are less sensitive to business cycle.

JEL Classification: C13, E32, J30, J52

Keywords: Business Cycles, Income Risk, Quantile Regression

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1. Introduction

In 2020, COVID-19 pandemic and the quarantine implemented by government authorities caused a sharp fall of about ten percent in Argentinean 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 drop in economic activity. Certainly, the fall in earnings hardly affected all workers with the same intensity since some lost more than others. In other words, the risk of falling wages is not homogeneous but 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. For example, Bell, Bloom, Blundell and Pistaferri (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, Schulhofer-Wohl, Song and Yogo, (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 worker's 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 distribution of income.

For example, 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 salary they obtain. However, even knowing the position held by the employees, if the complexity of the task that they develop in their work position -which has to do, but not strictly, with their level of formal education (Paz, 2007)- is unknown, it is not possible to isolate salaries 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 activity 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 workers have a complex structure due to how labor relations system of the country works. There is exclusivity of salary negotiations since only unions that have union status (union uniqueness) can carry them out. In addition, these are centralized by branch of activity 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 salary institution, have a fundamental role in determining the salary structure of an economy (Alejo and Casanova, 2016)

Taking in account the presence of unobservable factors mentioned above, an appropriate question for us is: how the remunerations of formal workers of Argentina are systematically affected by the movements of the business cycle? More precisely, are there asymmetries in this income risk along the conditional and unconditional distribution of salaries? That is, beyond the observable characteristics of the workers, does unobservable factors play a role in explaining how the business cycle affect the remunerations? 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. The focus on formal workers is due to the fact that for non-formal workers, no lesser part of the wage earners in Argentina, the amount of information required to answer these questions is not available. At this point, it is important to keep in mind that the income risk of non-formal workers is likely to be higher than that of their formal counterparts.

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

This paper is inserted in the empirical literature that investigates the risk of household or individual income during the economic 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, Diaz de Astarloa, Drenik, Moser and Trupkin, 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 distribution of wages. 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; 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.

The “mean” income risk results estimated by OLS including individual fixed effects suggest, for the entire period, that an 1.0% rise of the GDP generates, on average, an 1.8% increment of salaries in Argentina, while estimates obtained by quantile regression methods show an income risk that tends to decrease along the conditional and unconditional distribution of salaries, highlighting the importance of looking beyond the mean to capture the asymmetry of aggregate activity impacts on formal workers' remunerations. Although this income risk is not substantially different when comparing the effects of recessions and expansions on the conditional distribution of remunerations, 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 workers, but they suffer a stronger fall in wages when aggregate activity declines than the increase in remunerations that their experiment when business cycle is in its expansion phase. When we estimate models separately by economic sector, firm size, and region, the decreasing trend in remunerations' elasticity along the unconditional distribution remains for some categories, while others do not seem to show a clear pattern. Beyond this, there are some interesting specificities, since individuals that work in Construction sector are those with higher income risk, while workers' remunerations of large companies are less sensitive to business cycle fluctuations.

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

2. Related empirical studies

Various studies measure the impact of the economic cycle on salaries or wages using OLS and compare the results of estimates for different population groups. At this point, some of them try to build a conditional distribution of wages 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 distribution of a proxy of permanent income conditional to sex and age only. 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 to Guvenen's one, though imposing some restrictions in the sample, Broer *et al*. (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 Guvenen's study. 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 to 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 remunerations 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.

On the other hand, 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 have a stronger positive effect on lower quantiles of salaries distribution in Argentina, concluding that this labor institution seems to have an equalizing effect on income of formal salaried 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 distribution of wages could be associated with an increase in the lowest wages as a consequence of the "minimum salaries of the agreement"-i.e., the first salary ranges determined in collective bargaining agreements- which would mainly benefit the less qualified workers. These findings are 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 *et al.*, 2004: DiNardo *et al.*, 1996). 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. This result is consistent, in part, with the hypothesis of Freeman (1980), who argues that unions can achieve wage equalization among covered workers by reducing the importance of personal characteristics in determining wages. On the other hand, Alejo and Casanova (2016) attribute the lesser importance of seniority and task qualification to the fact that increases in the "minimum salaries of agreement" tend to benefit workers who perform tasks that require lower qualifications and those with less seniority. It is obvious the power of the unions is greater in times of expansion than in times of economic contraction, so the impact of the economic cycle on the distribution of wages will tend to be more equalizing in times of economic expansion, decreasing the dispersion in the distribution of wages (Alejo and Casanova, 2016; Etchemendy and Berins Collier, 2008; Palomino and Trajtemberg, 2012).

3. Data and methodology

3.1.Data

For the estimates, we use individual data of the MLER, a labor salary longitudinal sample, obtained from administrative records of the Argentinean 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 worker 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 estimating, with a reasonable level of precision, the effects of the Argentinean business cycle on real remunerations over the entire conditional and unconditional distribution of salaries.

Because the source arises from the administrative records of the social security system, the sample is representative of all persons of the private sector who had salaried employment registered in that period. This segment of the labour market represents, on average, approximately one third of total employment in the reference period. An important advantage of the record-base 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 labour 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 activity branch, activity year start (in tranches), among others- and workers, 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 branches of activity 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. Workers 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 registered employment, therefore the panel contains the information of the entire work history of the employee.

Individual monthly remuneration incorporates income from all labor relations, including remuneration amounts (salary, supplementary annual salary, fees, tips, gratuities, and additional supplements that have the character of habitual and regular) and non-remuneration (e.g., indemnifications), although, unfortunately, database does not include information on the number of hours worked. For estimates, remunerations are deflated and then annualized by adding the monthly values for each calendar year, in order 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 remunerations. This consisted in a micro-addition of remunerations greater than the 98th percentile per ISIC double-digit activity branch[1], ordering incomes from lowest to highest and averaging three continuous salaries, 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 greatest participation in his total annual remuneration. While MLER disaggregates economic activities at the branch level using the AFIP classification based on ISIC Review 3 and CLANAE 1997 (National Institute of Statistics and Censuses, INDEC, for its acronym in Spanish)[2], for models' parsimony purposes we define the following aggregate sectors: Primary Activities[3], Trade[4], Construction, Manufacturing Industry and Private Services[5],

[1] So, alter as little as possible the relationship of remunerations between the branches.
[2] See AFIP Resolution 485/99.
[3] Includes: Agriculture, livestock, hunting and forestry; Fishing and related services; Mining and quarrying.
[4] Includes: Wholesale and retail trade; Repair of motor vehicles, motorcycles, personal effects and household items.
[5] Includes: Electricity, gas and water; Hotel and restaurant services; Transportation, storage and communications services; Financial intermediation and other financial services; Real estate, business and rental services; Teaching; Social and health services; Community, social and personal services n.p.c.

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[6] and activity year start, 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.

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 regionalization of INDEC.[7]

To measure the level of economic activity, for most models we use the annual series of Argentinean GDP in millions of constant dollars of 2010 for the period 1996-2015, provided by the World Bank. However, to check the robustness of the estimates, in some models we measure business cycle using EMI and ISAC indexes, which are provided by INDEC and measure, respectively, the evolution of industrial production and construction activity.[8]

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 remuneration (expressed in thousands of Argentinean *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 salary, followed by Private Services, Trade, Primary Activities and, finally, Construction with a mean salary of less than half that of the first sector. This order is not altered when we focus on the median salary. However, when we look at remunerations' differentials by percentiles, the salaries in the Primary Activities sector exceed those of the rest of the branches at the top of the distribution. Regarding to the salary dispersion, the highest standard deviations

[6] This variable has no monthly frequency in the database but is available for the fourth quarter of each year.
[7] *Región Cuyo* includes *Mendoza, San Juan* and *San Luis*; *Región* NEA includes *Corrientes, Chaco, Formosa* and *Misiones*; *Región* NOA includes *Catamarca, Jujuy, La Rioja, Salta, Santiago del Estero* and *Tucumán*; *Región Pampeana* includes *Ciudad Autónoma de Buenos Aires, Córdoba, Entre Ríos, La Pampa, Provincia de Buenos Aires* and *Santa Fe*; *Región Patagonia* includes *Chubut, Neuquén, Río Negro, Santa Cruz* and *Tierra del Fuego*.
[8] Both indexes are provided on a monthly and annual frequency. Since data is not available for the last two months of 2015, in this case we compute the average across January to October. For more details about the construction of EMI and ISAC indexes, see INDEC´s web page.

