Consequences of the starting point: Locational scarring effects in Spain

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Abstract:

Scarring effects in the labour market can be defined as the impact that the early working life experiences have on the individual long-term employment prospects, reducing his/her productive potential and/or future earnings. This paper studies the effects that the first job experience has on the later outcomes of different age groups (from 30 to 64 years old), which represents the adult cohorts from a life cycle perspective. Particularly, we are focusing on the possible wage differences that might arise as a consequence of where the first job took place regarding population size tiers, arriving to the concept of a locational scarring effect. This idea explores whether start working in rural or urban areas affect the earnings of the employees at their labour prime, and if this locational scarring effect has a temporal or permanent influence. Using the administrative records of the Continuous Sample of Working Lives database, we compare the results for the years 2005 and 2015 to see if there have been significant changes during the last decade.

Keywords: *Scarring effect, Wage differences, Employment, Urban-rural gap*
JEL codes: R23, J13, J64

1. Introduction

There are several reasons that explain why the earnings of two individuals can be different in their adulthood ages. In cross-sectional analyses, individual characteristics such as gender, age, level of studies or years of experience in the labour market have been proven to play a significant role, but also the characteristics of the job are important to understand possible individual wage gaps. Among the latter, the duration of the contract (fixed term or permanent), the type of contract (part-time or full-time), the sector, the type of occupation, or where the activity takes place (in terms of rural or urban location) are the typical ones regarded by the literature.

From a life-cycle perspective, early labour market experiences may also affect the long-term employment prospects of workers, reducing their productive potential and/or future earnings (Nordstrom Skans, 2011). The related literature calls "scarring effect" or "state dependence" to this particular issue. It is founded on the idea that the individual human capital formation and accumulation will not be the same depending on the historical spells of inactivity, unemployment or employment they had under different circumstances (Edin and Gustavsson, 2008).

In this regard, it is especially well documented in the literature that episodes of unemployment in early stages of the working life reduces individual's future earnings (Narendranathan and Elias, 1993; Ryan, 2001; Caroleo et al., 2017). Gregg and Tominey (2005) obtained a wage scar penalty of 13-21% at the age of 41 that reduces to 9-11% if individuals avoid repeated exposure. Mroz and Savage (2006) found a catch-up response by those who suffer unemployment at the young age, but an overall negative effect persists on life-cycle earnings. The mentioned evidence points out that unemployment has not the same effect depending on when it happens. As Bell and Blanchflower (2011) demonstrate, early unemployment creates longer lasting scars than recent unemployment experiences (happening at the age of 50). Other authors, such as Jimeno and Rodríguez (2002), found that youth unemployment has a negative effect on human capital accumulation or, even, on fertility rates.

There are also some examples of how the conditions at the entrance in the labour market affect the later career development. Among them, De Lange et al. (2014) found that starting with a flexible contract in the Dutch labour market increases the probability of repeated fixed-term employment and unemployment spells in the early career. Additionally, their results suggest that the negative effects of flexible employment are temporary and diminish after some years in the labour market. Another studies deal with the effects of entering in the labour market through a temporary work agency in Germany (Buch and Niebuhr, 2013), with the impact of starting during a recession or in a place with high unemployment (Aslund and Rooth, 2007; Davis and Watcher, 2011; Guo, 2014), or with the consequences that the mobility during the beginning of the working life has on the adult labour market outcomes (Gardecki and Neumark, 1998).

However, we are not aware of any study in this line of research that combine both contemporary and life-cycle viewpoints focusing on the possible wage differences that might arise as a consequence of the characteristics of the first employment experience, and particularly, on where this first job took place. This idea explores whether start working in rural or urban areas affect the earnings of the employees at their labour prime, based on two concepts: the scarring effects of early labour market experiences, as stated above, and the urban wage premium on earnings derived from agglomeration.

