Departamento de Economía
Facultad de Ciencias Sociales
Universidad de la República

Documentos de Trabajo

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Documento No. 17/11
Agosto 2011

ISSN 0797-7484

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*González Pampillón acknowledges financial support from the dECON: "Premio Nacional de Economía Profesor Raúl Trajtenberg: Beca de iniciación a la investigación". We thank Bethany McCain, Alvaro Forteza and Marisa Bucheli for discussion and suggestions. We also wish to thanks comments received at the Network of Inequality and Poverty (NIP) Reunión Anual Capítulo de Uruguay, at the XXIV Jornadas Econonomía - Banco Central del Uruguay 2009 and at the dECON 2009 Workshop. All errors are ours.

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Abstract

This paper analyzes the role of the sharply increases in the minimum wage after 2004 in Uruguay in the slight decrease on wage inequality. We find no impact of the miminum wage increases on wage inequality. This results can be explained by the low starting level of the minimum wage or lack of compliance with it. The Uruguayan experience shows that the minimum wage is not always effective as a redistribution instrument.

Keywords: minimum wage, wage inequality, IV, semiparametric estimation

JEL classifications: J20,J31, J38

Resumen

Este trabajo analiza el rol del importante aumento del salario mínimo a partir de 2004 en Uruguay en la leve caída en la distribución del ingreso. No encontramos impacto del aumento del salario mínimo en la inequidad salarial. Este resultado puede ser explicado por el bajo nivel inicial del salario mínimo o por la falta de cumplimiento del mismo. La experiencia Uruguaya muestra que el salario mínimo no es siempre efectivo como instrumento de redistribución del ingreso.

Keywords: salario mínimo, inequidad salarial, variables instrumentales, estimación semiparamétrica

Códigos JEL: J20,J31,J38

1 Introduction

Uruguay introduced the national minimum wage in 1969 in order to establish a wage floor for private workers over 18 years of age, with the exception of rural and domestic employees. The government has discretionary authority to set it. During the nineties we observed a gradual decline in the national minimum wage and simultaneously a tendency toward wage inequality, while after 2004 the minimum wage increased sharply and earnings inequality dropped (see the top panel in Figure 1). The real mimimum wage increased 154% between 2004 and 2009. This fact motivates us to address the question of the role of the minimum wage as a redistributive policy. In particular, we analyze whether the variation in the minimum wage (or "effective minimum wage") could explain the observed patterns in wage inequality in the Uruguayan labor market. In other words, the aim of this study is to find out if there is a causal relationship between the minimum wage and wage inequality.

From a theoretical perspective the impact of minimum wage on wage inequality could go in either direction. In the “competitive supply-and-demand model” the minimum wage choice implies trade-offs. On the one hand, a rise in the minimum wage could produce an increase in the wage of individuals who are in the lower tail of the earnings distribution. On the other hand, a minimum wage set above the “market-clearing price” could lead to an employment reduction usually called “employment effects” of the minimum wage, thus offsetting the gains and increasing inequality. In this context, the net effect depends on the magnitude of gains and losses which arise from each effect, and the labor market alternatives for those who become unemployed. Nevertheless, if the assumptions of the perfectly competitive model do not hold, the predicted results could change considerably. In contrast to the competitive model, when the employer has monopsony power, the predictions are conflicting. In this case, we expect an increase in employment and wages when minimum wage is set between the monopsony and the competitive level. In addition, the search and matching models, which are based on the assumption of the presence of frictions in the labor market that generates rents whenever a match between employee and employer occurs, do not predict job losses as a result of a minimum wage increase and what is more, it also contributes to a redistribution of the generated rent in favor of the employee (see Mortensen and Pissarides, 1994 and Boeri et al., 2008).Therefore, assessing the impact of the minimum wage increases on wage inequality is ultimately an empirical question.