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 salary increases as firm size also increases. For example, mean remunerations in companies with more than two hundred employees are more than double that those corresponding to smallest firms. These remuneration's differentials tend to increase in relative terms at highest percentiles. Thus, while in the first decile there are minimal differences in salaries between the first three groups of company sizes, at the top of the distribution the remunerations 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 salary dispersion, we also observe that standard deviation increases as firm size is higher.

Table 1. Descriptive statistics for total annual remuneration by economic sector and firm size. Male workers whose age is between twenty-six and sixty-five years

Thousands of Argentinean *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

Note: missing values and zero values of remunerations (that represent unemployed individuals and licensed persons, respectively) are not considered for statistics computation.

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

3.2.Methodology

Traditional linear regression models estimated by Ordinary Least Squares (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 $\boldsymbol{x}$. 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 remunerations, they are not necessarily informative of the effects on the entire distribution of the latter variable, 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 a response variable, which will be explained below.

3.2.1. 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 economic cycle's effects on the real income of employees, by allowing model any quantile of the conditional distribution of remunerations 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 distribution of real remunerations.

[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 Argentinean economic cycle on different quantiles of the distribution of real income, with the following specification:

$$Q_\tau(y_{it}|\boldsymbol{x}_{it}) = \boldsymbol{x}_{it}\boldsymbol{\theta}(\tau), \qquad i = 1, 2, \dots, N; \quad t = 1, 2, \dots T$$

where $Q_\tau(y_{it}|\boldsymbol{x}_{it})$ is the τ-th quantile, $\tau \in (0, 1)$, of the distribution of the natural logarithm of the real remuneration (y_{it}) conditional to the vector of regressors ($\boldsymbol{x}_{it}$), where the latter is formed by the natural logarithm of 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 and the firm's activity period start (both variables per tranches) and the economic region. The vector $\boldsymbol{\theta}(\tau)$ explicitly depends on τ, and is formed by the intercept term $\alpha(\tau)$ and the vector $\boldsymbol{\beta}(\tau)$, which measures the marginal effects of the regressors on the τ-th conditional quantile. The subscripts i and t refers to individuals and time, respectively. As usual in empirical works, the application of natural logarithm transformation on remuneration and GDP variables allows us to measure, for each conditional quantile, the elasticity of salaries respect to product.[10]Also, with linear quantiles, we can write:

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\theta}(\tau) + u_{it}(\tau)\,, \qquad Q_\tau(u_{it}|\boldsymbol{x}_{it}) = 0$$

which 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, actually there is a substantial literature dealing with the challenges posed by QR models with individual effects (e.g., Canay, 2011; Galvao, 2011; Galvao and Wang, 2015; Galvao and Kato, 2016; Kato, Galvao and Montes-Roja, 2012; Koenker, 2004, Lamarche, 2010, Powell, 2016), but none of these methods gained widespread popularity, either because of their computational complexity or because they 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

[10] Equivariance property for conditional quantiles implies that, for any monotonic transformation $h(\bullet)$, $Q_\tau(h(y)|\boldsymbol{x}) = h(Q_\tau(y)|\boldsymbol{x})$. Then, $Q_\tau(ln(y)|\boldsymbol{x}) = ln(Q_\tau(y)|\boldsymbol{x})$. Although, strictly speaking, we are modeling the conditional quantiles of log-salaries (or, equivalently, the natural logarithm of conditional quantiles of salaries), for simplicity purposes we will use the term "conditional distribution of salaries".

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 estimators $\widehat{\boldsymbol{\theta}}(\tau)$ (pooled quantile estimator) solves the following optimization problem:

$$\min_{\theta} \sum_{i=1}^{N} \sum_{t=1}^{T} c_{\tau}(y_{it} - \boldsymbol{x}_{it}\boldsymbol{\theta}(\tau))$$

Where $c_{\tau}(\bullet)$ is the asymmetric absolute loss function[11] (Wooldridge, 2010), which asymmetrically penalizes positive and negative errors according to the conditional quantile which is modeled.[12] 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 economic cycle on the top of the conditional distribution of real income, 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 remuneration distribution conditional on activity branch, because the procedure applied on MLER to ensure the confidentiality of highest remunerations. 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.

3.2.2. 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 a response variable, reason why the technique is called "unconditional quantile regression" (UQR).[13] 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

[11] Let u_{it} be the error term, that is, $u_{it} = y_{it} - \boldsymbol{x}_{it}\boldsymbol{\theta}(\tau)$. Then, the asymmetric absolute loss function is $c_{\tau}(u_{it}) = (\tau 1[u_{it} \geq 0] + (1-\tau)1[u_{it} < 0])|u_{it}| = (\tau - 1[u_{it} < 0])u_{it}$, where $1[.]$ is the indicator function, which is equal to one if the statement in brackets is true and zero otherwise.
[12] In addition, one advantage of the estimators of quantile regression models over OLS is that its estimators are robust to outliers (Wooldridge, 2010).
[13] However, the method of Firpo *et al.* (2009) was extended to estimate, under certain conditions, 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.

that impacts on the remunerations of individuals located at any point of the unconditional distribution of salaries. This is very important when analyzing, for example, the effects of monetary or fiscal policy on labour income, since policy makers could be more interested in seeing how these interventions affect the remunerations 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 *et al.* (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_{y_i} 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_{y_i}. Intuitively, the IF can be interpreted as the influence that observation y_i has on the estimation of the distributional statistic v (see Firpo *et al.*, 2009; Huber and Ronchetti, 2009 for a more formal discussion).

Firpo *et al.* (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 (see Firpo *et al.*, 2009 for details) and for other distributional statistics.[14] On the other hand, since it can be shown that the unconditional expected value of the IF equals zero, it follows that $E[RIF\{y_i, v(F_Y)\}] = v(F_Y)$. This has a very important implication, because one can use the corresponding RIF as a dependent variable in a standard OLS framework to estimate the effect of a set of covariates on the unconditional τ-th quantile of y.

Beyond the interpretations of the estimated coefficients 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 to control for individual heterogeneity.

In this type of models, our dependent variable will be the RIF of log-GDP 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. We use standard errors clustered by individuals for the same reasons we mentioned in the previous subsection. 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.

[14] See Rios-Avila (2020) for a further discussion.

Finally, it is important to note some slight differences regarding the interpretation of estimated coefficients in QR and UQR methods. In the former, the coefficient corresponding to log-GDP variable for some quantile can be interpreted as a usual elasticity, that is, how much the τ-th quantile increases in relative terms when GDP increases by 1%. However, in UQR models we must interpret that coefficient as the relative change of real remuneration because of an "expected" 1.0% rise of GDP. This is a consequence of the fact that $v(F_Y) = E[RIF\{y_i, v(F_Y)\}]$ (Rios-Avila, 2020).

3.2.3. 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 in the distribution of a proxy of permanent income conditional to sex and age only. While this strategy makes it possible to quantify the sensitivity of wages to cyclical fluctuations 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 salaries. By contrast, quantile regression methods applied in this paper capture the effects of cyclic fluctuations on the different quantiles of the conditional and unconditional salary 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 constitute a reasonable first approximation to analyze the possible heterogeneity of income sensitivity to economic 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 workers 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, when an individual leaves the sample, we do not know if he moves to unemployment or to the informal labor market. Third, the models are static and do not consider the possible effects of the temporal trajectories of certain variables on real remunerations, 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 salaries, as in a standard Mincer equation.

