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THE FIRM SIZE WAGE PREMIUM: A QUANTILE ANALYSIS

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Abstract

Empirical evidence shows that larger firms pay higher wages than smaller ones. This wage premium is called the *firm size wage effect*. The firm size effect on wages may be attributed to many factors, as differentials on productivity, efficiency wage, to prevent union formation, or rent sharing. The present study uses quantile regression to investigate the firm size wage effect. By offering insight into who benefits from the wage premium, quantile regression helps eliminate and refine possible explanations. Estimated results are consistent with the hypothesis that the higher wages paid by large firms can be explained by the difference in monitoring costs that large firms face. Results also suggest that more highly skilled workers are more often found at larger firms.

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Empirical evidence shows that larger firms pay higher wages than smaller ones. This wage premium is called the *firm size wage effect*. The firm size effect on wages may be attributed to many factors. It may be true that workers hired by large firms are more productive than those hired by small firms (Brown and Medoff, 1989; and Evans and Leighton, 1989). It may be more difficult to monitor the labor force at large firms; this may make employers willing to pay higher wages to guarantee an *efficiency wage* (Oi, 1983; Akerlof, 1984; Yellen, 1984; and Kruse, 1992). Large firms may pay higher wages than smaller ones because they want to prevent union formation (Kahn and Curme, 1987; and Donohue and Heywood, 2000); they may even be able to share their profits with workers (Brown and Medoff, 1989; Oi and Idson, 1999). In fact, each of these factors could contribute partially to the differences observed between wages paid by large and small firms. The present study uses quantile regression to investigate the firm size wage effect. By offering insight into who benefits from the wage premium, quantile regression helps eliminate and refine possible explanations.

A common problem that investigators face when studying wage formation is the heteroscedastic behavior of the wage distribution (Brown and Medoff, 1989). Following Evans and Leighton's (1989) suggestion, Oi and Idson (1999) tried to divide the sample into different classes to lessen this effect. Quantile regression accomplishes a similar task in a more efficient way, using all the information available from the total sample[1]. All the observations are ultimately playing a role in the maximization problem that defines the choice of the estimated parameters at each quantile. However, the weights that these observations have over the total function varies according the target conditional quantile. Therefore, the outliers have smaller effects overall.

Estimated results are consistent with the hypothesis that the higher wages paid by large firms can be explained by the difference in monitoring costs that large firms face.

[1] "We have occasionally encountered the faulty notion that something like quantile regression could be achieved by segmenting the response variable into subsets according to its unconditional distribution and then doing least squares fitting on these subsets. (…) It is thus worth emphasizing that even for the extreme

Results also suggest that more highly skilled workers are more often found at larger firms.

In the next section, I present and examine different theories of the firm size wage premium. Section 2 describes the data set to be used and presents demographics for the sample selected for use in this study. A succinct explanation of the quantile regression method and a comparison between the results of ordinary least squares and quantile regression are the subject of section 3. In addition, this third section analyzes the potential reasons for the existence of the firm size wage effect and what we can conclude based on the quantile regression approach. Finally, in the last section, I summarize the results and note several conclusions.

1 - Firm size wage premium theory and applications

Using data from Italian workingwomen in textile mills, Moore (1911) related the existence of a wage premium for those who work in larger plants. A plethora of subsequent studies have been conducted in order to investigate the motives large firms have for paying higher wages to their employees. From the skills differences among workers to rent sharing and avoidance of unions' formation, different explanations have been offered and empirically tested. However, consensus has not yet been reached. In order to understand how each explanation can be linked to the firm size wage premium, this section examines the main models and theories used in several previuos studies.

Before entering into an explanation of the firm size wage premium, a modeling of the firm size distribution is valuable. Lucas (1978) based his model of the firm size distribution on the study of Kihlstrom and Laffont (1979)[2]. His model is specific to closed economies, with a fixed amount of capital and labor, which is homogeneous with respect to workers' productivity. The innovation of his study is the inclusion of a variable called *management talent* for each individual. Lucas assumes that the management talent of an entrepreneur determines the achievable firm size.

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quantiles all the sample observations are actively in play in the process of quantile regression fitting." Koenker and Hallock (2001).

[2] Calvo and Wellise (1980) use the Lucas model to incorporate age and learning effects.

Suppose there is a closed economy with N units of labor and K units of homogeneous capital. The combination of these factors yelds Y units of homogeneous output. The key assumption of the Lucas' model is the existence of a continuum of agents, with their talent following a Γ distribution. Functions *n(x)* and *k(x)* describe the endowments for each individual *x.* Given their abilities, each person chooses to be an entrepreneur or a worker. Individuals who have potential profits as entrepreneurs, π, that are higher than the competitive market wage rate, w, will comprise the management. Those with lower ability earn more as employees than they would as managers, and therefore they are the workers class. Consider $z>0$ *as* the cutoff point, from which individuals decide if they are able to be managers or workers. One key assumption of his model is the separation between the production technology, represented by *f(n,k)*, and the managerial knowledge, the $x\, g\, [\, f,\, k\,]$[3].

Giving a constant return technology, $f(n,k) = n\phi\left(k/n\right)$, an efficient allocation of resources and labor force will maximize the output represented by

$$\frac{Y}{N} = \int_z^\infty xg[f(n(x),k(x))]d\Gamma(x) \tag{1}$$

subject to two feasibility conditions:

i) The number of workers plus the number of entrepreneurs is less than or equal to the total population:

$$1 - \Gamma(z) + \int_z^\infty n(x)d\Gamma(x) \leq 1$$

ii) The capital utilized is less than or equal to the total available capital:

$$\int_z^\infty k(x)d\Gamma(x) \leq \frac{K}{N} = R$$

The solution to Equation (1) gives the multipliers w, the equilibrium wage rate, and u, marginal return of capital. The entrepreneur income comes from the residual

[3] Here, x represents the managerial skill and g is the span of control over it.

between the revenue subtracted from the total wages and total capital rent, mathematically expressed by

$$xg[f(n(x),k(x))]-wn(x)-uk(x) \tag{2}$$

Maximization of Equation (2) permits the determination of the optimal firm size. Using the first-order condition in relation to capital, we have

$$xg'(f)f_k(n(x),k(x))=u \tag{3}$$

and, substituting $f(n,k)=n\phi(r)$, where $r={k}/{n}$, we get

$$\frac{\phi(r)-r\phi'(r)}{\phi'(r)}=\frac{w}{u} \tag{4}$$

Equation (4) shows that the ratio of factor prices determines the capital-labor ratio for the firms. Substituting Equation (4) into Equation (3), we have

$$xg'[n(x)\phi(r)]\phi'(r)=u \tag{5}$$

The implicit function *n(x,w,u)*, that is the optimal level of employment. Using the cutoff value z and that $k(z)=rn(z)$ for all managers:

$$zg[n(z)\phi(r)]=w+(w+ur)n(z) \tag{6}$$

Equation (6) is a zero profit condition: *average cost = price.* Using this condition, that is based on the production factors prices, managerial talent and the production function, it is possible to determine the optimal firm size by its level of employment, *n.*

Oi (1983) extends the Lucas model to suggest that, besides the management talent of the entrepreneur, monitoring costs influence the achievable firm size. Each manager has to solve the following equation:

$$T=\lambda H=\lambda(\overline{H}-hN) \tag{7}$$

where T is the manager production, λ is the manager ability, and H is the result of the fixed time endowment minus the total time required to monitor workers. Therefore, an increase in the number of workers, N, will cause a decrease in the total manager production, since an increase in workers means an increase in the time the manager spends monitoring them.

Equation (7) determines the optimal firm size. This size depends both on the entrepreneur's management talent and the time required to monitor workers. Factors λ and *h,* the time required to monitor each worker, establish the manager production and set limits on firm growth. Oi explicitly derives how the substitution of labor by capital could decrease the need for monitoring and make an increase in firm size possible.

Monitoring costs are one of the most cited reasons for the firm size wage premium. Workers who have more ability would require less monitoring, and therefore lower costs. By this reasoning, they would deserve better wages. Empirical evidence shows that larger firms hire workers who are more able. Therefore, the difference in their abilities, which influences monitoring costs, would result in higher remuneration of their work compared to small firms' workers.

The efficiency wage theory can also be linked to the monitoring problem. According to this theory, workers would receive wages higher than the optimal competitive level and can be monitored with less cost. The cost of involuntary unemployment, raised along with wages, discourages employees shirking even without close monitoring. Akerlof (1984) presents different paradigms that justify efficiency wages. The most elaborate is the dual labor market hypothesis (Doeringer and Piore, 1971). Suppose the economy supports two types of jobs: the primary and the secondary sectors. The primary sector workers are well remunerated, have stability, low quit rates, a schedule of promotions, and investment in their human capital. The secondary sector counterparts suffer the opposite: low wages, instability, high quit rates, little chance of promotion, and low human capital investment. Since workers prefer the primary sector, but its opportunity is not available to all of them, the wage paid by the primary sector is higher than the competitive wage. However, the higher wage acts as an efficiency wage for workers who do not want to be forced into a secondary sector job, and guarantees worker productivity without high levels of monitoring.

Gibbons (1992) presents the efficiency wage hypothesis the light of game theory. Suppose there is a repeated game in which firms have to set wages and workers decide how much effort to spend on their professional activities. A given firm offers wage w^*

and the worker can accept it or remain self-employed. Given his/her acceptance, the next step is to decide the amount of effort this worker will supply. The optimal effort is defined by the present value of the worker's payoff:

$$V_e = {(w^* - e)}\big/{(1-\delta)} \tag{8}$$

where e is the level of worker's effort, and δ is the discount rate. If the worker shirks and is caught, then he/she will lose his/her job and receive a lower wage forever[4]. There is a probability *(1 – p)* of being caught shirking. Therefore, the present value of shirking is:

$$V_S = {[(1-\delta)w^* + \delta(1-p)w_o]}\big/{(1-\delta p)(1-\delta)} \tag{9}$$

The worker's optimal behavior is to supply effort if $V_e \geq V_S$, so the present value of supplying effort matches or exceeds the present value of shirking. This decision depends on the probability of being caught and the wage offered. Therefore, firms should offer not only wages that compensate workers for his/her self-employment and disutility of working. It should also pay a wage premium, ${(1-\delta)e}\big/{\delta(1-p)}$, that makes shirking more costly to workers, given the possibility of losing his/her job.

Another explanation for higher wages at larger firms is the tendency toward avoiding workers' unionizing. There is some evidence that employers prefer to concede more benefits to their workers to prevent the formation of unions, because unions may lead to more difficult negotiating conditions over regular and overtime schedules of work, increase of wages, etc. Therefore, it is believed that some part of the firm size wage effect is related to avoiding unionization.

Brown and Medoff (1989) test this hypothesis. They believed that, if preventing unionization was a relevant aspect of firm size wage differentials, then this effect should be reduced for workers with a low probability of seeking unions. They verify that there is no significant difference between these workers and those with a higher propensity to seek unions. They conclude that, although efforts to avoid union formation are considerable, their effects are not reflected in the firm size wage effect.