Empirical literature suggests that the average wages in large cities tend to be higher than those in smaller places. This gap receives the name of urban wage premium. It accounts for approximately a 30% difference in earnings for the U.S. (Glaeser and Maré, 2001; Gould, 2007) and between a 15% and 60% difference for France, depending on the urban tiers compared (Combes et al., 2008). After controlling for some basic characteristics, the estimations of this gap for Britain lies at 14% (D'Costa and Overman, 2014). For the Spanish case, there is little empirical evidence on local wage differentials due to the lack of data, but there are some authors that tried to explain regional wage differentials, providing a valuable background for this analysis. Simón et al. (2006) found that there exist marked regional wage differences between workers with the same skills at the autonomous community (NUTS 2) level, induced by the collective bargaining system. These disparities increase or decrease following the upturns and drops of the business cycle, more intensively than in other European countries, as discussed by Bande et al. (2008). On the same line, Ramos et al. (2015) show that there are significant spatial spillover effects between the provincial (NUTS 3) wage curves, and that wage differentials are low but persistent in time as a consequence of the rigidities of the Spanish labour market. Finally, the work of De la Roca and Puga (2017) represents the first analysis of the urban wage premium for Spain. Raw figures indicate a wage difference around 55% and 21%, depending on the tiers of the urban hierarchy regarded, while for the period 2004-2009 the estimations show that relocating to a city that doubles the population size of the previous one translates into an increase in earnings of around 5%. The reasons regarded in the literature can be divided into static and dynamic effects, as reviewed in Yankow (2006) and in De la Roca and Puga (2017).

The static components of the urban wage premium are granted to the individual as soon as he/she starts working in a large city, and are lost when the worker moves back to a smaller area. Into this class falls the compensation that firms should offer because of the higher cost of living in larger cities (price effect). If controlling for price differentials evens out the difference in wages, it can be said that the urban wage premium is a nominal effect. Another static component is the higher firm-level productivity stemming from the advantages of agglomeration, which translates into a higher marginal labour contribution. This effect has been widely studied, as shown by Ciccone and Hall (1996), Duranton and Puga (2004), Rosenthal and Strange (2004) or Holmes (2010), among others. The last component in this category is the sorting effect caused by the preference of the most productive workers for largest cities, which has an impact on the skill composition of the labour force of different areas. This sorting is based on unobserved abilities, as observable characteristics are generally considered in previous steps of the estimation process. The empirical evidence suggests that this effect accounts for a large share of the urban wage premium (Fuch, 1959; Glaeser and Maré, 2001; and Combes et al., 2008).

On the other hand, the dynamic effects are related to the interaction of workers and firms in the urban setting. Large cities offer a wider scenario for the creation and development of connections that become inherent to the worker, therefore the part of the wage premium associated to this dimension is only acquired through time, but it remains with the worker as she/he relocates. Included in this group is the learning effect, coming from the speeding up of human capital accumulation that takes place in cities, which becomes more valuable experience (Glaeser, 1999; Duranton and Puga, 2001); and the coordination effect, related to the improved job search and job-worker matching (Helsey and Strange, 1990; Sato, 2001).

For the Spanish case, De la Roca and Puga (2017) found that the static and dynamic components are balanced in terms of explanatory power regarding the urban wage premium, being more significant the effects of agglomeration on the static share, and the effects of learning in the dynamic one.

Under the "imperfect information" hypothesis, firms hire people under uncertainty about worker's actual productivity, so employers use information of the previous labour market experiences to select between the possible candidates (Agell and Bennmarker, 2002; Erikson and Lagerstrom, 2004). If working in a large city provides you with static and dynamic advantages, which are not assimilated if you are working in a small area, employers might have a preference (or a taste) for hiring those profiles that have longer experiences working in bigger places.

Based on the combination of the notions of different scarring effects at different points in life, and the wage disparities along the urban-rural gradient of areas, the aim of this paper is to analyse the effects that the starting point (taking into account six different population size tiers) has on the later earnings of different age groups (mid-30 years old, mid-40 years old and mid-50 years old) that represent the adult cohorts from a life-cycle perspective. Therefore, we will explore the resulting wage gap as a consequence of a potential individual different path in terms of human and social capital accumulation, depending on whether the initial job was in a rural or urban area. In this sense, the subject of this analysis can be defined as the study of "locational scarring effect", dividing and comparing the results for the age groups mentioned earlier and for the years 2005 and 2015.

The rest of the paper is divided into four additional sections. In the first one we describe the methodological approach considered for the analysis, based on an extended mincerian equation. In the following section we explain the principal databases and variables used, and after that, we present the results obtained for the global assessment (Ordinary Least Squares) and the Quantile Regressions for 2005 and 2015. Finally, the last section explains the main conclusions reached through the paper.