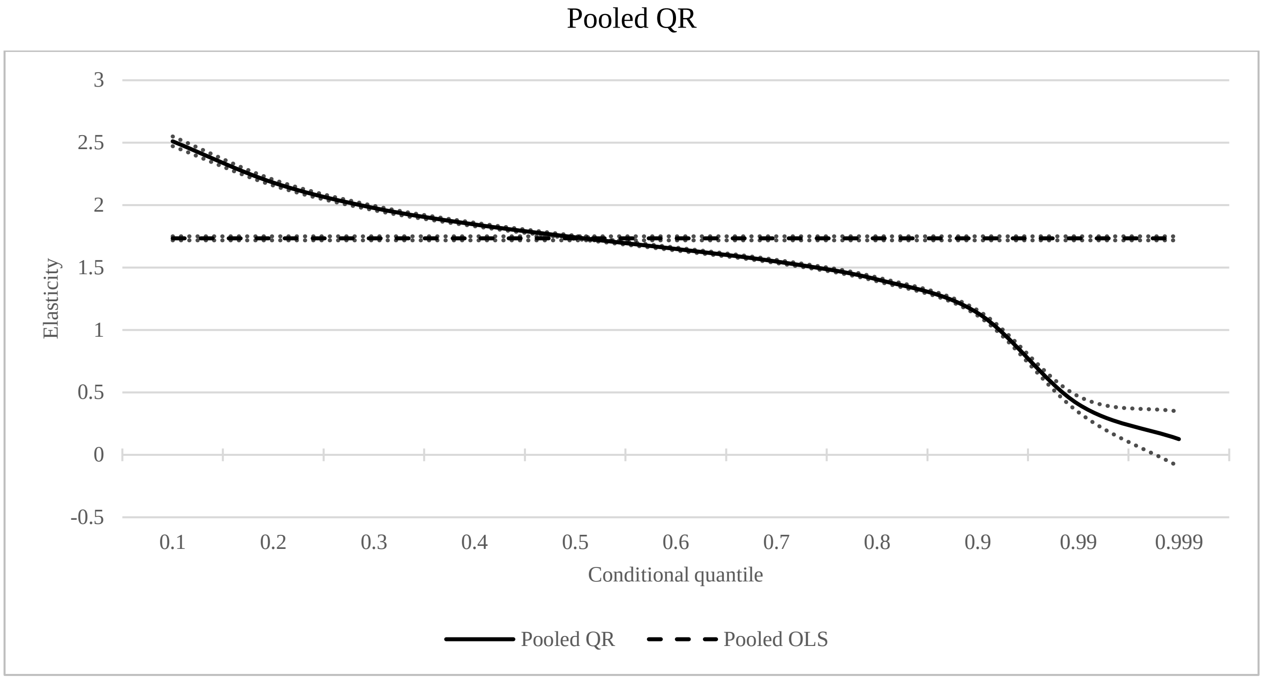
4. Results

4.1. QR models

As a first approach, we estimate a basic linear quantile regression model using the log of remunerations 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. Both estimation results are shown in the Table A.1 of the Appendix.

Figure 1 reports estimated elasticities of real salaries respect to GDP for Argentina across the conditional salaries' 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 salary decile -i.e., the 0.1 quantile- this effect is reduced to 1.7% and 1.1% in the median remuneration 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 remunerations 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 salaries 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 salaries respect to GDP



Note: dotted lines represent 95% confidence intervals.

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

The estimated elasticities show that male private employees belonging to the first segments of conditional remuneration distribution have a higher income risk, i.e., salaries 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 salaries 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 distribution of salaries in Argentina? In other words, through which channels cyclical fluctuations are transmitted heterogeneously to the salary conditional quantiles? As commented previously, since, with favorable rules in labor market, union power tends to move in the same direction as economic activity 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 salaries. That is, we can interpret that the individuals whose salaries correspond to the lowest quantiles are those who benefit the most from collective bargaining, either through the increase in the minimum salaries of the agreement and fixed components or due to the lesser importance of individual characteristics in determining salaries. However, it is important to note that, since we can not 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 labour institution affects the conditional distribution of remunerations. On the one hand, the decreasing pattern on elasticities could respond to the heterogeneous effect of collective bargaining on the conditional income distribution of workers covered by this labour institution. On the other hand, the aforementioned pattern could be reflecting the remunerations differential between the workers that are covered by collective bargaining and those that are not covered, being this difference higher on lower quantiles. 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 salary cuts than the decline in economic activity 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 labour 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 Labour 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).

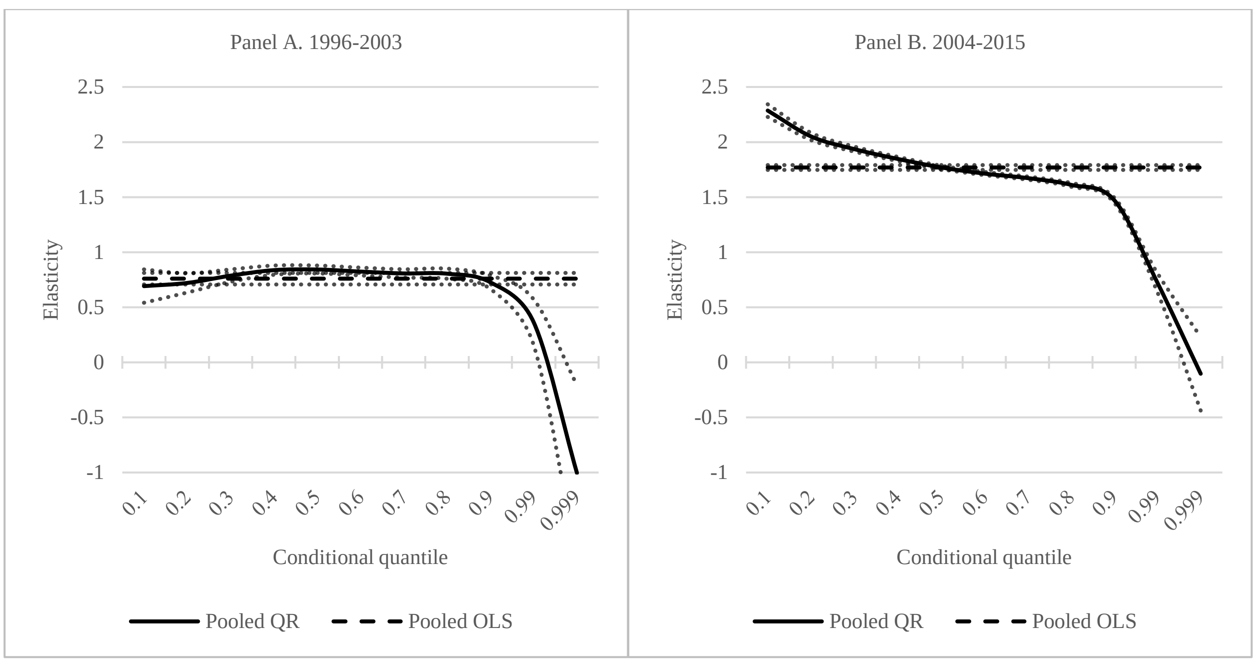
Figure 2 show QR estimates for the periods 1996-2003 and 2004-2015.[15] As can be seen, the results of the models for the 1996-2003 subsample -when the unions had little power in the wage determination process- show that income risk is practically the same throughout most of the conditional distribution of salaries, 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 (0.8) suitably sums

[15] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

up income risk across conditional distribution of remunerations. Also, it is interesting to note that, given the fact that elasticity for this subsample is positive but less than one, the salaries of formal workers 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 remunerations 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 workers, 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 workers, which shows a decreasing pattern along the conditional distribution of remunerations.

Figure 2. Elasticities of real salaries respect to GDP for two separate periods (1996-2003 and 2004-2015)