Kahn and Curme (1987) argue that lower wage workers receive more benefits because firms fear unions. These workers have a higher propensity to join unions, since unions increase wages and reduce wage dispersion. Using CPS data, Kahn and Curme find evidence that, under union threat, nonunion wage dispersion decreases, implying that the lower end of wage distribution is the major beneficiary of this threat. Donohue and Heywood (2000) use the same methodology as Kahn and Curme (1987) and incorporate the hypothesis that workers support union formation only if they believe their employment conditions, i.e. to continue to be employed at the same or better level, will be sustained. Donohue and Heywood question whether low-wage workers have lower marginal productivity and, therefore, would be the first to be dismissed in the case of union formation. Their empirical findings partially support the view that the firm size wage premium derives from avoidance of union formation. For the higher and lower ends of the wage distribution, unions are not a positive influence on wages or employment, respectively.

Several authors[5] verified that wages paid in the same establishment are positively correlated. If in some establishment, blue-collar workers receive wages above the average, white-collar workers will also receive higher remuneration. This positive correlation would imply that firms with higher ability to pay prefer to *share their rents*.

Katz and Summers (1989) use data from 74 industries to measure the negative correlation between wages and quit rates. They argue that the industry wage structure can be explained by labor rents. In this case, the firm size wage effect is the representation of the ability of wealthier employers to pay higher wages.

A final explanation for the firm size wage premium is the working conditions differential between larger firms and smaller ones. Larger firms may be more likely associated with adverse working conditions. The dissociation of the labor force from the entire production process is considered to cause larger losses in the utility of those

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[4] By assumption, a worker has the possibility of working at this unique firm or being self-employed.
[5] Slichter (1950), Katz and Summers (1989), and Weiss (1966), for example.

working[6]. Working in larger firms could make it more difficult to meet people and build relationships with them, since larger firms can create a more impersonal work atmosphere. A way to test this hypothesis is to include information about employees' levels of pleasure in working[7] or including very detailed occupational variables. Brown and Medoff (1989) do not find evidence to support the working conditions hypothesis.

In the next sections, I will present the Ordinary Least Squares (OLS) and Quantile Regression estimates of the firm size wage premium. Using the 1999 CPS and the 1998 NLSY, I will test and analyze the hypotheses presented in this section. The hypothesis of paying a wage premium to avoid unionization will be tested by the inclusion of a union indicator. If this inclusion modifies significantly the firm size or/and plant size variables, a share of the explanation may be attributed to this cause. The rent sharing, the working conditions and the workers ability differential theories will be tested by the inclusion of industries and occupations indicators. Better the specification of the wage equation, lower is expected to be the firm size wage effect. Using the NLSY98 data, the ability differential among workers will be tested using the variable ASVAB, which represents the respondents results to the Armed Services Vocational Aptitude Battery. Finally, the monitoring cost idea will be analyzed in the light of the descriptive characteristics of the quantile regression method. Having different magnitudes and significance levels for the different quantiles may indicate returns specifically for the workers who deserve higher or lower degree of monitoring on their work. For instance, it will be seen on the next sections, when analyzing the CPS99 results, that the lower conditional quantiles receive higher returns for firm size than the upper quantiles. This result may be indicating that the workers who deserve more monitoring, the ones located at the lower quantile, receive an efficiency wages.

[6] Usually, microeconomics considers *leisure* as a good and *work* as the opposite. However, in practice, workers can increase their level of utility by doing something they like. Inability to control the whole process of production is generally considered to decrease the utility of work. An alternative way to understand this effect is by considering that work always causes disutility. Still, the dissociation of the entire process causes a larger disutility to the worker.

[7] The CPS does not include questions referring to this aspect of working.

2 - Data and Demographics

Two datasets are used in the present study: the Current Population Survey (CPS) and the National Longitudinal Survey of Youth (NLSY). The latter database has fewer observations and a more restricted sample than the former, since it includes only persons that were between 14 and 21 years old in 1979, however some of its features are relevant to this investigation, such as its panel structure and more specific questions.

The U.S. Census Bureau conducts the Current Population Survey (CPS) monthly. It interviews over 50,000 households and gathers information on various areas of interest such as: education, labor force status and participation, demographics, and others. The sample used in the present study is the March 1999 Survey. Although this study uses only the March 1999 Survey, the March files have existed since 1962 and they contain the Annual Demographic File and the Income Supplement. While the March file has changed some of its questions over the years, different years of the March file are recommended for wage analysis because this series combines demographic information[8] and details about labor force participation[9]. The March 1999 CPS file is especially interesting for the present study since it contains a specific firm size variable, divided in six categories: fewer than 10 employees, between 10 and 24 employees, between 25 and 99 employees, between 100 and 499 employees, between 500 and 999 employees, and 1,000 or more employees.

Table 1 presents some demographic information for the sample. The first column describes the most general sample. It contains 29,513 observations for men, between ages 20 and 60, inclusive. The average individual is 39 years old, with an annual income of 39,067 dollars. He is white, completed high school, and is married. A large portion of the sample, 39.5%, works in a firm with 1,000 or more employees. The second column restricts the sample to full-time workers[10] and those who were engaged in the labor force for at least 48 weeks per year. In this second sample, 24,233 men are included. Age, race,

[8] For instance: age, race, education, marital status, residence area, etc.
[9] Such as: wages, industry, occupation, firm size, etc.
[10] Full time workers are the ones who work at least 35 hours per week.

educational profile, and firm size participation remain similar to those in the first sample. The average annual income, increased as expected, to 43,614 dollars per year.

Finally, the sample that will be used in this investigation restricts the individuals to those who earn at least 4 dollars per hour and are not top coded by their income[11]. The variable hourly wage is constructed by dividing annual wage and salary income by the number of hours usually worked per week multiplied by the number of weeks worked last year[12]. This sample is based on 23,292 observations of men between 20 and 60 years old, inclusive, full-time workers, and who worked during at least 48 weeks in the year before the interview. The average individual in this sample is 39 years old, white, married, and did not complete a college degree. The mean hourly wage in the sample is $18.75.

Firm size is a variable is divided into six categories, according to the total number of employees in all organization plants[13]. As cited before, the categories are: fewer than 10 workers, 10 - 24 workers, 25 - 99 workers, 100 - 499 workers, 500 - 999 workers and 1,000 or more workers[14]. In the final sample, roughly 37% of the respondents work for firms with fewer than 100 employees. The majority of the other 63% of the sample work for firms with 1,000 or more employees (41%).

The National Longitudinal Survey (NLS) is a study sponsored by the Bureau of Labor Statistics. It is composed by a set of surveys designed to gather information at several points in time on the labor market experiences of diverse groups of men and women. From the six NLS samples, the one used in this study is the National Longitudinal Survey of Youth (NLSY), with a sample of boys and girls that were

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[11] The importance of restricting the wages to those equal or higher to some minimal amount, in this case, four dollars, is to avoid errors in the answers. The majority of observations that were dropped had declared themselves to earn less than 7,000 dollars per year from wages and salaries and to work more than 35 hours per week, 48 weeks per year. I. e., to be full time workers who receive much less than the minimal wage. 684 observations were dropped because they had computed wages that were abnormally low. Concerning top coded observations, only 257 individuals declared receiving wages and salaries above the maximum wage declarable by CPS. Regressions were made including them and results are similar to the ones presented here at all.

[12] This calculation results in the hourly wage. The same method is used in other studies, for example Evans and Leighton (1989).

[13] Evans and Leighton (1989), and Oi and Idson (1999) report results with the inclusion of a plant size variable. This variable does not exist for the March files.

[14] These categories are valid after 1992. From 1962 to 1991, there were only 5 categories. The first one was “less than 25 workers”.

between 14 and 21 years old on the last day of 1978. The investigation of the respondent's labor force performance and attachment, and education and training investment are the main purposes of the NLSY. However, its actual content is much broader than that, including questions about military participation, vocational aptitude, school performance, alcohol and substance use, fertility, and child care.

For the present paper, three points about the NLSY must be highlighted. First, the NLSY contains variables that measure the implicit ability of each person in its sample. The NLSY respondents were tested following the Armed Services Vocational Aptitude Battery (ASVAB) criteria[15]. Either the results of these tests can be used to capture the ability of the respondent on specific subjects, or the raw and percentual scores may be used to obtain a measure of the respondent's "abilities" on general matters. This feature of NLSY is important to this study, since it constitutes the only variable that actually captures differences in workers implicit abilities. The inclusion of the ASVAB variable in the last specification of the wage equation indicates if the usual measures of skills make some difference on the wage differentials between firms of dissimilar sizes. Second, the panel structure of the NLSY may help to seize another kinds of influences that may lead to the firm size wage differences. Using panel data, a specific variable relative to each of the respondents is included in the regression and eliminates doubts about unobserved personnel differences influencing wage's formation. The panel structure of the NLSY helps the understanding of the same factor as the ASVAB variables. However, results differ since the use of a specific variable is different from the analysis made by the use of each individual response over time. The panel structure captures a lot more than the *ability* differences between each individual. It also computes personnel differences that cannot be sized by a particular variable. Finally, the NLSY contains two variables on the size of firms. One is the number of employees at the plant where the respondent works. In contrast to the CPS, the NLSY reports the actual number of employees, instead of an indicator variable. The other variable is an indicator for the size of the firm, which is also

[15] The ASVAB consists of a battery of tests that measure knowledge and skill in the areas of general science; arithmetic reasoning; word knowledge; paragraph comprehension; numerical operations; coding

informative. This variable assumes a value of 1 if the whole firm has more than 1,000 employees and zero otherwise. Therefore, using the NLSY data it is possible to infer both the plant size and the firm size effect over wages, which cannot be made using the CPS99, which does not contain a plant variable.

Table 2 reports the demographics for the NLSY98. Once more, the sample is restricted to men, however restrictions about income and hours of work are not made, since the number of observations is much lower than in the CPS sample. This youth sample is based on 1,919 observations of men between 34 and 41 years old, inclusive. The average individual in this sample is 36.7 years old, white, married, and did not complete a college degree. The mean hourly wage[16] in the sample is $17.96. The average number of workers at each plant is more than 2,000, and the majority of the sample works for firms with 1,000 or more employees (60.7%).

3 - Ordinary least squares and quantile regression: the empirical evidence

Much attention has been devoted to the firm size wage effect. Different methods and various datasets can be used with the same objective. While some authors use data from individuals or from firms to investigate the firm size wage effect, there is a more recent trend of using employer-employee matched data to do the same thing[17]. Although this is a valuable approach, the present paper will rely entirely on employee answers to investigate firm size, and it will be comparable with Brown and Medoff (1989), Evans and Leighton (1989) and Oi and Idsen (1999).

Using data from individuals[18] and establishments[19] separately, Brown and Medoff (1989) test the main hypothesis about the firm size wage effect. Using ordinary least squares estimation and appropriate corrections for unspecified heteroskedasticity, they conclude that the firm size wage effect exists even when grouping individuals by specific

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speed; auto and shop information; mathematics knowledge; mechanical comprehension; and electronics information. See NLSY79 User's Guide for more detail.

[16] NLSY reports the hourly wage.