2. Methodology

As was discussed in the previous section, job experience and years of schooling are the usual suspects regarding the potential differences in earnings, but these factors are not the only ones at play. The most common model specification for estimating the effect of the main determinants of the earnings in a particular moment in time is the so-called Mincer equation (Mincer, 1974):

$$\ln w_i = \beta_0 + \beta_1 s_i + \beta_2 x_i + \beta_3 x_i^2 + \varepsilon_i$$

Where w is the individual earnings or wages, β_1 is the average return to schooling s, x stands for years of experience in the labour market (its quadratic specification accounts for an inverted U-shaped behaviour), and ε is the residual. This design reflects the idea that earnings respond to the human capital accumulation and investment, i.e. both the formal education at school and additional on-the-job acquired skills (based on Ben-Porath, 1967). In this paper, we use the Mincer specification as a starting point and we extend it to account for where the first job experience took place, controlling also for other individual characteristics, and for present and past employment features. As Heckman et al. (2005) have pointed out, Mincer's model is still a suitable approach to explain cross sections of earnings.

The first extension of the semi-logarithmic mincerian equation introduces a categorical variable for the size of the area where the first labour market experience happened:

$$\ln w_i = \beta_0 + \beta_1 s_i + \beta_2 x_i + \beta_3 x_i^2 + \sum_{s=1}^{n-1} \beta_4 C_i^0 + \varepsilon_i$$

In this equation, C_i^0 represents the effect associated to the size tier *s* (that ranges from 1 to *n* total number of size tiers) of the city/area of the first job. From here we further extend the formulation to include other individual characteristics, characteristics of the present job (incorporating the size tier of the area), and other characteristics of the initial job that have an influence on wages.

$$\ln w_i = \beta_0 + \beta_1 s_i + \beta_2 x_i + \beta_3 x_i^2 + \sum_{s=1}^{n-1} \beta_4 C_i^0 + \sum_{s=1}^{n-1} \beta_5 C_i^1 + \beta_6 Z_i + \beta_7 Y_i^0 + \beta_8 Y_i^1 + \varepsilon_i$$

In this specification, *C* stands for the categorical variable of the size of the area where the individual work, *Z* is a set of individual characteristics that may affect the earnings of a worker (other than the years of schooling and the total experience at work), and *Y* denote the characteristics of the job, while superindexes *0* and *1* represent the first and the present job, respectively. We finally include another categorical variable to control for the possibility of moving between the time periods (initial and present). There are three feasible options: moving up in the urban hierarchy (to a larger city), moving down (to a smaller city) or staying in the same place.

This classical linear regression, i.e. Ordinary Least Squares (OLS), estimate a conditional mean function. This handy procedure is widely accepted as a benchmark to build up more complex and accurate formulations, and as such it should be taken into account that this method represents one of the many possible approximations to the conditional distribution of a variable (Mosteller and Tukey, 1977). In an effort to complete the picture and provide more information on the possible disparities at different points of the distribution, we are also going to implement a Quantile Regression (Koenker and Bassett, 1978).

The mechanism to perform a Quantile Regression is analogous to the one followed in an OLS regression, being the main distinction that instead of pursuing the minimization of the sums of the squared (symmetrical) deviations with respect to the mean μ, expressed as a function of x and β, $min \sum_{i=1}^{n} (y_i - \mu\,(x_i, \beta))^2$, Quantile Regression looks for the minimization of the weighted sums of the absolute (asymmetrical) residuals, where the weights depend on the quantiles regarded (τ), $min \sum_{i=1}^{n} \rho_\tau (y_i - \xi\,(x_i, \beta))$. For an extensive review of this methodology and a number of applications in several fields, see Koenker and Hallock (2001) and Koenker (2005).

3. Database

To distinguish the impacts of the starting point on present wages, we will use the data from the Continuous Sample of Employment Histories (MCVL in Spanish) released by the Ministry of Employment and Social Security of Spain. This database contains comprehensive information about the labour records of more than a million individuals, including their spatial location at a highly disaggregated level (municipalities with more than 40,000 inhabitants), which enables the identification of city-size effects. Moreover, it provides with some individual characteristics of the population (as the Social Security records are complemented with data from the Municipal Registry of Inhabitants), and the information of the employment histories, which we need in order to obtain data on the first labour market experience.

The MCVL is available, upon request, in two versions: with and without tax data. Although both versions include comparable information, their identifiers are different, preventing their combined use. In this case, the version at hand is the MCVL with tax data, despite the fact that the tax information is not considered in this preliminary study.