Pooled QR



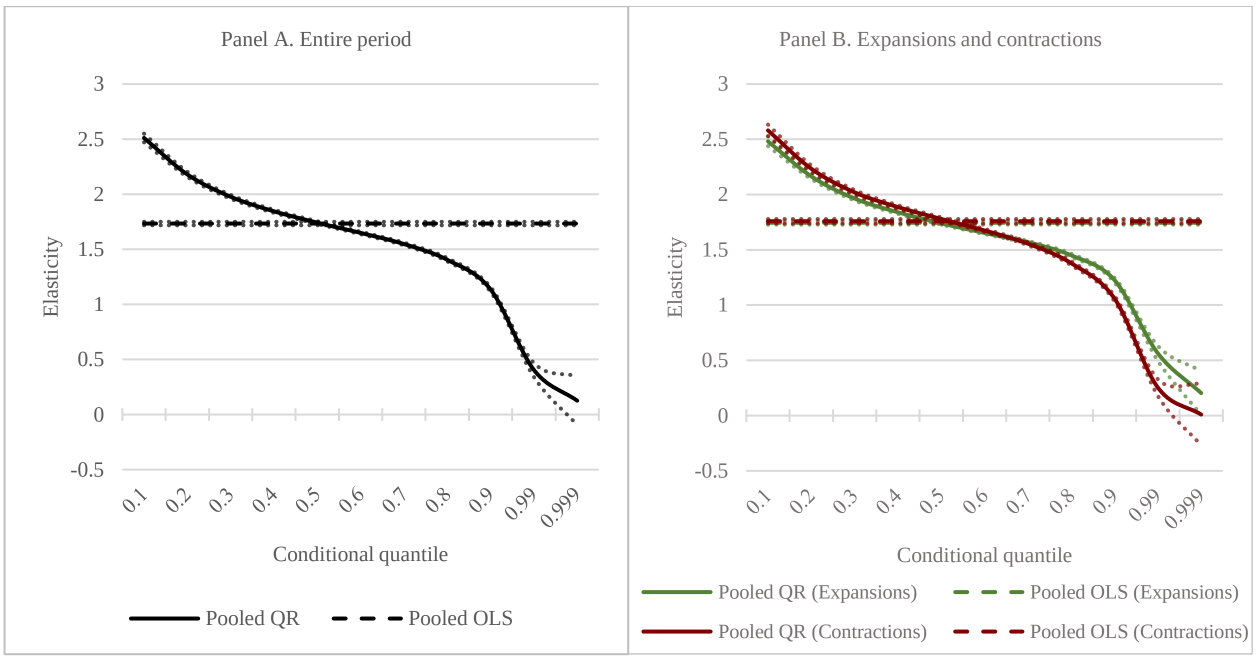
<u>Note:</u> dotted lines represent 95% confidence intervals.

<u>Source:</u> own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Finally, since the relationship between salaries and economic activity could differ according to the different phases of the business cycle (Guvenen *et al.*, 2014), we estimate QR models by pooling respectively the periods of annual expansion and contraction of GDP, on the other hand (Figure 3).[16] It is important to note that the decreasing pattern in estimated elasticity across the conditional salaries' distribution remains when we model separately periods of expansion and recession in economy's production. While the effect of GDP on real remunerations 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 remunerations risk comparing the different phases of economic 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.

Figure 3. Elasticities of real salaries respect to GDP by business cycle phases

Pooled QR



Note: dotted lines represent 95% confidence intervals.

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

Given these results, the decrease in the elasticity of salaries as we move away from the lowest deciles has two main implications for the inequality in the distribution of conditional salaries 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

[16] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

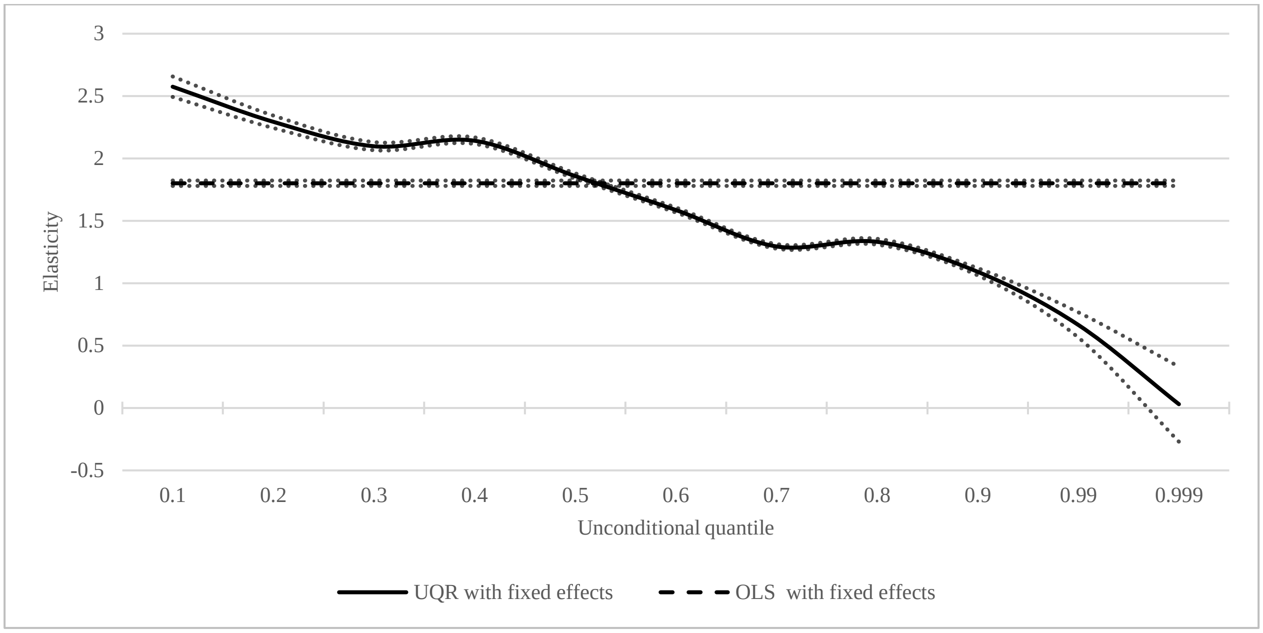
affected -in proportional and negative terms- that conditional rich. Hence, within-group income inequality may be affected differently depending on economic cycle phase.

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 previous section. Estimation results are shown in the Table A.2 of the Appendix. As can be seen, the estimated elasticities are positive as expected and, in general terms, show a decreasing pattern along the unconditional distribution of remunerations. For example, and while an "expected" 1.0% rise of the GDP generates a 2.6% increment on the 0.1 unconditional quantile of remunerations, this effect is reduced to 1.9% and 1.1% in the median remuneration 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 distribution of remunerations 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 remunerations have a higher income risk than their rich counterpart, regardless of their observable characteristics.

Figure 4. Elasticities of real salaries respect to GDP

UQR with individual fixed effects



Note: dotted lines represent 95% confidence intervals.

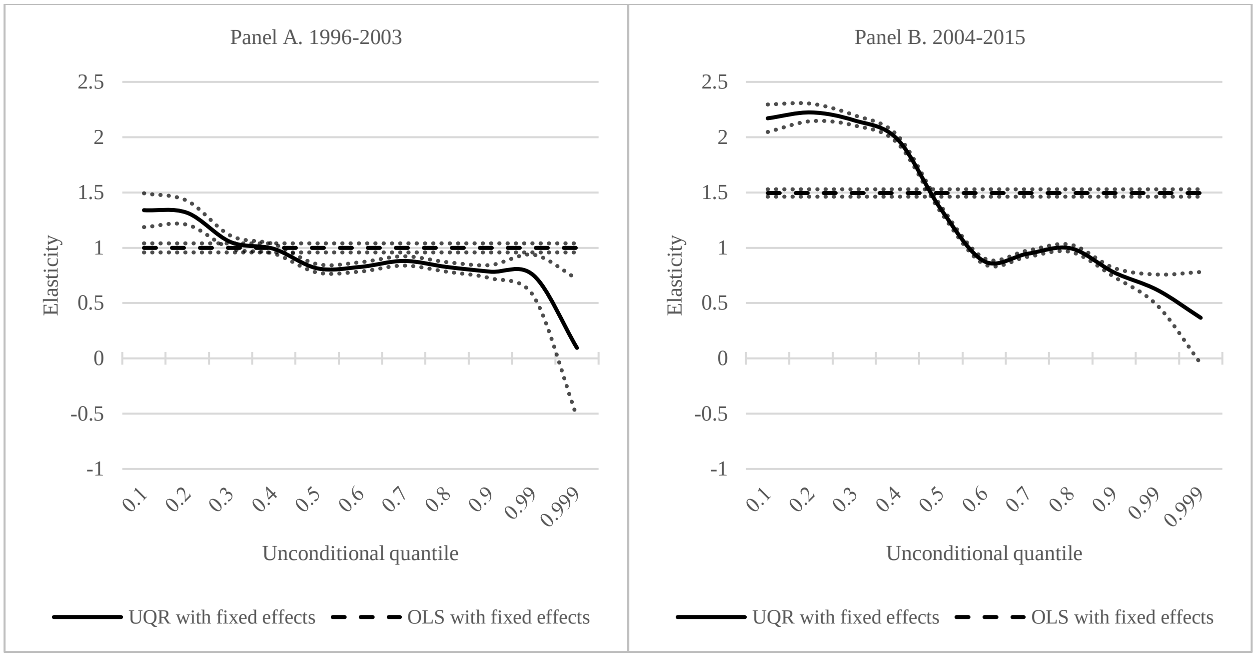
Source: own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

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 distribution of salaries.[17] Panel A show that in the 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 distribution of remunerations, 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.