[17] Haltiwanger, Lane, Spletzer, Theeuwes and Troske (1999) present a compilation of papers with estimatives concerning the firm size wage effect from matched data.

[18] As the Current Population Survey (CPS) and Quality of Employment Survey (QES).

[19] Namely: the Survey of Employer Expenditures for Employee Compensation (EEEC), the Wage Distribution Survey (WDS), and Minimum Wage Employer Survey (MWES).

characteristics (e.g., union status, industry), and that the effect comes both from the plant and from the firm size. They conclude further that the effect derives mainly from the higher quality of the workers, because they are not able to confirm the effects of unionization, better working conditions, higher ability to pay, smaller supply of labor or elevated monitoring costs that might have motivated the higher wages in larger firms.

Evans and Leighton (1989) use both the May 1983 CPS and the 1981 data from the National Longitudinal Survey (NLS) of Young Men to investigate the same effect. Their conclusions, based on ordinary least squares regressions and first differences estimators, are that the firm size wage effect exists and that the plant effect can be neutralized by properly controlling for the total number of employees at all sites. They also suppose that the reason larger firms pay higher wages is a matter of how they evaluate workers' characteristics; i.e., larger firms recruit workers with higher degrees of education and training, and the firm size wage effect is derived from this *selection of workers*.

Based on 1993 CPS data, Oi and Idson (1999) use a different approach to investigate the effect of firm size on wages: the bivariate association between firm size and selected variables. They estimate that a man with selected characteristics could earn an additional 45.2% working in a firm with 1,000 or more employees as he would have earned if he worked in a firm with fewer than 25 employees. Using the May 1983 CPS, in order to control for small and large establishment size, they conclude that the wage difference between larger and smaller firms could decrease to 27.8% if adequate controls are added.

These three studies conclude that the firm size wage effect exists and, for lack of stronger evidence toward another factor, that this difference between wages is generated by the higher skills of larger firms' workers. My paper will develop the idea of wage formation along the lines of these three previous studies.

The main innovation of this study is the use of quantile regression. By using this method, it will be possible to investigate the firm size wage effect along the conditional distribution of wages. The following sub-section reviews the ordinary least squares results and compares them with the findings from previous studies. After that, the second sub-section describes the quantile regression method and results.

3.1 - Ordinary least squares results

The objective of this paper is to better understand the effect of firm size on wages. The sample is restricted to men; between 20 and 60 years old, inclusive; full-time workers, i.e. working at least 35 hours per week; and those who were engaged in the labor force for at least 48 weeks during the year that precedes the CPS interview. Restrictions were also made by dropping individuals who earn less than four dollars per hour or are top coded by their wage and salaries' income[20]. The estimation of a wage equation based on two different methods, namely ordinary least squares and quantile regression[21], follows Equation 10:

$$\ln(wage) = \alpha + \sum_{i=1}^{13} \beta_i X_i + \sum_{i=1}^{6} \delta_i Z_i + \sum_{i=1}^{11} \phi_i Ind_i + \sum_{i=1}^{7} \varphi_i Occ_i + \sum_{i=2}^{6} \gamma_i FirmSize_i + \varepsilon \qquad (10)$$

where:

X_i represents age, age squared, indicator variables for race (Categories: white, black, and others. The excluded category is "white".), education (Categories: less than high school, high school degree, college dropouts, vocational degree, college degree, graduate degree, with the excluded category "less than high school".), and marital status (Categories: never married, married, separated, divorced, widowed. The excluded category is "married".);

Z_i represents indicator variables for central city status (indicator variable that equals 1 if the person resides in a central city (SMSA) and zero otherwise), region of residence (Categories are: northeast, north central, south and west. The excluded category is "south".), and union membership (indicator variable that equals 1 if the person is member of a union and zero otherwise);

Ind represents two-digit industry;

Occ represents one digit occupation;

[20] See Table 1.

FirmSize represents firm size indicators with 6 categories[22], with the excluded category "fewer than 10 employees".

Following the suggestions of Brown and Medoff (1989), the indicator for union membership, and the industry and occupation indicators were included one at a time, each inclusion representing a new specification. Results from a basic regression compared with the estimations that include the union indicator may shed light on the suspicion that large firms pay larger wages to prevent unionization of their workers. The additions of industry and occupation indicators imply a more direct control for labor quality, i.e. workers' unmeasured ability, and particular trends of specific industries and occupations. Table 3 presents the results for these three specifications.

Not much difference can be seen between the estimated coefficients from the alternative specifications. The return to the variable age, of approximately 5%, is positive and significant for all regressions. The concave behavior of the wage profile, is confirmed by the coefficient of age squared, which is negative and significant in all specifications. Expected results are reached for the race and education indicators. White males earn from 8 to 20% more than non-white males, while education has a positive and increasing return. Indicators for marital status show that married men, the excluded category, are better remunerated than non-married men[23].

The inclusion of the union membership indicator does not change the firm size indicators' estimated coefficients. Being a union member, as suggested by previous papers, has a positive effect on wages.

The final estimation in Table 3 is the most complete mean wage equation. Inclusion of industry and occupation categories does not alter the magnitude of the

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[21] Quantile regression coefficients and confidence intervals were estimated using S-Plus Package. The OLS results were estimated in Stata.

[22] The categories are:
1=fewer than 10 employees,
2=10-24 employees,
3=25-99 employees,
4=100-499 employees,
5=500-999 employees and
6=1,000 employees or more in all locations.
Excluded category: 1 = less than 10 employees.

coefficients on the demographic, residential, and union indicator very much. Nevertheless, there are some differences concerning the firm size wage premium. In columns 1 and 2, the firm size indicator for firms with 10 to 24 employees revealed a wage effect of 9%[24] in relation to those working in firms with fewer than 10 employees, the excluded category. The larger firm size indicator, i.e. for firms with more than a thousand employees, had an effect of 22%. Column 3 shows a stable estimated coefficient in the firm size wage effect for the category of firms with 10 to 24 workers of 9%, however, there is a decrease in the effect for larger firms employees, from 22 to 20%.

The NLSY98 was used to estimate the model specified in Equation (10). Given particular characteristics of these data, four specifications were tested. The first one includes age, age squared, indicator variables for race (Categories: white, black, and others. The excluded category is "white".), education (Categories: less than high school, high school degree, college dropouts, college degree, graduate degree, with the excluded category "less than high school".), and marital status (Categories: never married, married, separated, divorced, widowed. The excluded category is "married".); and indicator variables for central city status (indicator variable that equals 1 if the person lives in a central city (SMSA) and zero otherwise), region of residence (Categories are: northeast, north central, south and west. The excluded category is "south".). To deal with the plant and firm size wage effects, two variables were included. The first one is the logarithmic value of the actual number of employees at the plant where the respondent works[25]. To deal with the firm size, an indicator for firms that have more then 1,000 employees was included.

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[23] Several papers direct attention to the subject of wage differences between married and non-married men in the U.S. For example, see: Korenman and Neumark (1992), and Waite (1995).

[24] Firm size wage effect = $e^{\hat{\beta}_i} - 1$, where $\hat{\beta}_i$ is the estimated coefficient for each firm size category.

[25] Alternative regressions using the actual number of employees as the plant size, instead of the logarithmic of this value, were tried. Results remain similar, however the use of a logarithmic transformation is more intuitive, given that the larger the plant size, the lower the impact of an additional worker to the plant size wage effect. Since NLSY allows the quantification of employees, the use of a logarithmic transformation is welcome.

Following the same pattern revealed by the CPS99 results, not much difference can be seen between the estimated coefficients of the alternative specifications presented in Table 4. However, the significance of some variables varies widely between regressions. For instance, the variables age and age squared follow the expected behavior only in the first specification, the baseline regression. In the more complete version, the one that includes an ability measure, neither of these variables is significant. Concerning race, education and marital status, NLSY regressions reinforce the CPS results, where white males earn more than non-white males, education has a positive increasing return, and married men receive higher wages than non-married men.

The inclusion of the union membership indicator does not significantly change either the plant size variable or the firm size indicator' estimated coefficients. Being a union member, as suggested by previous papers, has a positive effect on wages.

The third estimation in Table 4 is the one that includes occupation and industry indicators in the wage equation. Inclusion of industry and occupation categories changes the magnitude of the coefficients of the education, union indicator (lower), and plant size variables. The plant size wage effect that was more than 2% decreases to 1.5% after this latter inclusion of variables. The effect on the firm size indicator does not change significantly.

The last column of Table 4 presents the results for the most complete estimation of the wage equation. The fourth specification includes a variable that measures the percent scores on the ASVAB test, described in the previous section. This variable was included with the intention of measuring part of the ability differential among respondents, and, with this, to separate this effect from the plant and firm size wage effects. Besides the unexpected results on the age and age-squared variables, the estimated coefficients for the other variables remain similar. Results for the plant size and firm size variables do not change much either in magnitude or significance. The plant size wage return is 1.4% and, the firm size, is roughly 5%.

Overall, ordinary least squares results confirm the previous findings of the existence of the firm size wage premium and encourages the use of a new approach to clarify reasons for the firm size wage premium. Linear regression cannot support or disprove some explanations that focus on preventing union formation, efficiency wage premiums, or employee monitoring, given the available variables from the data set. Differences in workers' abilities are the only explanations that can be currently assessed using the ordinary least squares regressions, particularly by the inclusion of occupation and industry indicators, and the ASVAB results, in the NLSY sample. A brief description of the quantile regression approach and its advantages compared to the linear regression follows, along with the description of results.

3.2 - Quantile regression approach and results

One of the challenging points of this study is the econometric tool used to analyze the firm size wage effect: quantile regression. Using the same principles that make the ordinary least squares result in the conditional mean estimation, Koenker and Bassett (1978)[26] introduced quantile regression as the estimator of the conditional quantile function. This innovative approach brings not only more explanatory power to the results when compared to the details captured by the least squares approach, but also decreases the influence of outliers in the estimations.

The least squares approach solves the minimization problem:

$$\min_{\beta \in \Re^p} \sum_{i=1}^{n} (y_i - x_i'\beta)^2 \tag{11}$$

Equation (11) results in the conditional mean function *E(Y|x)*. Quantile regression proceeds in the same way, directing its attention to the p-dimensional optimization problem:

$$\min_{\beta \in \Re^p} \sum_{i=1}^{n} \rho_\tau (y_i - x_i'\beta(\tau)) \tag{12}$$

[26] See also Koenker and D'Orey (1987), Koenker and Portnoy (1996), Buchinsky (1999), and Koenker and Hallock (2001). Novo (2000) has an intuitive and straightforward application.

Using linear programming methods, Equation (12) results in the conditional quantile functions. The ρ represents a loss function that can be calculated conditioned to each selected quantile τ, where $\tau \in (0,1)$[27].

Some benefits of quantile regression are especially interesting in the present study. Its low sensitivity to outliers is one. In the linear squares regression, the failure of the normality assumption, especially with outliers that result in a long-tail distribution, results in a poor estimation of parameters. Quantile regression estimations, imposing different weights on observations according to the quantile to be estimated, are robust even for cases with a distribution far from Gaussian. A second plus of quantile regression is its descriptiveness. OLS regression estimators, as a conditional mean estimation, present a result for the average point. Quantile regression opens the possibility of multiple estimators for the same variable depending on the targeted quantile.