Regarding the information related to wages that can be extracted from the sample, the contribution base for common contingencies works as an appropriate proxy in this analysis provided that it is closely associated to the gross earnings that the employee receives (excluding overtime earnings). Its importance as an item of the final wage is officially acknowledged since it is the reference amount used to compute the retirement and unemployment benefits. There are other sources that provides information about wages in Spain, namely the Wage Structure Survey or the Labour Cost Survey, but in these cases the data is referred to the national or autonomous community (NUTS 2) level, leaving the MCVL as the only source that makes the analysis of wages at the city level feasible, as it allows to identify the municipality of work of the individual when the workplace is located in an area of more than 40,000 inhabitants. It is also the only database that provides historical data, which allows us to identify the conditions of the first job.

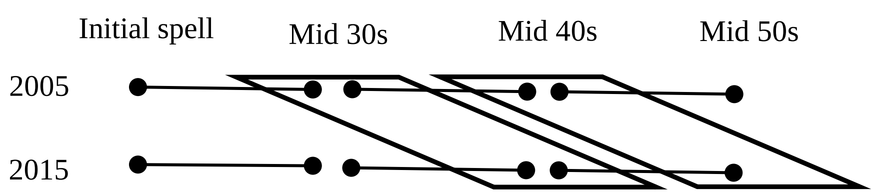
There is an important limitation in this data set: the earnings are censored as the contribution base is subject to a minimum and a maximum value. This means that the earnings below or above these values are affected by the fixed amount set every year by the administration, which prevents the identification of the actual earnings in far-left and far-right tails of the distribution. Nonetheless, the comparison made in the work of De la Roca and Puga (2017) for the period 2004-2009 using the censored contribution base and the uncensored tax records revealed that there are not significant differences in the results, which justifies the use of this measure in this preliminary analysis.

The dependent variable is the present individual wage (2005 and 2015) expressed as the logarithm of the last monthly labour earnings, and the main explanatory factor of interest will be the municipal size of the first place where the individual found a job, represented by a set of six categories, being the reference tier the one containing the largest cities in the country, namely Madrid and Barcelona. The second tier contains those municipalities with less than one million but more than 500,000 inhabitants, the third one goes down to a population size between 500,000 and 250,000, the fourth category accounts for those municipalities between 250,000 and 100,000 inhabitants, the fifth one gathers cities between 100,000 and 40,000, and the last tier includes cities of less than 40,000 inhabitants. The estimation of the parameters associated to each tier in this size hierarchy will show the differences in wage levels due to the locational scarring effect.

Other control variables will be taken into account in order to observe the effect of the initial population size as clearly as possible. The variables included are factors widely used in wage equations, related to the worker and the company: the experience and the squared experience of the worker, the gender, the initial and the present occupational skill level (low, medium-low, medium-high or high), the initial and the present sector (disaggregated into 21 CNAE-09 letters), the present urban wage premium, the initial and the present type of contract (full-time or part-time), and the migration to a different place along the Spanish urban hierarchy.

In our analysis, three different comparisons can be performed. The first one is a horizontal comparison of the effect of the initial spell between the different age cohorts considered in the current year. As can be seen in Figure 1, we include 3 different groups: mid 30s (between 33 and 37 years old), mid 40s (between 43 and 47 years old) and mid 50s (between 53 and 57 years old). Implementing the same model for different subsequent years (in our case 10 years later) give us the opportunity to make an additional comparison between the effects along time and check if the situation of the same age cohort improves or worsen in different points of time. Finally, the diagonal approach allows us to compare the situation of a particular group of the population by tracking the same group along the years and seeing its dynamic evolution. This can help us to assess if the impacts of the initial job experience are permanent or temporal in three different ways.

Figure 1 - Representation of the horizontal, vertical and diagonal analysis



4. Results and main findings

This forth section shows first the Ordinary Least Squares (OLS) model, which will serve as a first approximation to the relationship between the individual earnings and the factors presented in the previous section (experience, individual characteristics, characteristics of the initial job, and characteristics of the present job). Then, the results of the Quantile Regression will be reviewed, focusing the discussion on the impact of the size of the city where the initial job spell took place along the distribution of wages by age cohort, providing also the results of the global estimation (on the conditional mean).