[17] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

Figure 5. Elasticities of real salaries respect to GDP for two separate periods (1996-2003 and 2004-2015)

UQR with individual fixed effects



Note: dotted lines represent 95% confidence intervals.

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

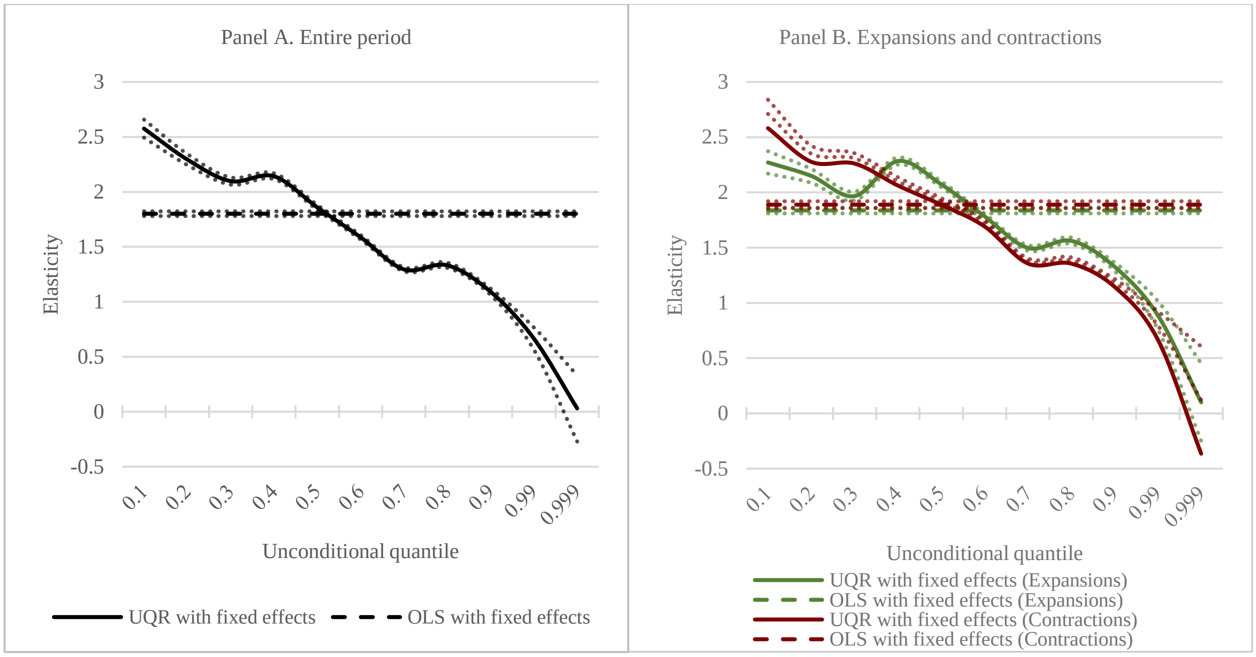
On the other hand, Figure 6 shows UQR estimates by business cycle phases.[18] As can be seen, results for contraction phase subsample exhibit, in general terms, a decreasing pattern on income risk along unconditional distribution of remunerations, in a similar way that elasticities estimated for the 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 remunerations 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 remunerations that their experiment when business cycle is in its expansion phase. Another consequence is that expansions

[18] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

(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.

Figure 6. Elasticities of real salaries respect to GDP by business cycle phases

UQR with individual fixed effects



Note: dotted lines represent 95% confidence intervals.

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

4.2.1. Estimation results by economic sector, firm size, and region[19]

To explore the possible differences on salary elasticities between economic sectors, we now estimate UQR models separately by activity sector (Figure 7).[20] 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. Instead, Primary Activities and Trade sector does not seem to show a clear pattern on elasticities, with estimates that increase in some quantiles of the distribution and decrease in other segments. Besides these differences, it is clear that OLS estimates does not captures the heterogeneity business cycle impacts in any of the activity 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 salaries triple the "expected" percentage changes on GDP in this part of the unconditional distribution. This

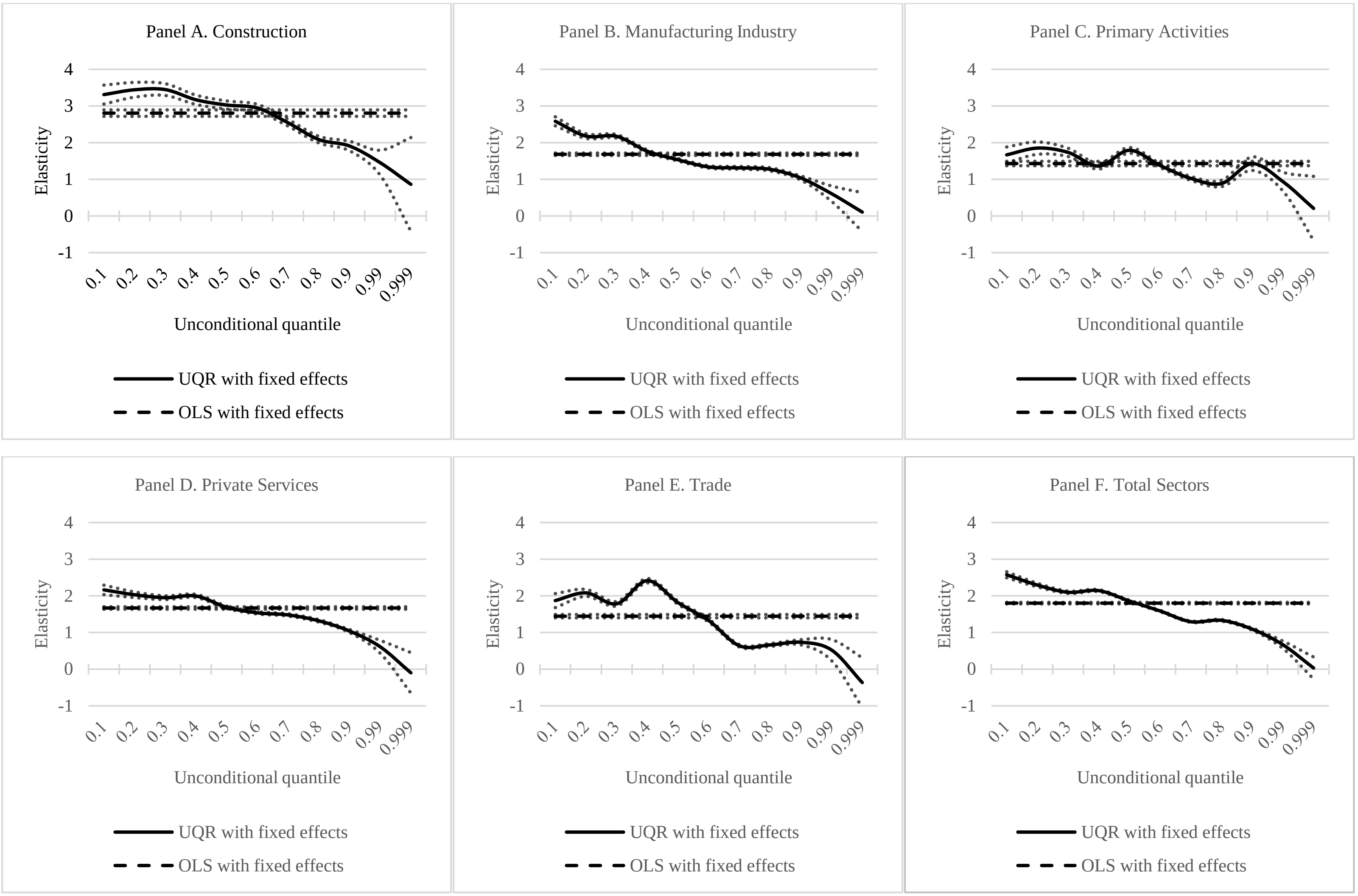
[19] For brevity, we do not show the result of these models for QR, but estimates are available upon request from the authors.