These two advantages of quantile regression over OLS estimation have been highlighted for their importance in the present study. Even with the increased number of observations in the sample to be investigated, the income distribution does not follow a normal distribution. The presence of outliers and their influence on the estimations can be seen in the next section. The level of descriptiveness achieved by quantile regression helps us answer fundamental questions. For instance, quantile estimations are very good at answering the question of which workers benefit most from large firms' employment.

A final note about how to interpret the estimated coefficients: as in the OLS regression the interpretation of the coefficients is made by evaluating the partial derivative of the dependent variable, Y, with respect to one of the regressors, X_i. In quantile regression, the procedure is the same; only now, the partial derivative is of the conditional quantile of the dependent variable in relation to one of the independent variables, X_i. I.e., the interpretation comes from $\frac{\partial Y}{\partial X_i} = \beta_i(\tau)$, where τ represents the targeted quantile. However, the reader should keep in mind that the observation

[27] Robust standard errors are available to each quantile using the modified Barrodale and Roberts (1974) method, as described in Koenker and D'Orey (1987).

belonging to the $\tau - quantile$ in one conditional distribution may not belong to the same quantile with changes in its covariates (Buchinsky, 1998).

The wage equation, Equation (10), was estimated using the procedures explained in the previous section. Table 5 and Figures 1 - 3 present the results for the firm size indicators of the CPS99 sample. Table 6 and Figure 4 present the results for the NLSY98 sample[28], with regressions that include both the plant and firm size wage effects. For the both samples, the observable trend of decreasing return of plant and/or firm size, as the quantiles get higher, is the same for all sets of estimations; the variability is related to the confidence intervals in each specification.

Concerning the CPS99 sample, the trend for all regressions is a higher wage return in relation to the firm size variable for the lower quantiles and a lower return, even zero return, for the higher ones. The lower quantile, the 5%, has a return of 19% for the second firm size category and more than 30% for the sixth firm size category. The 95% quantile, the highest one estimated, has no significant returns, positive or negative, for any of the firm size categories. Figure 5 tries to show in a more intuitive way the CPS99 quantile regression results compared to the OLS estimations. Recall that the firm size variable is not continuous for the CPS, therefore we have one indicator variable for each different firm size category. On the vertical axes, we measure the firm size effect on wages. On the horizontal line we have the representation of the firm size variable, from firms that have between 10 and 24 employees, so called "firm size 2", to firms with more than 1,000 employees, the "firm size 6". The upper line represents the wage return to the firm size variable for the 5% quantile. The lower line represents the firm size wage return for the 95% quantile. This graph does not affirm that workers in larger firms receive lower wages than the ones at smaller firms. It is showing that the return to the firm size is larger for the workers belonging to the lower quantiles than for the ones workers on the higher conditional distribution.

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[28] Estimated coefficients for the other variables, for the samples of CPS99 and NLSY98, and results for regressions containing only the Plant Effect of the Firm Size effect are available upon request. Results do not change significantly from the ones presented here.

For the regressions that do not include occupation and industry indicators, specifications 1 and 2, the quantile regression results are significantly different from the OLS estimation for the majority of the quantiles. It is possible to notice that the return to firm size increases along with the number of employees that each category represents. For the category 2, firms with 10 to 24 employees, individuals belonging to the 5% quantile have wages 19% higher than the individuals in the same quantile that work for firms with fewer than 10 employees. For the 5% quantile, returns vary between 21%, for the category 3[29], to 37%, for the category 6, which includes firms with 1,000 or more workers.

The closer the estimations get to the 75% quantile, the more the results from the quantile regression approach the ordinary least squares estimates. Returns vary between 4 and 16% for this quantile, given each firm category in relation to the excluded one. At the 95% quantile, neither one of the categories present positive or negative returns to the firm size indicators.

The regression that includes occupation and industry indicators, specification 3, is different from the ordinary least squares estimation for the lowest and highest quantiles; however, for the middle quantiles, i.e., 50%, and 75%, results are not significantly different. Only for the firm size categories 4 and 6[30] are returns to firm size significantly different from linear regression results for the majority of the quantiles. For the latter category, workers in the lower quantile, 5%, have returns to firm size 34% higher than the individuals from the excluded category do. This return decreases as the quantiles get higher: for the 25% quantile, return is 29%; for the 50%, return is 26%; for the 75% quantile, return is 15%; and, for the higher quantile, 95%, the return is not significantly different from zero.

The NLSY98 sample maintains the results reached by the previous related regressions on the CPS99 sample. Figure 4 presents the results. In this figure, one can notice that the plant size effect follows a pattern similar to the one presented by the firm

[29] I.e., firms with 25 to 99 employees.
[30] I.e., firms with 1,000 or more employees.

size indicators on the CPS99 sample[31]. There is a positive and significant plant size effect on the lower quantiles for the specifications 1 and 2 that is reduced to zero on the 95% quantile. An interesting result is that, on the latter specifications, the plant size effect is significant only for the middle and upper quantiles, not being significant for lower end of the conditional distribution. The firm size wage effect, presented at the right side of Figure 4, only is significant and positive for the middle quantiles in all specifications.

Quantile regression estimations, by disaggregating the mean effect, make the analysis of the estimated results to be much deeper than when using OLS. A different return for each quantile in the same firm size category is inconsistent with the hypotheses of rent sharing and bad working conditions as possible explanations for the firm size wage premium. If this wage premium came from firms able and willing to pay more for their labor force, as the rent-sharing hypothesis predicts, we would expect a surplus to be paid to the higher quantile in each category and we cannot verify that this happens. According to the results presented before, the higher conditional quantile receives no significant return to the firm size variable, using the CPS results, or receives a smaller return than the lower quantiles, using the NLSY data. Without that surplus, this explanation can be dropped.

The suggestion that the firm size wage premium originates in bad working conditions is also not consistent with the findings. If worse labor conditions existed at large firms, all quantiles should receive a premium with an increase in firm size. However, the highest quantile, as described before, does not receive wage premiums at all.

The explanation that larger firms pay higher wages to prevent union formation is also not sustained by presented estimations, neither by ordinary least squares, as in Brown and Medoff (1989), nor by the quantile regression approach. The inclusion of a variable related to union membership does not significantly alter results to the firm size indicators. Therefore, the present study is also inconsistent with this hypothesis.

[31] It was suggested that the CPS firm size variable may be actually capturing the plant size instead of the number of employees at all locations. This cannot be tested here, however the NLSY98 results are consistent with this.

Many authors have cited differences in workers' abilities as the cause for the firm size wage effect if no other explanation can be found in the estimated models. However, the true skill of a worker is an implicit measure. It is not adequate to measure skill by education achieved, because persons with the same degree of education may have very distinct skills. The effort that workers take to complete their tasks, which could also imply a difference in skills, is also not easily measured.

Brown and Medoff (1989) use information about levels of responsibility as a measure of skill. They conclude that the firm size wage effect declines with an increase in skill level (for example, among white collar occupations such as managers and professionals). They also assume that any firm size wage effect stems from differences between large and small firms' abilities to measure workers' skills. This set of conclusions implies that blue-collar workers receive the premiums available at larger firms because their skills are more easily measured. In the present study, Figures 1-3 show those workers in the lower conditional quantile of the wage distribution can achieve a large impact on their own wages by working at a large firm. Thus, results presented here are in accord with the previous literature.

Although not the best way to measure skills or abilities, the differences between educational degrees in the firm labor supply is also used to this end. Evans and Leighton (1989) find evidence of higher skilled workers being employed at larger firms. They characterize *ability* by level of education and stability in a job. Table 7 presents the proportion and the frequency of workers at each degree of education classified by firm size based on the CPS sample. Results are similar to those from previous studies: the larger the firm, the larger the proportion of workers with college degrees or more. For firms with fewer than 10 employees, 29.7% of workers have college or graduate degrees. Firms with 1,000 or more employees have this estimative increased to 40%. The same rationale works for lower degrees of education as well. Only 6.2% of the workers who belong to a firm with 1,000 or more employees have less than a high school degree, in comparison to 17% for firms with fewer then 25 employees. Even if one chooses to measure ability by the imperfect variable of educational degree, there is some indication that more highly skilled workers are allocated preferentially to larger firms.

In the effort to better control for workers ability, the NLSY98 was used. Although it contains fewer observations than the CPS, this sample helps to explore whether better measures of workers ability change the conclusions, but can partially explain the difference on the wages among firms of different size[32]. The introduction of the plant size variable showed that the upper conditional quantile has positive returns to it, even if the return to the firm size variable is not significant.

As a final point, estimates shown in this paper suggest that the firm size wage premium can be partially explained as an efficiency wage to compensate for monitoring costs. Small firms can monitor their workers at lower costs than larger companies. Knowing this difference in the cost of monitoring, larger firms would pay larger wages to their employees in order to guarantee that they work efficiently with low supervision. As described in the first section, this *efficiency wage* both compensates workers for their lower supervision and imposes a larger penalty for those caught shirking. In addition, efficiency wage payment is an alternative for those firms whose monitoring costs are too high. The efficiency wage theory points out that workers who deserve more monitoring may receive higher wages as a way to incentive them to do their work better.

The employees who typically have their work monitored are at the lower quantiles. These workers have a direct superior who controls their production. The workers at the upper quantiles have more independence in the way they can act; monitoring their work does not necessarily mean *watching* the way the person is working. Instead, results signal the quality of their work.

The importance of quantile regression can be seen here. Using OLS, it is more difficult, if even possible, to conclude that low ability workers receive larger premiums for working in larger firms than workers at the opposite end of the distribution. The idea

[32] Appendix A shows the results for 6 different specifications of a wage equation estimation based on a NLSY panel sample. The inclusion of variables that capture the particularities of each individual, as it does a fixed effect regression, may clear the effect of a plant and firm size wage effect. Considering that the sample used on those regressions is adequate, results indicate that individual unobserved abilities play a greater rule than the one that can be assumed by OLS and quantile regressions conclusions.

of dividing the sample between blue-collar and white-collar workers and estimating their wage effects[33] was intended to check for the same aspects that quantile regression presents. However, with quantile regression, a more efficient way to consider the total information from the sample is achieved, since it uses the information from the entire distribution to estimate the coefficients for every quantile.

The results derived in this paper are consistent with at least two of the theoretical reasons discussed. The larger effects of the firm size wage difference apparently comes both from differences in workers' skills and from higher monitoring costs at larger firms. Both of these factors are accepted by other authors and verified with the quantile regression approach.