As can be seen in Table 1, the OLS specification shows the expected signs for all the variables for the year 2005. Especially interesting is the significant effect that starting the labour market career in the largest cities of the country has on the later outcomes, as it is predominantly larger, with the remaining (smaller) size tiers exhibiting a relative reduction on the earnings in all cases. This effect is generally higher for the oldest than for the youngest group, which suggest that workers who started their employment history in the 70s suffer a larger locational scarring effect in the present than those who started working in the 90s. Another interesting finding is that for all ages, the third initial size tier (municipalities between 500,000 and 250,000 inhabitants) bears the lowest wage penalty with respect to Madrid and Barcelona, followed by the fourth one (localities with a population between 250,000 and 100,000) for the workers in their 30s and 40s. This result may be indicating an "urban competition process" where the second ranked cities were losing economic momentum in front of the largest metropolises and the small and medium sized localities in the previous decades (when workers found their first job).

The initial type of contract does not have a significant scarring effect on present wages, but the actual type of contract is very important in the determination of the earnings, as expected. This suggests that having a part-time job when you are young and starting your work life does not mean an "entrapment" but a "stepping stone", consistent with the findings of previous case studies mentioned in the introduction.

Both the initial and the last skill level of the worker present the expected behaviour, growing in effect for higher categories. The current skill has a more marked effect in terms of magnitude at explaining the present earnings, not only larger than the initial one, but also than most of the factors included in the model, only matched by the influence of the type of contract.

Table 1 – Results of the OLS estimation for 2005

	Log W		Log W (mid 30s)		Log W (mid 40s)		Log W (mid 50s)	
Constant	5.28162	***	5.28556	***	5.15914	***	5.06940	***
x	0.00006	***	0.00014	***	0.00007	***	0.00007	***
x2	0.00000	***	0.00000	***	0.00000	***	0.00000	
(ref=Male)								
Female	-0.10637	***	-0.12199	***	-0.08456	***	-0.05602	***
(ref=largest cities)								
Size 2 initial	-0.02725	***	-0.03744	***	-0.02684	***	-0.02433	*
Size 3 initial	-0.01294	**	-0.01599	**	-0.01671	**	-0.01901	
Size 4 initial	-0.02134	***	-0.02291	***	-0.02411	***	-0.03695	***
Size 5 initial	-0.04023	***	-0.03814	***	-0.05097	***	-0.06452	***
Size 6 initial	-0.04521	***	-0.03870	***	-0.06995	***	-0.06529	***
(ref=highest skill)								
Skill initial 2	0.02930	***	0.05803	***	0.02662	***	0.02388	***
Skill initial 3	0.03246	***	0.09179	***	0.04153	***	0.02993	***
Skill initial 4	0.08489	***	0.13789	***	0.10743	***	0.08528	***
(ref=part-time)								
Full-time initial	0.00097		0.00164		-0.00210		0.02208	*
(ref=largest cities)								
Size 2 last	-0.05895	***	-0.07023	***	-0.04127	***	-0.04614	***
Size 3 last	-0.05758	***	-0.07766	***	-0.03237	***	-0.03370	***
Size 4 last	-0.06280	***	-0.07524	***	-0.04518	***	-0.04493	***
Size 5 last	-0.08092	***	-0.09970	***	-0.06089	***	-0.04070	***
Size 6 last	-0.12154	***	-0.14095	***	-0.08822	***	-0.09304	***
(ref=highest skill)								
Skill last 2	0.25809	***	0.21772	***	0.22987	***	0.28078	***
Skill last 3	0.53995	***	0.48241	***	0.50592	***	0.54324	***
Skill last 4	0.75543	***	0.74296	***	0.71340	***	0.65375	***
(ref=part-time)								
Full-time last	0.66602	***	0.60079	***	0.68931	***	0.66213	***
(ref=not move)								
Move to a bigger city	0.02399	***	0.05366	***	0.00418		-0.01565	
Move to a smaller city	0.02726	***	0.03120	***	0.03514	***	0.02052	*
Sectors initial	yes		yes		yes		yes	
Sectors last	yes		yes		yes		yes	
Number of obs	210596		96361		71675		42560	
F Statistic	3599.78		1653.95		1350.26		724.64	
Prob > F	0.0000		0.0000		0.0000		0.0000	
Robust Regression measures of fit								
R-square	0.3423157		0.3410027		0.3579457		0.3570299	
AICR	304230.79		135043.23		106296.03		61522.168	
BICR	304912.19		135676.21		106908.42		62099.247	
Deviance	52973.741		22079.845		17691.8		12136.562	

Another interesting results shown in Table 1 are the ones that drop some hints on the relationship between the age group and gender wage gap or the urban wage premium, as represented by the coefficients of the sex variable. The gender wage gap is higher for the mid-30s cohort, and lower for the mid-50s, reflecting a higher negative effect for the youngest workers that might be related to the different fertility profiles of both groups.