[20] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

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.

Figure 7. Elasticities of real salaries respect to GDP by economic sector

UQR with individual fixed effects



Note: dotted lines represent 95% confidence intervals.

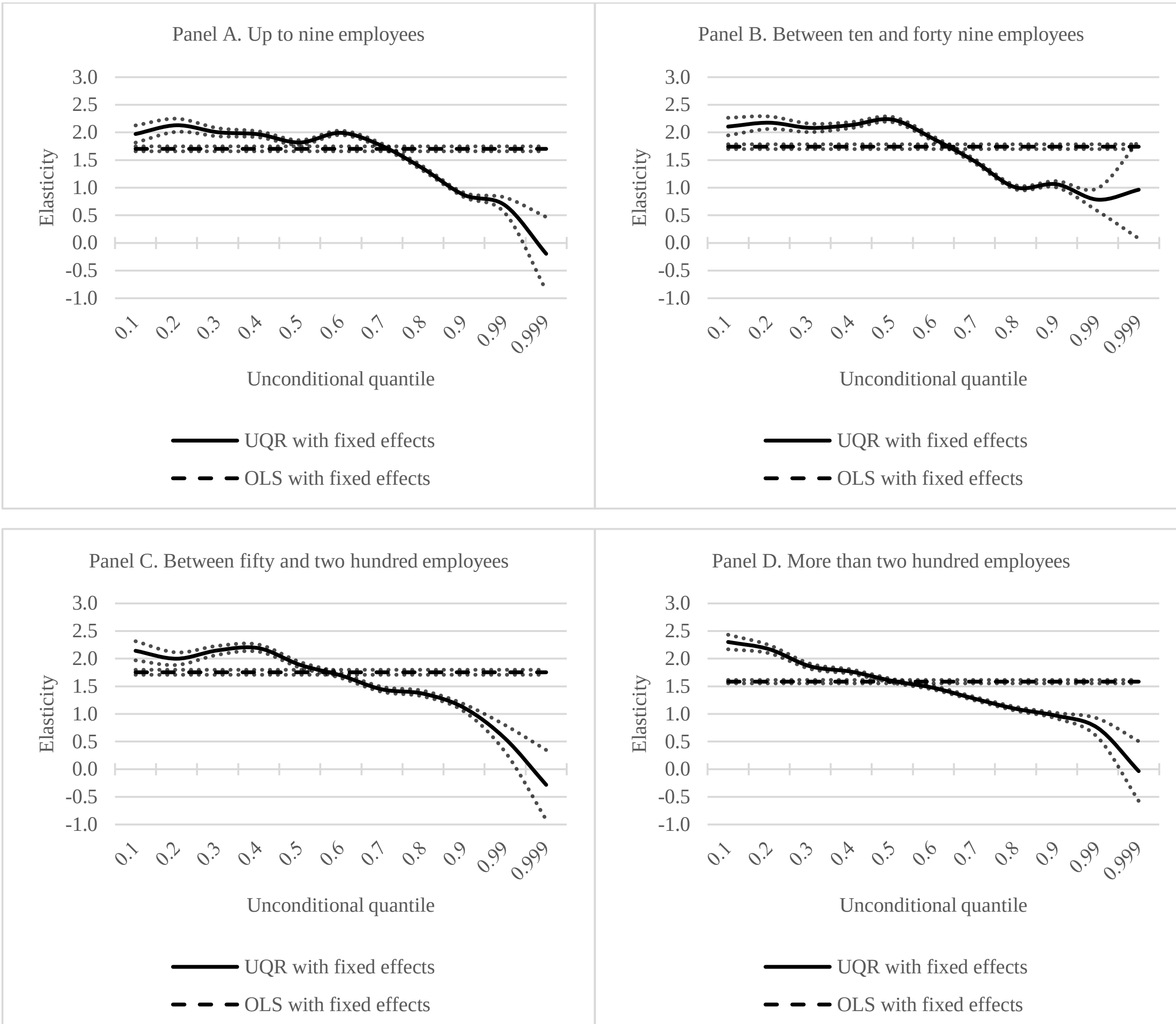
Source: own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

Figure 8 shows estimated income risk by firm size.[21] In the first place, it can be observed that income risk for individuals that work in large companies clearly decreases along the unconditional distribution of remunerations, 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 labour 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.

[21] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

Figure 8. Elasticities of real salaries respect to GDP by firm size

UQR with individual fixed effects



Note: dotted lines represent 95% confidence intervals.

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

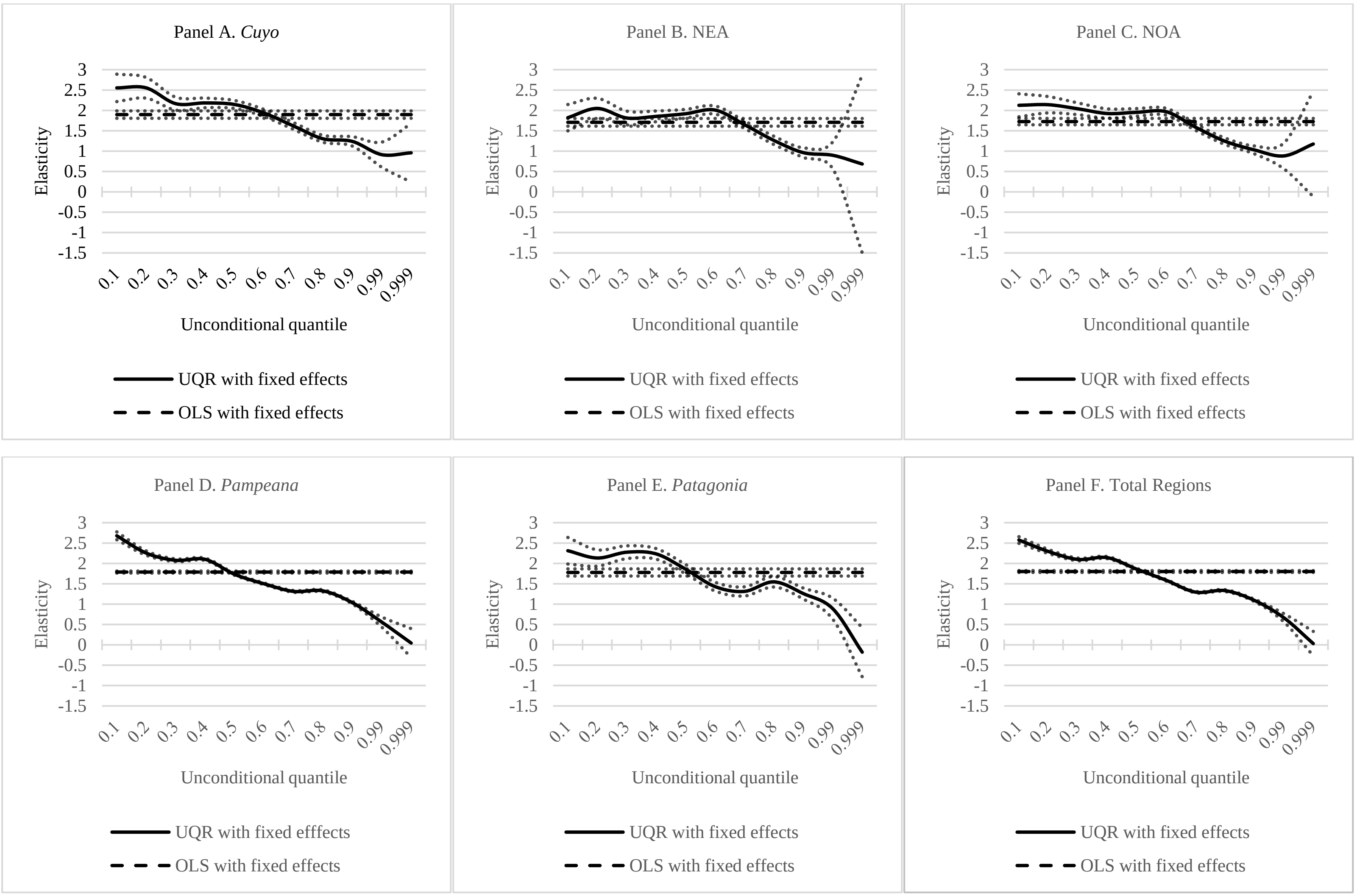
Finally, Figure 9 shows estimated elasticities by economic regions of Argentina.[22] As can be seen, *Cuyo*, *Pampeana*, and *Patagonia* appear to be, with some differences, the only regions that show a clearly decreasing trend on income risk along unconditional distribution of remunerations, while regions of the north of Argentina (NEA and NOA) show elasticities that are homogenous until the sixth decile and then tend to decline. In the first four deciles, the northeastern region of Argentina (NEA) exhibits an income risk

[22] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

that is lower than the other regions. In the intermediate quantiles (0.5, 0.6 and 0.7), *Pampeana* and *Patagonia* regions show similar elasticities to each other, which are less than those corresponding to the remaining regions. On the other hand, when we look at the top deciles of the distribution, no notable regularities seem to be detected about the income risk of the economic regions.