4 - Conclusion

The previous literature has not been entirely successful at analyzing the possible reasons for the firm size wage effect. Empirical applications to deal with the subject were restricted to ordinary least squares regressions and the analysis of the partitioned sample by characteristics. Brown and Medoff (1989) investigate different databases in a careful way with the objective of discovering the most influential causes of the firm size wage premium. They conclude that differentials between workers' abilities are responsible for the greatest part of this wage premium. Oi and Idson (1999) gather conclusions from several authors, at different periods, and also conclude in favor of the higher abilities presented by large firms' workers to justify the wage differential of these workers relative to those who are employed at small firms. Meanwhile, several authors argue in favor of avoidance of unions by large firms (Kahn and Curme, 1987), rent sharing (Katz and Summers, 1989), or efficiency wages (Akerlof, 1984; Yellen, 1984; and Kruse, 1992). The present study uses the Current Population Survey from March 1999 to investigate these hypotheses and employs an innovative technique for the analysis: the quantile regression approach.

[33] Brown and Medoff (1989) proceed this way. Evans and Leighton (1989) suggest a similar idea.

The use of quantile regression improves the previous analyses by allowing more of the sample information in the estimation of each coefficient and at the same time estimates coefficients for different points of the conditional distribution. One of the advantages of quantile regression is its low sensitivity to outliers. Even when the sample fails to fulfill the normality assumption, quantile regression, imposing different weights to observations according to the quantile to be estimated, has robust estimators. A second benefit of quantile regression is its descriptiveness. Quantile regression, opens the possibility of multiple estimators for the same variable depending on the targeted quantile, and portrays the behavior of the estimation for different points of the variable distribution. In contrast with linear regression estimators, quantile estimations permit a profound knowledge of the sample characteristics, by supplying conditional estimated coefficients at selected quantiles.

Skills or abilities are not easily measured, but with the available evidence, there is evidence consistent with the hypothesis that workers at large firms are better prepared to do their jobs. Monitoring costs are not explicit either. The conjunction of the results that better skilled workers are allocated to larger firms and that these workers receive differentiated wage premiums indicates that employees who deserve a higher degree of supervision[34] receive higher firm size wage premiums than the workers who do not need as much monitoring[35].

Examination of the data and regression results, especially the results pointed out by the panel data regressions, shows that it is possible to support the ideas that the differentials in workers' abilities and in the costs of monitoring play a relatively large role in the firm size wage effect. While the firm size wage premium varies from between 19 and 37% for the 5% conditional quantile, depending on the firm size indicator analyzed, returns are not significantly different from zero for the 95% conditional quantile for any of the firm size indicators. Results from quantile regression and its conditional quantile analysis reinforce the arguments in favor of monitoring costs and

[34] Usually the ones at the lower conditional quantiles.
[35] I.e., those at the higher conditional quantiles.

efficiency wages being paid by larger firms, and is not consistent with the hypotheses of rent sharing and poorer working conditions at those firms.

References

Akerlof, G.A. (1984) *"Gift Exchange and Efficiency-Wage Theory: four views"* American Economic Review (Papers and Proceedings), Vol. 74, pp. 79-83.

Barrodale, I. and Roberts, F. (1974) *"Solution of an overdetermined system of equations in the L_1 Norm"* Communications of the ACM, Vol. 17, pp. 319-320.

Brown, C. and Medoff, J. (1989) *"The Employer Size-Wage Effect"* The Journal of Political Economy, Vol. 97, Issue 5, pp. 1027-1059.

Buchinsky, M. (1998) *"Recent Advances in Quantile Regression Models: a Practical Guideline for Empirical Reseach"* Journal of Human Resources, Vol. 3, Issue 1, pp. 88-126.

Calvo, G. and Wellise, S. (1980) *"Technology, Entrepreneurs, and Firm Size"* Qurterly Journal of Economics, Vol. 95, pp. 663-78.

Doeringer, P. and Piore, M. (1971) *" Internal Labor Markets and Manpower Analysis"* Health Lexington Books. (book)

Donohue, S. and Heywood, J. (2000) *"Unionization and Nonunion Wage Patterns: Do Low-Wage Workers Gain the Most?"* Journal of Labor Research, Vol. 21, Issue 3, pp. 489-502.

Evans, D. and Leighton, L. (1989) *"Why Do Smaller Firms Pay Less?"* The Journal of Human Resources, Vol. 24, Issue 2, pp. 299-318.

Gibbons, R. (1992) *"Game Theory for Applied Economists"* Princeton University Press. (book)

Haltiwanger, J.; Lane, J.; Spletzer, J.; Theeuwes, J. and Troske, K. (1999) *"The Creation and Analysis of Employer-Employee Matched Data"* Elsevier Science B.V.

Kahn, L. and Curme, M. (1987) *"Unions and Nonunion Wage Dispersion"* Review of Economics and Statistics, Vol. 69, pp. 600-07.

Katz, L. and Summers, L. (1989) *"Industry Rents: evidence and implications"* Brookings Papers on Economic Activity, Microeconomics, pp. 209-275.

Kihlstrom, R. and Laffont, J. (1979) *"A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion"* Journal of Political Economy, Vol. 87, Issue 4, pp. 719-48.

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

Koenker, R. and D'Orey, V. (1987) *"Computing Regression Quantiles"* Applied Statistics, Vol. 36, Issue 3, pp. 383-93.

Koenker, R. and Hallock, K. (2000) *"Quantile Regression: an Introduction"* Department of Economics, University of Illinois at Urbana-Champaign. (forthcoming in the Journal of Economic Perspectives *"Symposium on Econometric Tools"*).

Koenker, R. and Pornoy, S. (1996) *"Quantile Regression"* Working paper, University of Illinios at Urbana-Champaign, ORWP number 97-0100.

Kruse, D. (1992) *"Supervision, Working Conditions, and the Employer Size-Wage Effect"* Journal of Industrial Relations, V. 31, Issue 2, pp. 229-49.

Korenman, S. and Neumark, D. (1991) *"Does Marriage Really Make Men More Productive?"* The Journal of Human Resources, v. 24, n. 2, pp. 282-307.

Lucas, R. (1978) *On the Size Distribution of Business Firms"* The Bell Journal of Economics, Vol. 9, Issue 2, pp. 508-23.

Moore, H. (1911) *"Laws of Wages"* Mackmillan. (book)

Novo, A. A. (2000) *"Openness and Money Growth: Dynamic Consistent Monetary Policy? And an Empirical Assessment with Quantile Regression"* Mimeog.

Oi, W. (1988) *"Heterogeneous Firms and the Organization of Production"* Economic Inquiry, Vol. 21, pp. 147-71.

Oi, W. and Idson, T. (1999) *"Firm Size and Wages"* in: Handbook of Labor Economics, Vol. 3, edited by O. Ashenfelder and D. Card, pp. 2165-2214.

Slichter, S. (1950) *"Notes on the Structure of Wages."* Review of Economics and Statistics, Vol. 32, pp. 80-91.

Waite, L. (1995) *"Does Marriage Matter?"* Demography, v. 32, n. 4, pp. 483-507.

Weiss, L. (1966) *"Concentration and Labor Earnings"* American Economic Review, Vol. 56, pp. 96-117.

Yellen, J. (1984) *"Efficiency Wage Models of Unemployement"* American Economic Review (Papers and Proceedings), Vol. 74, Issue 2, pp. 200-05.