The current urban wage premium, as represented by the current city size tier, shows the wage gap between urban and rural areas in Spain. In general, the gap between tiers is wider than in the past, and it grows as we move towards the smallest size tier following the urban hierarchy except when the third tier is regarded. Similarly to the results for the initial size tier, municipalities in the third category have a smaller gap with respect to Madrid and Barcelona for workers in their 40s and 50s. Intriguingly, the ordering of the wage premium effect does not follow the size rationale for the last age group. Apparently, the magnitude of the effect of the wage penalty suffered for working in smaller areas in the present is larger for the youngest cohort, conversely to the situation with the size tier of the initial job.

To complement the global analysis presented in Table 1, Figures 2, 3 and 4 present the results of the Quantile Regressions for the model specified, showing different impacts of the factor depending on the point of the quantile distribution of wages considered for the three age cohorts. In Figures 2.1 and 2.2, it can be seen that the effects are persistently more negative for those individuals of the youngest group in the lower quantiles of the wage distribution. These employees are suffering a stronger locational scarring effect from starting their working life in a smaller area, and the effect is more negative the smaller that area was

Figure 2.1 – Quantile Regression results of the size tier of the first job for the mid-30s (2nd, 3rd and 4th tiers)

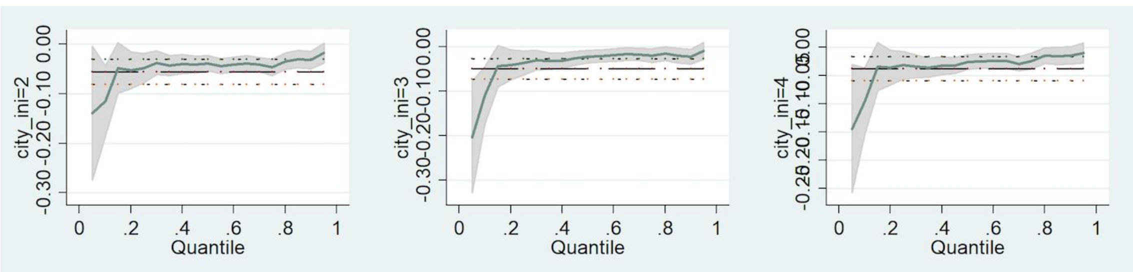
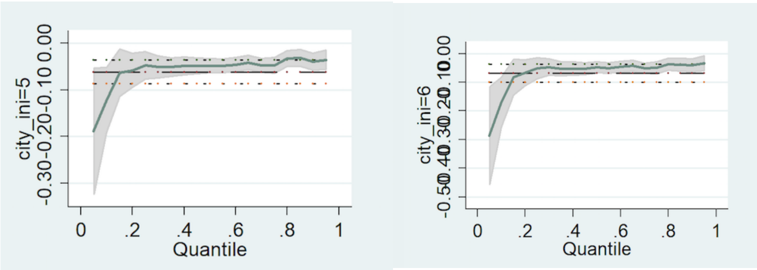


Figure 2.2 – Quantile Regression results of the size tier of the first job for the mid-30s (5th and 6th tiers)



For the group in their mid-40s, the result is not that different from the global OLS estimation (conditional mean) as shown in Figure 3, being the locational scarring effect always higher for starting in smaller areas. Finally, Figure 4 shows the Quantile Regressions for the group of mid-50s. It is clearly seen that the higher wages are less affected by the locational scarring effect (coefficient closer to zero) than the low wages.