Figure 9. Elasticities of real salaries respect to GDP by economic region

UQR with individual fixed effects



<u>Note:</u> dotted lines represent 95% confidence intervals.

<u>Source:</u> own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

4.2.2. Some robustness checks[23]

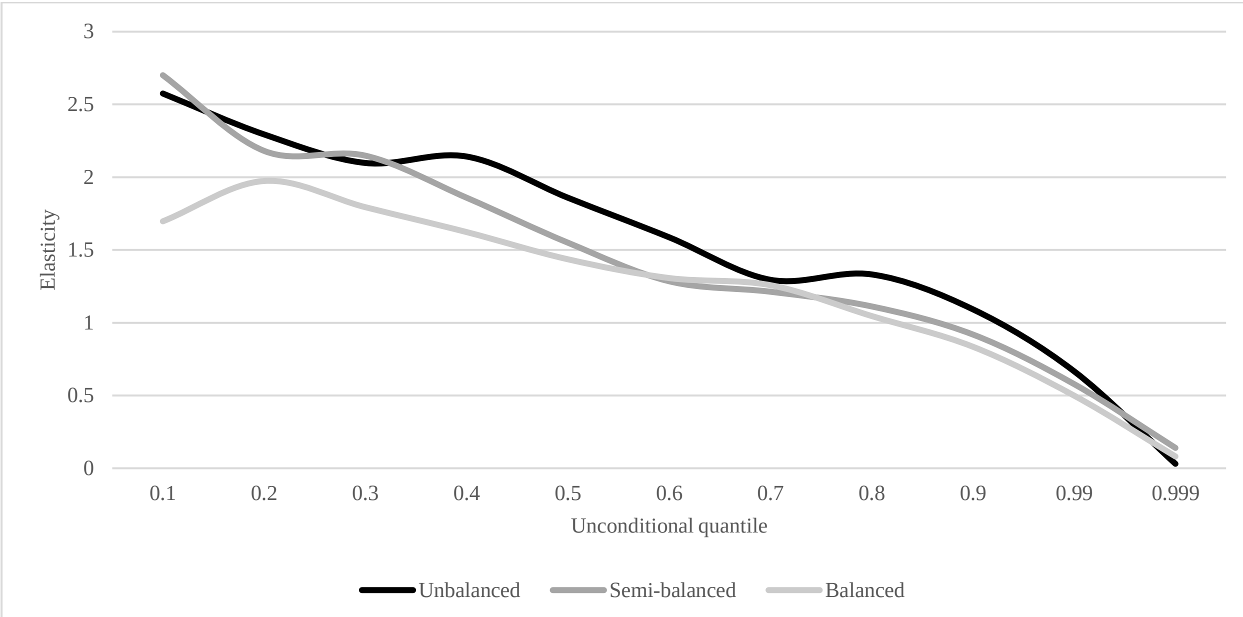
As previously discussed, when an individual leaves the MLER database, we do not know if he moves to unemployment or to the informal labor market. In either case, for many workers the sequence of observations of their income is not complete, affecting the panel balance and, if entries and exits are non-random, 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 if we restrict the number of missing values on income history of each worker. Particularly, we estimate our general UQR models using information from a "semi-balanced" sample (resulting from limiting the missing values on income history to ten) and from a "balanced" sample (resulting from limiting the missing values to zero). These results are shown in Figure 10.[24] It is important to note that restrictions on labour income history of workers does not affect our conclusion that income risk tends to decrease along the unconditional distribution of remunerations. 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.

[23] For brevity, we do not show the result of these models for QR, but estimates are available upon request from the authors.

[24] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

Figure 10. Elasticities of real salaries respect to GDP by sample balance

UQR with individual fixed effects



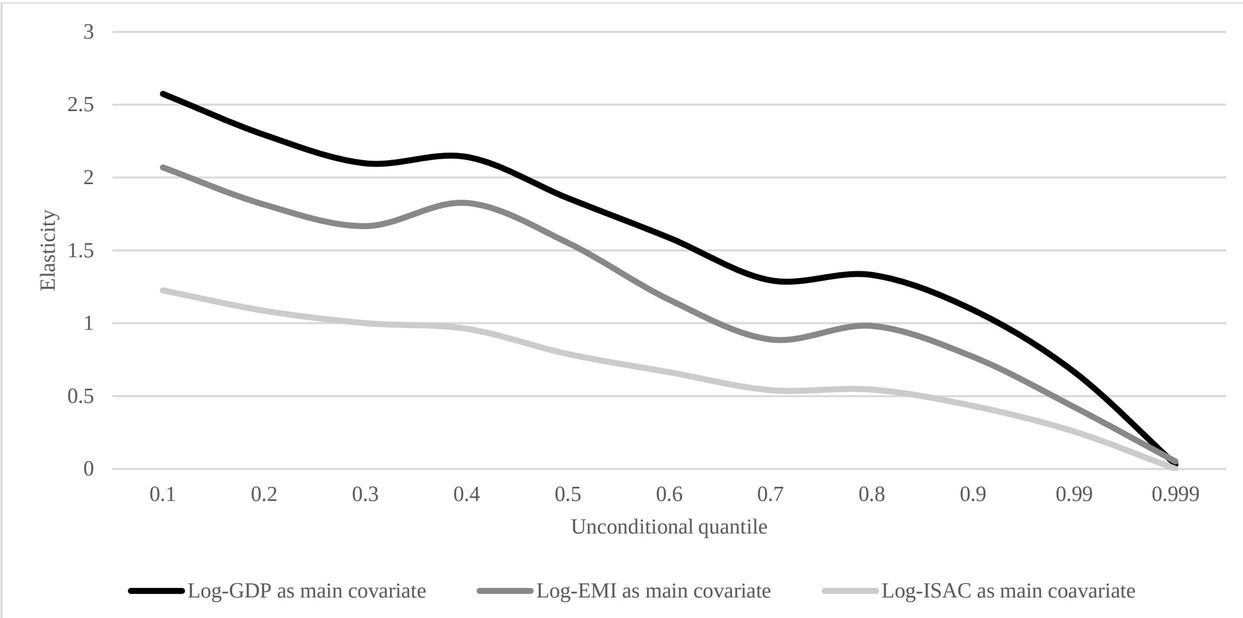
Source: own elaboration based on data from MLER, INDEC, provincial statistical institutes and the World Bank.

On the other hand, to explore whether our UQR results change when using other variables to measure the business cycle, we estimate the general models by replacing log-GDP by the log of EMI and ISAC indexes, which measure the evolution of industrial production and construction activity, respectively. Results are shown in Figure 11.[25] As can be seen, the decreasing trend on income risk along the unconditional distribution of salaries remains even when we measure business cycle by using industrial production and construction indicators. However, it is important to note that the level of the estimates' curves show some differences, since the highest elasticities are obtained using log-GDP as the main covariate, followed by the estimates corresponding to log-EMI and log-ISAC.

[25] The tables with estimates outputs of these models are not presented in this paper but are available upon request from the authors.

Figure 11. Elasticities of real salaries respect to business cycle measured by different indicators

UQR with individual fixed effects



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

5. Concluding remarks

Income risk analysis using QR and UQR models allows to measure the sensitivity of salaries respect to aggregate economic fluctuations along the whole conditional and unconditional distribution of salaries, 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 workers of Argentina, taking advantage of a large longitudinal administrative database with information of approximately half a million salaried workers for a span of twenty years (1996-2015), which allowed us to estimate income risk for different quantiles of conditional and unconditional distribution of remunerations with a reasonable level of precision.