Figure 1: Firm Size Effects, Specification 1

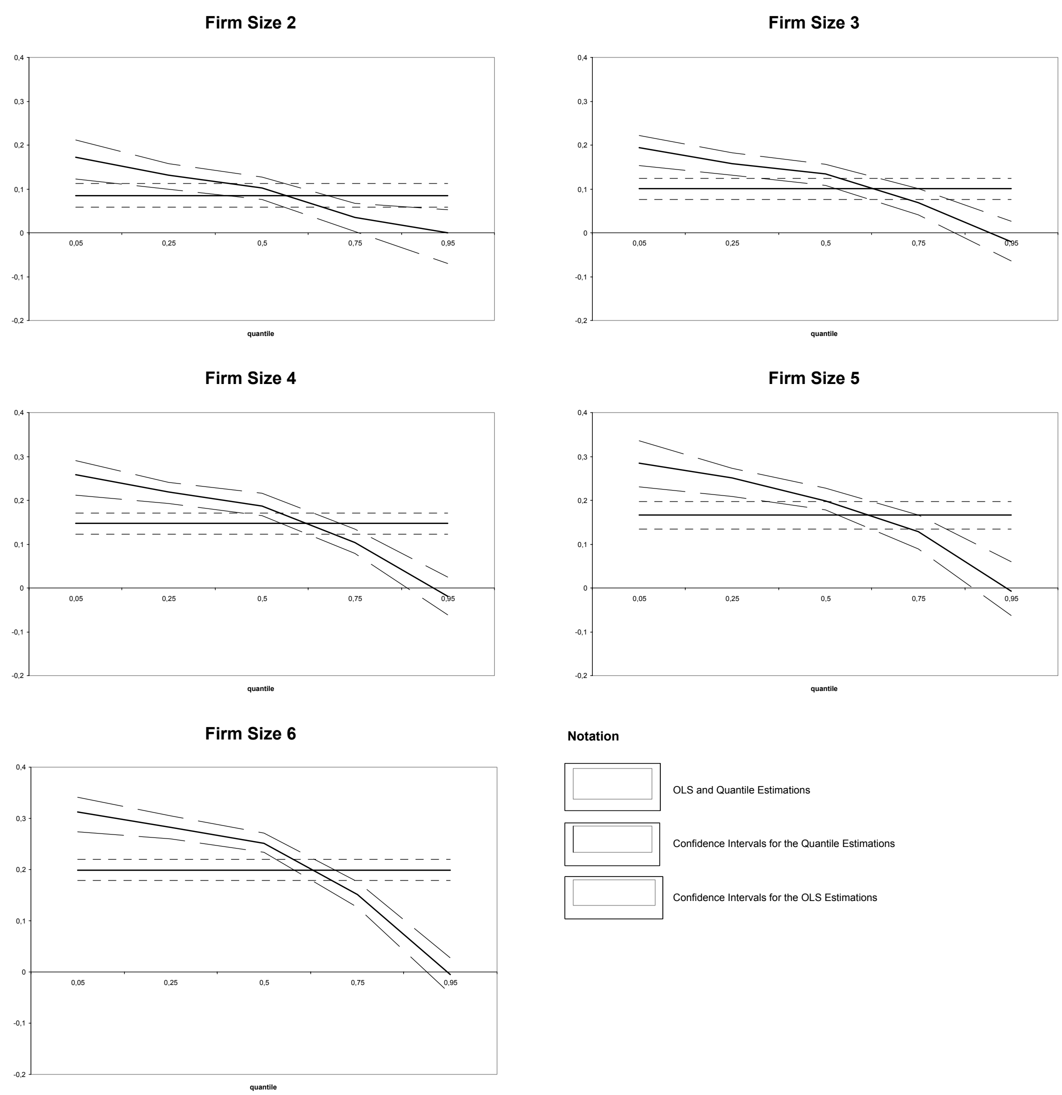

Figure 2: Firm Size Effects, Specification 2

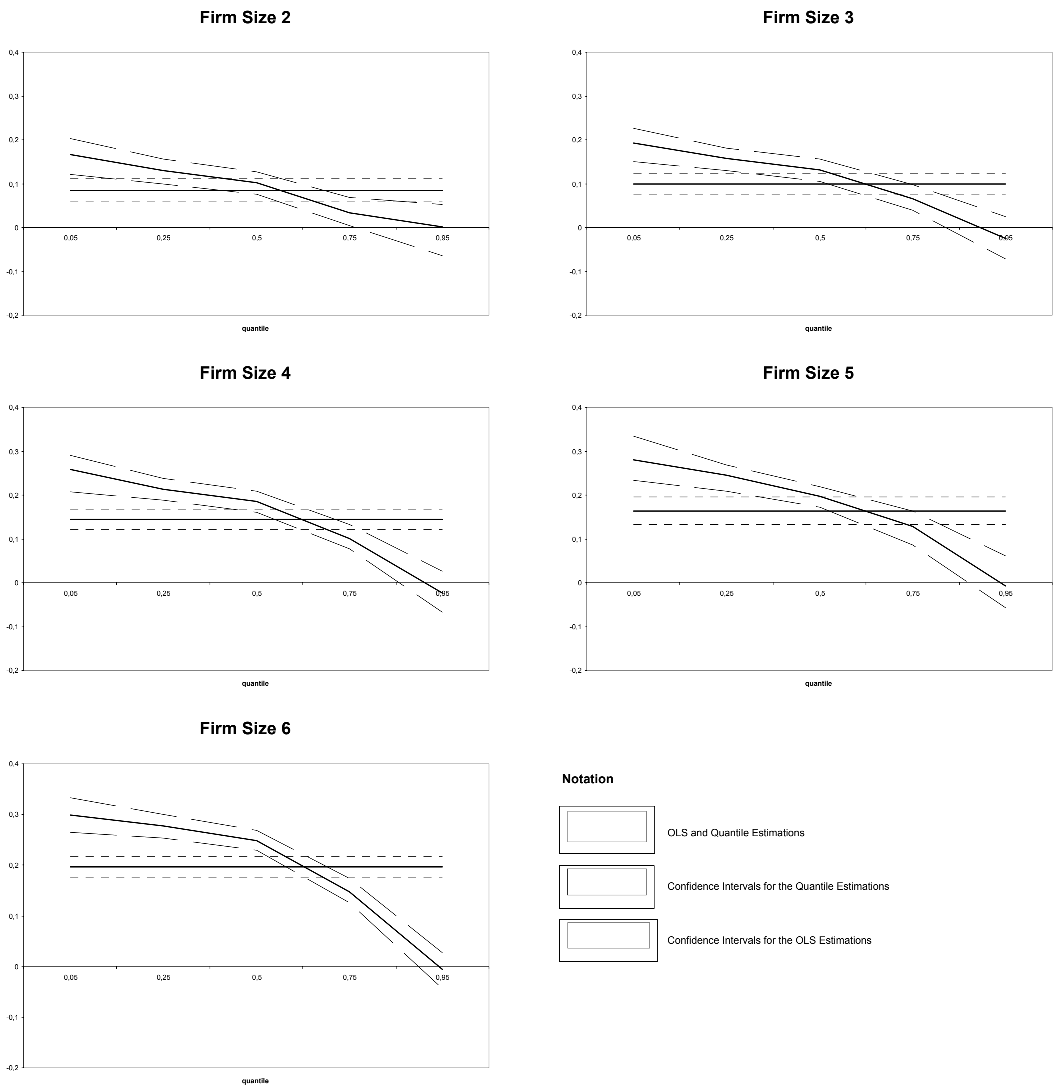

Figure 3: Firm Size Effects, Specification 3

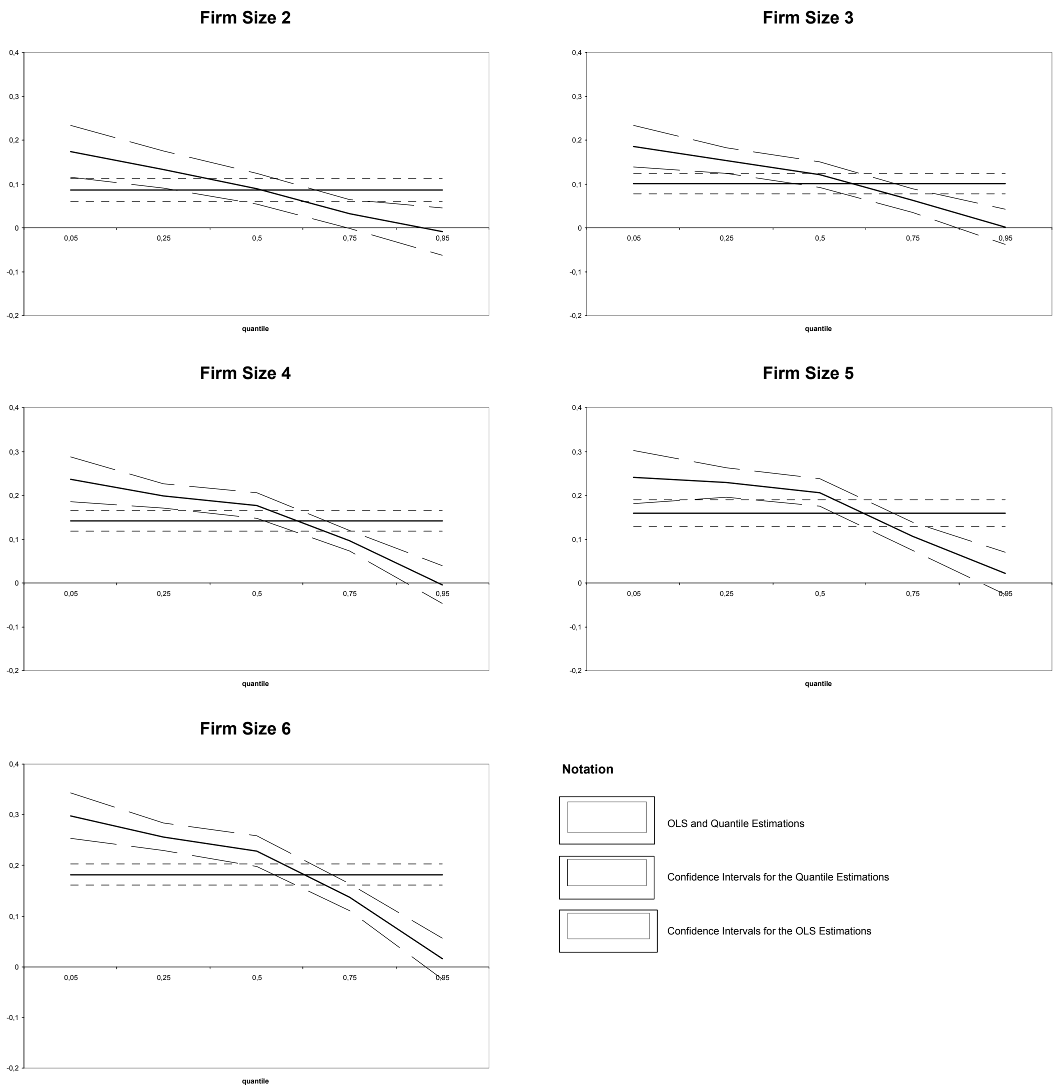

Figure 4: Ln(Plant) and Firm Size Specifications

NLSY 1998 Sample

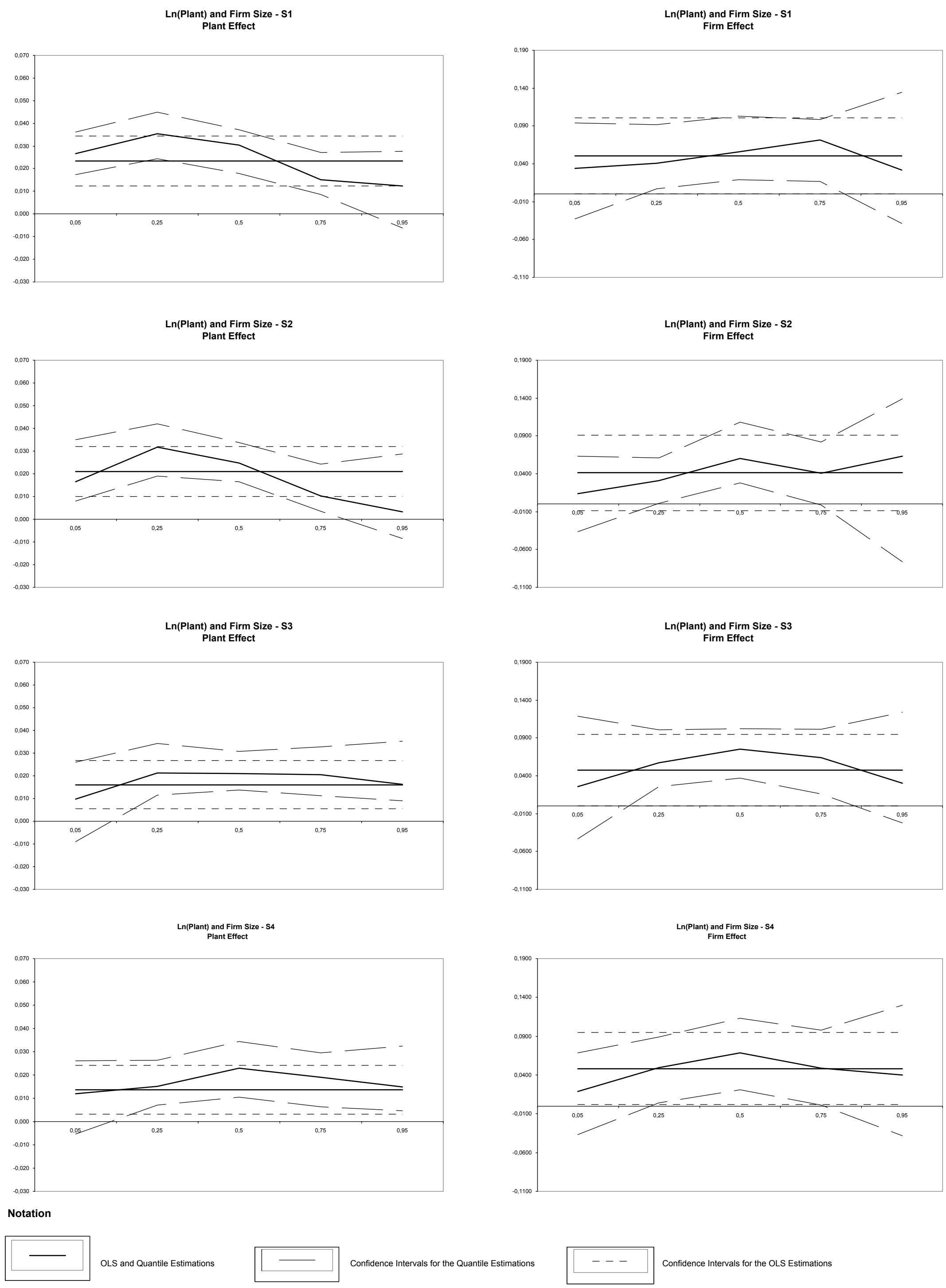

Figure 5: Conditional Quantiles Returns to Firm Size

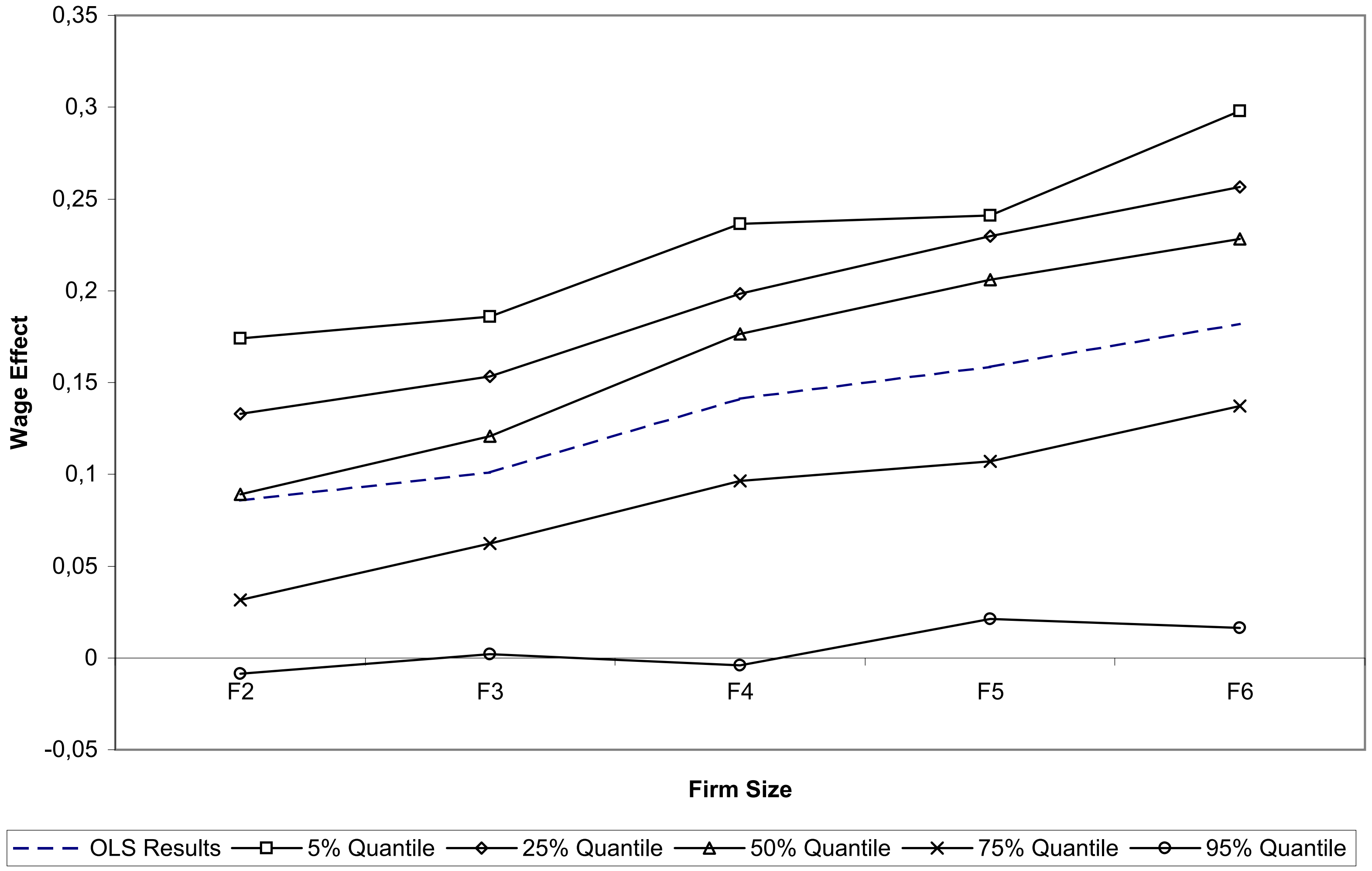

Table 1: Demographics CPS March 1999[1]

	Sample 1[2]	Sample 2[3]	Sample 3[4]
Age	38.55	39.39	39.47
	(.062)	(.065)	(.066)
Race: (%)			
White	.876	.882	.883
	(.002)	(.002)	(.002)
Black	.078	.074	.074
	(.002)	(.002)	(.002)
Others	.046	.044	.043
	(.001)	(.001)	(.001)
Education Attainment: (%)			
Less than High School	.128	.117	.114
	(.002)	(.002)	(.002)
High School Graduate	.318	.318	.319
	(.003)	(.003)	(.003)
Some College	.198	.183	.184
	(.002)	(.002)	(.002)
Vocational Degree	.044	.048	.048
	(.001)	(.001)	(.001)
College Degree	.221	.236	.238
	(.002)	(.003)	(.003)
Pos-College Degree	.091	.098	.097
	(.002)	(.002)	(.002)
Marital Status: (%)			
Never Married	.252	.207	.204
	(.003)	(.003)	(.003)
Married	.635	.679	.682
	(.003)	(.003)	(.003)
Separated	.019	.019	.018
	(.001)	(.001)	(.001)
Divorced	.090	.090	.090
	(.002)	(.002)	(.002)
Widowed	.004	.005	.006
	(.001)	(.001)	(.001)
Annual Income	39,067	43,614	44,052
	(239.58)	(268.53)	(270.38)
Hourly Wage	20.00	18.54	18.75
	(1.24)	(.106)	(.106)
Firm Size: (%)			
Less than 10 employees	.153	.140	.129
	(.002)	(.002)	(.002)
10-24 employees	.100	.095	.095
	(.002)	(.002)	(.002)
25-99 employees	.146	.144	.146
	(.002)	(.002)	(.002)
100-499 employees	.151	.154	.156
	(.002)	(.002)	(.002)
500-999 employees	.055	.057	.059
	(.001)	(.001)	(.002)
More than 1,000 employees	.395	.410	.415
	(.003)	(.003)	(.003)
Number of Observations	29,513	24,233	23,292

Notes: (1) Standard errors are in parentheses.
(2) Sample 1 composed by men, 20 to 60 years old, inclusive.
(3) Sample 2 restricted to those who were full-time workers and worked at least during 48 weeks in the year before the interview.
(4) Sample 3 restricted to those who earn 4 dollars/hour or more, and are below the income top code limit.

Table 2: Demographics NLSY 1998

	NLSY 98[1]
Age	36.70
	(.052)
Race: (%)	
White	.655
	(.011)
Black	.283
	(.010)
Others	.062
	(.005)
Education Attainment: (%)	
Less than High School	.089
	(.007)
High School Graduate	.439
	(.011)
Some College	.226
	(.010)
College Degree	.147
	(.008)
Pos-College Degree	.099
	(.007)
Marital Status: (%)	
Never Married	.191
	(.009)
Married	.630
	(.011)
Separated	.035
	(.004)
Divorced	.141
	(.008)
Widowed	.003
	(.001)
Hourly Wage	17.96
	(.383)
Plant Size	2,145
	(276.9)
Firm Size Indicator (more than 1,000 employees)	.607
	(.011)
Number of Observations	1,919

Notes: (1) Standard errors are in parentheses.

Table 3: Ordinary least squares results for wage regression (Equation 10)[1]
CPS99 Sample

	Specification 1[2]	Specification 2[3]	Specification 3[4]
Age	.052	.052	.046
	(.003)	(.003)	(.002)
Age Squared	-.0005	-.0005	-.0004
	(.00003)	(.00003)	(.00003)