Figure 3 – Quantile Regression results of the size tier of the first job for the mid-40s

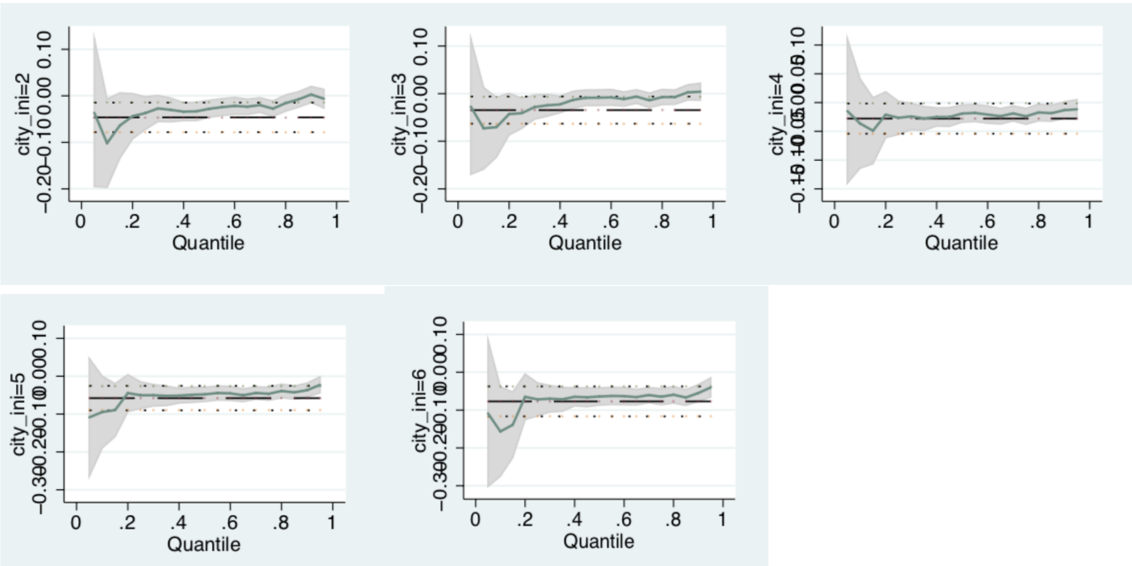
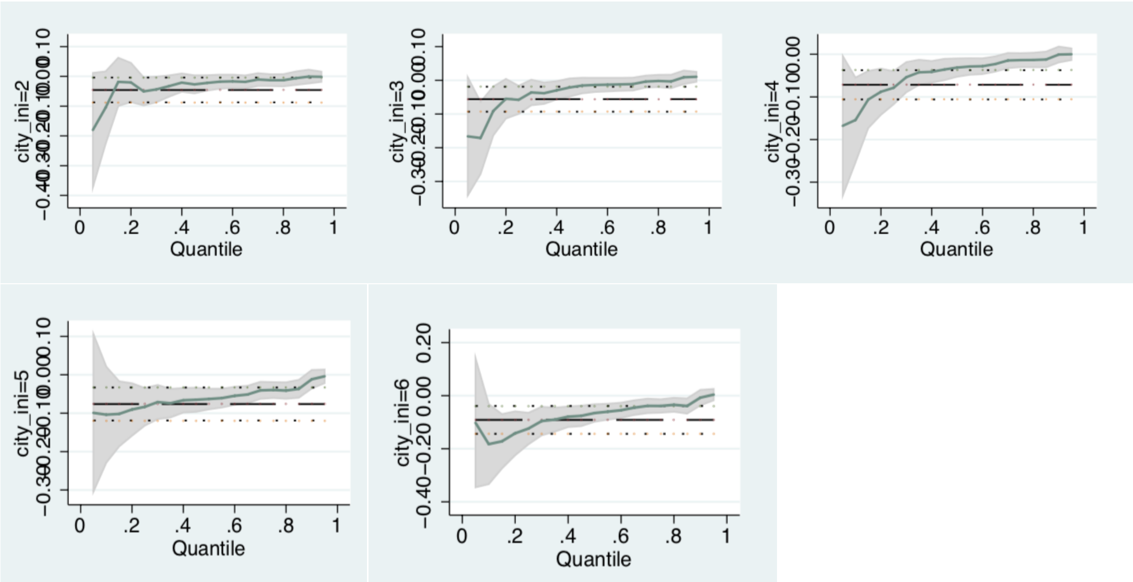


Figure 4 – Quantile Regression results of the size tier of the first job for the mid-50s



5. Conclusions

In this paper was shown how the initial job experience can affect later wages at different moments of the life cycle. We were specially focused on presenting a new hypothesis: the locational scarring effect. Based on the literature on urban wage premium and on the later effects of previous labour market circumstances, the locational scarring effect can be defined as the negative effect that starting your labour market career on a rural or an urban area has on your future labour outcomes. By means of the historical and present administrative records of the Spanish Continuous Sample of Working Lives, we compared the results obtained for three different age cohorts (mid 30s, mid 40s and mid 50s).