The pooled OLS estimates for entire period show that an 1.0% rise of the GDP generates, on average, an 1.7% increment of salaries, *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 distribution of salaries, highlighting the importance of looking beyond the mean to capture the heterogeneity of GDP impacts on real remunerations of formal workers. Indeed, these results can be extrapolated to the unconditional distribution of salaries, 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 rich counterpart, 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 what happens in the unconditional distribution, poor individuals are not only more affected by business cycle expansions and contractions compared to rich workers, but they suffer a stronger fall in wages when aggregate activity declines than the increase in remunerations that their experiment when business cycle is in its expansion phase. On the other hand, when we estimate UQR models separately by economic sector, firm size, and region, the decreasing trend in remunerations' elasticity remains for some categories, while others do not seem to show a clear pattern. There are also some specificities, since, for example, individuals that work in Construction sector are those with higher income risk, while workers' remunerations of large companies are less sensitive to business cycle fluctuations. In addition, it is important to note that decreasing pattern in income risk remains when we apply some robustness checks to our UQR models, related to the balance of the panel and the variable to measure business cycle.

The interpretation of the income risk of salaried workers in Argentina must consider the labor relations system of the country. Hence, one hypothesis is that the asymmetry of GDP impact on salaries could respond to the bargaining power of unions -which varies throughout the business cycle- and to the structure of salary agreements, with fixed components and minimum salaries -which also vary due to economic fluctuations- that benefit in a greater proportion the workers 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 distribution of salaries and our estimates suggest that they are the most benefited by GDP expansions. Inversely, their salaries tend to reduce in greater magnitude in periods of economic recession, compared to individuals with higher remunerations. 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 distribution of salaries.

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 distribution of wages, 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 distribution of remunerations in Argentina (variance, asymmetry, among others), which are also an important part of the concept of income risk.

References

Abrevaya, J., and Dahl, C. M. (2008). The Effects of Birth Inputs on Birthweight: Evidence From Quantile Estimation on Panel Data. *Journal of Business and Economic Statisties*, 26(4), 379-397.

Alejo, J., and Casanova, L. (2016). Negociación Colectiva y Cambios Distributivos en los Ingresos Laborales en Argentina. *Revista de Economía Política de Buenos Aires*, 15, 65-97.

Arellano, M. (2017). Econometría de la desigualdad: de la persona promedio a la persona cuantil. In J. García, J. González-Páramo, and A. Matas, *Análisis empíricos sobre la economía española. Ensayos en homenaje a Josep Lluís Raymond Bara*. Capítulo 9: Funcas, Thomson Reuters Aranzadi.

Bell, B., Bloom, N., Blundell, J., & Pistaferri, L. (2020). Prepare for large wage cuts if you are younger and work in a small firm.

Blanco, A., Diaz de Astarloa, B., Drenik, A., Moser, C., & Trupkin, D. (2021). The Evolution of the Earnings Distribution in a Volatile Economy: Evidence from Argentina. *Documento de Trabajo Nro. 280*. CEDLAS.

Broer, T., Kramer, J., and Mitman, K. (2020). The Curious Incidence of Shocks Along the Income Distribution. Working Paper.

Canay, I. A. (2011). A simple approach to quantile regression for panel data. *Econometrics Journal*, *14*(3), 368-386.

Card, D. (1996). The Effect of Unions on the Structure of Wages: A Longitudinal Analysis. *Econometrica*, 64(4), 957-979.

Card, D., Lemieux, T., and Riddell, W. C. (2004). Unions and wage inequality. *Journal of Labor Research*, 25(4), 519-559.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5), 1001-1044.

Etchemendy, S., and Berins Collier, R. (2008). Golpeados pero de pie. Resurgimiento Sindical y Neocorporativismo Segmentado en Argentina (2003-2007). *POSTdata* (13), 145-192.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, *77*(3), 953-973.

Freeman, R. B. (1980). Unionism and the Dispersion of Wages. *ILR Review*, 34(1), 3-23.

Galvao, A. F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*, *164*(1), 142-157.

Galvao, A. F., & Kato, K. (2016). Smoothed quantile regression for panel data. *Journal of Econometrics*, *193*(1), 92-112.

Galvao, A. F., & Montes-Rojas, G. V. (2017). Multi-dimensional Panels in Quantile Regression Models. In *The Econometrics of Multi-dimensional Panels* (pp. 239-261 (Chapter 8)).

Galvao, A. F., & Wang, L. (2015). Efficient minumum distance estimator for quantile regression fixed effects panel data. *Journal of Multivariate Analysis, 133*, 1-26.

Guvenen, F., Ozkan, S., and Song, J. (2014). The Nature of Countercyclical Income Risk. *Journal of Political Economy*, 122(3), 621-660.

Guvenen, F., Schulhofer-Wohl, S., Song, J., and Yogo, M. (2017). Worker Betas: Five Facts about Systematic Earnings Risk. American Economic Review: Papers and Proceedings, 107(5), 398-403.

Hampel, F. R. (1968). Contributions to the theory of robust estimation. *Ph. D. in Statistics University of California 1968.*

Hampel, F. R. (1974). The Influence Curve and Its Role in Robust Estimation. *Journal of the American Statistical*, *69*(346), 383-393.

Huber, P. J., & Ronchetti, E. M. (2009). *Robust Statistics, Second Edition.* Wiley Series in Probability and Statistics.

Kato, K., Galvao, A. F., & Montes-Rojas, G. V. (2012). Asymptotics for panel quantile regression models with individual effects. *Journal of Econometrics*, *170*(1), 76-91.

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis, 91*(1), 74-89.

Koenker, R. (2005). Quantile Regression. Cambridge.

Koenker, R., and Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1), 33-50.

Lamarche, C. (2010). Robust penalized quantile regression estimation for panel data. *Journal of Econometrics*, *157*(2), 396-408.

Lancaster, T. (2000). The incidental parameter problem since 1948. *Journal of Econometrics*, *95*(2), 391-413.

Lombardo, C., and Martínez Correa, J. (2019). Convenio Colectivo, Sindicatos y Dispersión Salarial: Evidencia de Argentina. Anales LIV Reunión Anual Asociación Argentina de Economía Política.

Machado, J. F., and Santos Silva, J. C. (2019). Quantiles via moments. *Journal of Econometrics*, 213(1), 145-173.

Neyman, J., & Scott, E. (1948). Consistent Estimates Based on Partially Consistent Observations. *Econometrica, 16*(1), 1-32.

Palomino, H., & Trajtemberg, D. (2006). Una nueva dinámica de las relaciones laborales y la negociación colectiva en la Argentina. *Revista de Trabajo*, 2(3), 47-68.

Palomino, H., & Trajtemberg, D. (2012). Negociación colectiva y recuperación económica en Argentina. In *Macroeconomía, empleo e ingresos. Debates y politicas en Argentina frente a la crisis internacional 2008-2009.* Buenos Aires: Oficina Internacional del Trabajo.

Parente, P. M., and Santos Silva, J. M. (2015). Quantile Regression with Clustered Data. *Journal of Econometric Methods*, 5(1), 1-15.

Parker, J. A., and Vissing-Jørgensen, A. (2009). Who Bears Aggregate Fluctuations and How? *American Economic Review: Papers and Proceedings*, 99(2), 399-405.

Parker, J. A., and Vissing-Jørgensen, A. (2010). The Increase in Income Cyclicality of High-Income Households and Its Relation to the Rise in Top Income Shares. Working Paper 16577. NBER Working Paper Series.

Paz, J. A. (2007). Retornos laborales a la educación en la Argentina. Evolución y estructura actual. Serie Documentos de Trabajo. Universidad del CEMA. Buenos Aires-Argentina.

Powell, D. W. (2016). Quantile Regression with Nonadditive Fixed Effects.

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF descomposition. *The Stata Journal, 20*(1), 51-94.

Scanlon, P. (2020). Aggregate risk and wage dispersion. *Economics Letters*, 194, 1-4.

Trajtemberg, D. (2009). El Impacto de la Determinación Colectiva de Salarios Sobre la Dispersión Salarial. *Trabajo, Ocupación y Empleo. Serie Estudios Laborales*, 8, 123-148.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. London, England: The MIT Press.