Black	-.136	-.137	-.097
	(.013)	(.013)	(.012)
Other Races	-.088	-.087	-.066
	(.016)	(.016)	(.015)
High School Graduate	.267	.266	.213
	(.011)	(.011)	(.011)
Some College	.374	.373	.277
	(.012)	(.012)	(.012)
Vocational Degree	.431	.430	.325
	(.018)	(.018)	(.017)
College Degree	.598	.598	.420
	(.012)	(.012)	(.013)
Pos-College Degree	.844	.845	.644
	(.014)	(.014)	(.016)
Never Married	-.153	-.153	-.132
	(.009)	(.009)	(.009)
Separated	-.130	-.130	-.109
	(.024)	(.024)	(.023)
Divorced	-.107	-.106	-.096
	(.011)	(.011)	(.011)
Widowed	-.206	-.204	-.197
	(.045)	(.045)	(.043)
Union Member Indicator	-	.060	.076
		(.017)	(.016)
Firm 2 (10-24 employees)	.085	.085	.086
	(.014)	(.014)	(.013)
Firm 3 (25-99 employees)	.100	.099	.101
	(.012)	(.012)	(.012)
Firm 4 (100-499 employees)	.147	.145	.141
	(.012)	(.012)	(.012)
Firm 5 (500-999 employees)	.166	.164	.159
	(.016)	(.016)	(.016)
Firm 6 (>1,000 employees)	.199	.196	.182
	(.010)	(.010)	(.011)
Constant	.902	.906	1.02
	(.052)	(.052)	(.053)
Occupation's Indicators Included?	No	No	Yes
Industries' Indicators Included?	No	No	Yes
Adjusted R-Squared	.317	.317	.376
Number of Observations	23,292	23,292	23,292

Notes: (1) Standard errors are in parentheses.
(2) Baseline Regression
(3) Specification 2 includes the Union Membership Indicator in the Baseline Regression.
(4) Specification 3 includes Occupations and Industries' Indicators in the Specification 2.

Table 4: Ordinary least squares results for wage regression (Equation 10)[1]
NLSY98 Sample

	Specification 1[2]	Specification 2[3]	Specification 3[4]	Specification 4[5]
Age	.060 (.171)	.076 (.170)	.015 (.157)	-.059 (.155)
Age Squared	-.0006 (.002)	-.0008 (.002)	-.00001 (.002)	.0009 (.002)
Black	-.186 (.029)	-.194 (.028)	-.126 (.026)	-.060 (.028)
Other Races	-.008 (.050)	-.017 (.049)	-.019 (.046)	.049 (.046)
High School Graduate	.171 (.043)	.158 (.043)	.105 (.040)	.045 (.040)
Some College	.318 (.046)	.306 (.046)	.177 (.044)	.072 (.047)
College Degree	.622 (.050)	.641 (.050)	.409 (.051)	.255 (.056)
Pos-College Degree	.729 (.055)	.745 (.054)	.521 (.056)	.351 (.062)
Never Married	-.277 (.031)	-.262 (.031)	-.201 (.029)	-.192 (.029)
Separated	-.216 (.065)	-.203 (.064)	-.136 (.060)	-.136 (.059)
Divorced	-.173 (.034)	-.164 (.034)	-.141 (.032)	-.138 (.031)
Widowed	.026 (.207)	.031 (.206)	-.002 (.189)	-.020 (.188)
Union Member Indicator	-	.156 (.029)	.207 (.028)	.208 (.028)
ASVAB results	-	-	-	.003 (.0005)
Ln(plant size)	.023 (.005)	.021 (.006)	.016 (.005)	.014 (.005)
Firm Size Indicator	.051 (.026)	.041 (.026)	.047 (.024)	.048 (.024)
Constant	5.43 (3.14)	5.16 (3.12)	6.27 (2.89)	7.69 (2.87)
Occupation's Indicators Included?	No	No	Yes	Yes
Industries' Indicators Included?	No	No	Yes	Yes
Adjusted R-Squared	.286	.297	.406	.418
Number of Observations	1,919	1,919	1,919	1,919

Notes: (1) Standard errors are in parentheses.
(2) Baseline Regression
(3) Specification 2 includes the Union Membership Indicator in the Baseline Regression.
(4) Specification 3 includes Occupations and Industries' Indicators in the Specification 2.
(5) Specification 4 includes ASVAB results variable in the Specification 3.