Results show that starting the labour market career in the largest cities of the country translate into a better outcome in terms of current wage for all cohorts. This effect is higher for the oldest than for the youngest groups, which suggest that workers that had their first job spell in the 70s suffer now more locational scarring effect than those who started their working lives in the 90s. In all cases, the smaller the size of the starting area, the more negative the effect on the present wages. The locational scarring effect is more marked for younger workers in the lowest part of the distribution of wages, as shown by the quantile results.

In the course of the analysis, other interesting findings appeared, as the comparative effect across age cohorts of the gender wage gap and the urban wage premium, uncovering wider differences at younger ages between men and women, and worst penalties for younger cohorts working in smaller cities.

In light of the results obtained, this paper presents a promising first attempt to analyse the caveats that workers in different points of their working development have to face under common current labour market circumstances. In these sense, the research conducted here adds to the existing academic attempts to shed some light on both, the past and present challenges of each cohort, and can also serve as a starting point to understand some of the current regional and intergenerational imbalances of the Spanish labour market, their possible sources, and potential ways to correct them.

References

Bande, R., Fernández, M., & Montuenga, V. (2008). Regional unemployment in Spain: Disparities, business cycle and wage setting. *Labour Economics*, 15(5), 885-914.

Bell, D. N., & Blanchflower, D. G. (2011). Youth unemployment in Europe and the United States. *Nordic Economic Policy Review*, 1(2011), 11-37.

Caroleo, F. E., Ciociano, E., & Destefanis, S. (2017). Youth Labour-Market Performance, Institutions and Vet Systems: A Cross-Country Analysis. *Italian Economic Journal*, 3(1), 39-69.

Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters!. *Journal of Urban Economics*, 63(2), 723-742.

D'Costa, S., & Overman, H. G. (2014). The urban wage growth premium: Sorting or learning?. *Regional Science and Urban Economics*, 48, 168-179.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In *Handbook of regional and urban economics* (Vol. 4, pp. 2063-2117). Elsevier.

Edin, P. A., & Gustavsson, M. (2008). Time out of work and skill depreciation. *Industrial and Labour Relations Review*, 61(2), 163-180.

Glaeser, E. L., & Mare, D. C. (2001). Cities and skills. *Journal of Labor Economics*, 19(2), 316-342.

Gould, E. D. (2007). Cities, workers, and wages: A structural analysis of the urban wage premium. *The Review of Economic Studies*, 74(2), 477-506.

Gregg, P., & Tominey, E. (2005). The wage scar from male youth unemployment. *Labour Economics*, 12(4), 487-509.

Jimeno, J. F., & Rodriguez-Palenzuela, D. (2002). Youth unemployment in the OECD: demographic shifts, labour market institutions, and macroeconomic shocks. *ECB Working Paper*, No. 155.

Mroz, T. A., & Savage, T. H. (2006). The long-term effects of youth unemployment. *Journal of Human Resources*, 41(2), 259-293.

Narendranathan, W., & Elias, P. (1993). Influences of past history on the incidence of youth unemployment: empirical findings for the UK. *Oxford Bulletin of Economics and Statistics*, 55(2), 161-185.

Nordstrom Skans, O. (2011). Scarring effects of the first labor market experience. *IZA Discussion Paper*, No. 5565.

Ramos, R., Nicodemo, C., & Sanromá, E. (2015). A spatial panel wage curve for Spain. *Letters in Spatial and Resource Sciences*, 8(2), 125-139.

Roca, J. D. L., & Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1), 106-142.

Rosenthal, S. S., & Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In *Handbook of regional and urban economics* (Vol. 4, pp. 2119-2171). Elsevier.

Ryan, P. (2001). The school-to-work transition: a cross-national perspective. *Journal of Economic Literature*, 39(1), 34-92.

Simón, H. J., Ramos, R., & Sanroma, E. (2006). Collective bargaining and regional wage differences in Spain: An empirical analysis. *Applied Economics*, 38(15), 1749-1760.

Yankow, J. J. (2006). Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. *Journal of Urban Economics*, 60(2), 139-161.

Guo, N. (2014). The Impact of an Early Career Recession on Schooling and Lifetime Welfare. *Publicly Accessible Penn Dissertations*, 1300.