Table 5: Quantile regression results[1] - CPS99 sample

	Specification 1[2]	Specification 2[3]	Specification 3[4]
Firm 2 (10-24 employees)			
.05 Quantile	.172 (.020)	.167 (.018)	.173 (.030)
.25 Quantile	.131 (.014)	.130 (.014)	.133 (.021)
.50 Quantile	.102 (.013)	.101 (.013)	.089 (.018)
.75 Quantile	.035 (.017)	.034 (.017)	.032 (.017)
.95 Quantile	-.001 (.027)	.001 (.026)	-.009 (.027)
Firm 3 (25-99 employees)			
.05 Quantile	.195 (.014)	.192 (.017)	.186 (.025)
.25 Quantile	.157 (.012)	.157 (.012)	.153 (.015)
.50 Quantile	.134 (.011)	.132 (.012)	.121 (.015)
.75 Quantile	.069 (.016)	.066 (.016)	.062 (.014)
.95 Quantile	-.021 (.024)	-.025 (.026)	.002 (.020)
Firm 4 (100-499 employees)			
.05 Quantile	.259 (.016)	.258 (.017)	.237 (.026)
.25 Quantile	.218 (.012)	.213 (.012)	.198 (.014)
.50 Quantile	.187 (.014)	.185 (.012)	.176 (.015)
.75 Quantile	.103 (.016)	.101 (.016)	.096 (.012)
.95 Quantile	-.019 (.023)	-.023 (.025)	-.004 (.022)
Firm 5 (500-999 employees)			
.05 Quantile	.285 (.026)	.281 (.027)	.241 (.031)
.25 Quantile	.251 (.012)	.245 (.012)	.230 (.017)
.50 Quantile	.199 (.015)	.197 (.011)	.206 (.016)
.75 Quantile	.128 (.019)	.128 (.018)	.107 (.016)
.95 Quantile	-.008 (.035)	-.007 (.035)	.021 (.025)
Firm 6 (>1,000 employees)			
.05 Quantile	.312 (.015)	.300 (.017)	.298 (.023)
.25 Quantile	.283 (.011)	.278 (.012)	.257 (.014)
.50 Quantile	.251 (.011)	.249 (.010)	.228 (.015)
.75 Quantile	.151 (.013)	.148 (.013)	.137 (.013)
.95 Quantile	-.043 (.017)	-.006 (.017)	.016 (.021)

Notes: (1) Standard errors are in parentheses.
(2) Baseline Regression
(3) Specification 2 includes the Union Membership Indicator in the Baseline Regression.
(4) Specification 3 includes Occupations and Industries' Indicators in the Specification 2.

Table 6: Quantile regression results[a] - NLSY98 sample

Panel A: Inclusion of plant size and firm size variables

	Specification 1[b]	Specification 2[c]	Specification 3[d]	Specification 4[e]
Ln(Plant Size)				
.05 Quantile	.027	.017	.010	.012
	(.005)	(.009)	(.008)	(.007)
.25 Quantile	.035	.032	.021	.015
	(.005)	(.005)	(.007)	(.006)
.50 Quantile	.030	.025	.021	.023
	(.003)	(.004)	(.005)	(.006)
.75 Quantile	.026	.010	.021	.019
	(.006)	(.007)	(.006)	(.005)
.95 Quantile	.012	.003	.016	.015
	(.008)	(.013)	(.010)	(.009)
Firm Size Indicator				
.05 Quantile	.094	.014	.026	.019
	(.031)	(.026)	(.047)	(.025)
.25 Quantile	.041	.031	.057	.050
	(.026)	(.015)	(.022)	(.020)
.50 Quantile	.056	.060	.075	.068
	(.024)	(.024)	(.014)	(.023)
.75 Quantile	.071	.041	.064	.049
	(.014)	(.021)	(.019)	(.025)
.95 Quantile	.032	.063	.030	.040
	(.052)	(.038)	(.048)	(.046)

Panel B: Inclusion of only plant size variable

	Specification 1[b]	Specification 2[c]	Specification 3[d]	Specification 4[e]
Ln(Plant Size)				
.05 Quantile	.026	.019	.012	.014
	(.006)	(.009)	(.007)	(.006)
.25 Quantile	.039	.035	.024	.020
	(.005)	(.004)	(.008)	(.005)
.50 Quantile	.036	.030	.027	.027
	(.003)	(.004)	(.005)	(.006)
.75 Quantile	.021	.014	.027	.021
	(.005)	(.006)	(.005)	(.005)
.95 Quantile	.013	.010	.021	.016
	(.010)	(.009)	(.007)	(.008)

Panel C: Inclusion of only firm size indicator

	Specification 1[b]	Specification 2[c]	Specification 3[d]	Specification 4[e]
Firm Size Indicator				
.05 Quantile	.059	.065	.036	.045
	(.046)	(.018)	(.044)	(.027)
.25 Quantile	.087	.079	.080	.059
	(.023)	(.016)	(.017)	(.022)
.50 Quantile	.109	.109	.107	.096
	(.017)	(.017)	(.012)	(.019)
.75 Quantile	.087	.061	.084	.075
	(.016)	(.017)	(.025)	(.017)
.95 Quantile	.050	.069	.045	.080
	(.048)	(.035)	(.063)	(.035)

Notes: (a) Standard errors are in parentheses.
(b) Baseline Regression
(c) Specification 2 includes the Union Membership Indicator in the Baseline Regression.
(d) Specification 3 includes Occupations and Industries' Indicators in the Specification 2.
(e) Specification 4 includes the ASVAB results in the Specification 3.

Table 7: Education distribution – CPS99 sample

PANEL A: Percentual of workers at each category

	Firm Size 1	Firm Size 2	Firm Size 3	Firm Size 4	Firm Size 5	Firm Size 6
Less than High School	.175	.165	.157	.137	.105	.062
High School Degree	.325	.374	.352	.338	.308	.287
College Dropouts	.162	.177	.175	.176	.159	.201
Vocational Degree	.041	.045	.047	.046	.059	.051
College Degree	.204	.177	.202	.222	.268	.277
Graduate Degrees	.093	.062	.067	.081	.101	.122
Number of Observations	2,996	2,202	3,403	3,626	1,367	9,698

PANEL B: Frequency of workers at each category

	Firm Size 1	Firm Size 2	Firm Size 3	Firm Size 4	Firm Size 5	Firm Size 6	Number of Observations
Less than High School	524	364	533	496	144	599	2,660
High School Degree	973	823	1,199	1,226	421	2,780	7,422
College Dropouts	485	390	596	638	218	1,952	4,279
Vocational Degree	124	99	161	167	81	490	1,122
College Degree	610	389	686	804	366	2,685	5,540
Graduate Degrees	280	137	228	295	137	1,192	2,269
Number of Observations	2,996	2,202	3,403	3,626	1,367	9,698	23,292

APPENDIX A

The National Longitudinal Survey of Youth has an additional feature that can be explored to understand better the firm size wage effect: its panel structure. Using the data from respondents that changed jobs between once during the period of 1986 and 1998, we estimated a fixed effect regression on six different specifications. Table A1 presents the results for these estimations.

Columns 1 and 2 show the results for regressions that included both the plant size variable[1] and the firm size indicator[2]. Results differ on these columns by the inclusion of occupations and industries indicators on the regression presented on column 2[3]. Columns 3 and 4 present the results for specifications that include only the plant size variable, without occupations and industries, and with them, respectively. Finally, columns 5 and 6 bare results for the estimations with firm size variable only. Once again, the former presents estimation results without the inclusion of the occupations and industries indicators and, the latter, with these additions.

The common point to all estimations is that neither the plant size nor the firm size effects are significantly different from zero. This result may indicate that what the literature calls firm size wage effect is the implicit ability among workers. Larger firms may be more capable to hire workers that are more talented and, for this reason, they pay higher wages to their labor force.

Because the panel sample used here is too restricted, both in the number of observations as in the sample selected, results may be analyzed with prudence. Additionally, quantile estimations for panel samples were not made on this study. Future developments of this paper will include the analysis of both subjects and, luckily, will clarify these conclusions.

[1] Following the previous estimations, the plant size variable is the logarithmic transformation of the actual number of workers at the respondent's plant.

[2] Which is the indicator that assumes value 1 if the total number of workers at all firm locations is equal of greater than 1,000 and zero otherwise.

[3] The union membership variable was not included on these regressions because it would reduce too much the number of observations, since the question that originates was first asked on 1988.

Table A1: Panel Results – NLSY 1986 to 1998

	S1[1,2]	**S2**[3]	**S3**[4]	**S4**[5]	**S5**[6]	**S6**[7]
Age	1.043	1.052	1.042	1.050	1.052	1.060
	(.059)	(.060)	(.059)	(.060)	(.059)	(.060)
Age Squared	-.022	-.022	-.022	-.022	-.022	-.022
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Single	-.113	-.099	-.110	-.097	-.105	-.091
	(.091)	(.091)	(.091)	(.091)	(.090)	(.091)
Separated	-.015	-.020	-.026	-.030	-.019	-.023
	(.190)	(.191)	(.190)	(.191)	(.190)	(.191)
Divorced	-.067	-.056	-.070	-.059	-.069	-.056
	(.137)	(.138)	(.137)	(.138)	(.137)	(.138)
Widow	-.909	-1.034	-.970	-1.08	-.996	-1.10
	(1.33)	(1.33)	(1.33)	(1.33)	(1.33)	(1.33)
Occupations Indicators?	No	Yes	No	Yes	No	Yes
Industries Indicators ?	No	Yes	No	Yes	No	Yes
Ln(Plant)	.025	.025	.019	.020	-	-
	(.015)	(.015)	(.014)	(.015)		
Firm Size	-.102	-.095	-	-	-.075	-.069
	(.063)	(.064)			(.061)	(.062)
Categories	1,213	1,213	1,213	1,213	1,213	1,213
# Observations	3,281	3,281	3,281	3,281	3,281	3,281

Notes:

1) Standard errors are in parenthesis.
2) S1 uses both the Ln(Plant Size) and Firm Size Indicator.
3) S2 uses both the Ln(Plant Size) and Firm Size Indicator. 2-Digit Industries and 2-Digit Occupations indicators are included.
4) S3 uses only the Ln(Plant Size).
5) S4 uses only the Ln(Plant Size). 2-Digit Industries and 2-Digit Occupations indicators are included.
6) S5 uses only the Firm Size Indicator.
7) S6 uses only the Firm Size Indicator. 2-Digit Industries and 2-Digit Occupations indicators are included.