Beyond the theoretical framework selected, institutional factors play a determinant role in assessment of the minimum wage and thus, making this kind of studies more complex. As institutional factors we refer to the level of enforcement of the minimum wage law (for instance, by monitoring and applying fees when is not fulfill), the level of compliance and the size of the informal labor market. There is no reason to expect minimum wage effects if there is not enforcement rules which control the fulfillment of the law. When there is a dual labor market, one formal and another informal, the rationale behind the minimum wage could be not as simple as in the one market case. Generally, the economic theory predicts that the displaced workers from the formal labor market, which are those with a marginal productivity below the minimum wage after it increases, go to the informal labor market. As a consequence of this reallocation of workers from the formal to the informal labor market, in this latter market wages tend to decrease and hence inequality rises. However, the empirical evidence is not in line with the latter theoretical predictions and in some Latin American (LA) countries wages in the informal labor market grow after a minimum wage increment. This phenomenon is usually called the "lighthouse" effect, that is, the minimum wage works as a reference wage in the informal sector so as to set a wage bargain.[1] This explanation is based on the assumption that informal workers have some bargaining power. Based on the idea that the increase in wages of the informal sector may be "induced by significant sorting and composition effects between the formal and the shadow sectors", Boeri et al. (2011) developed and test an alternative explanation.

In regard to the effect of minimum wage on wage inequality in Uruguay, González and Miles (2001) analyze the effect of a 56% decrease in real terms of the minimum wage (4.7% the yearly average) in the wage structure during the period 1986 -1997. Following a non-parametric quantile regression approach, they conclude that the decline in the minimum wage does not explain the increase in wage inequality. Furthmore, they observe an upward movement of the lower conditional quantile which implies a negative link between the lower tail of the distribution and minimum wage. They argue that this result could be explained by the effect of sector bargaining, or by the low level of compliance with the minimum wage. Instead of using the statutory minimum wage as a redistributive tool, the government employs it as a policy instrument to reduce (or control) government expenditure since it was indexed to social security variables such as unemployment insurance, pensions and income taxes. Between 1985 and 1991 the minimum wage that matters in terms of the wage structure resulted from a sectorial wage bargaining process between employers and employees. In 2005, with the introduction of the BPC (Bases de Prestaciones y Contribuciones) which is the new reference measure for social security benefits, the national minimum wage began to be used as a redistributive tool. Additionaly, the statutory minimum wage has increased

[1] Souza and Baltar, (1980) were the first in explaining and denoting this fact as "Efeito Farol" ("lighthouse effect"). Maloney and Nunez (2004) provide empirical evidence of this effect for LA countries.

dramatically since 2005.

Based on the previously described picture, this research seeks to analyze the effect of the minimum wage on wage inequality observed during the period 1996-2009. This period is particulary interesting because the national minimum wage dropped slighlty between 1996 and 2004 and after that it increased 153% in real terms between 2004 and 2009, 26% the yearly average. These facts provide us with a better identification strategy which is based on the variation of the relative minimum wage over time and across regions. It necessary to point out that between 1996 and 2004 the national minimum wage was not being used with redistributive purpose. After 2004, the national minimum wage was reintroduced as a redistributive policy and turned out to be an important feature in the labor market. Thus, our research could be considered an assessment of the contribution of the "new minimum wage" to wage inequality. In other words, we investigate the effectiveness of the recent increase of the minimum wage as a redistributive tool.

In order to analyze the impact of the minimum wage on inequality, we use the theoretical model proposed by Lee (1999). Lee developed a model which explains the theoretical relationship between percentile gaps (for instance the 10th - 70th percentile gap) across states and over time and the "effective" minimum wage (minimum wage less the 70th percentile). From an empirical point of view, the variation of the latter measure across states and over time enables him to identify the "latent" wage inequality that arises after accounting for the effective minimum wage. In the case of the United States, there is a national minimum wage, but each state also sets a federal minimum wage and therefore has the advantage of an additional source of minimum wage variation. In Uruguay, there is only a national minimum wage despite the fact of different costs of living across regions. Thus, our identification strategy is to focus on two possible sources of variation: 1) the variation of the national minimum wage across time, which as we mentioned experienced great variability in recent years; and 2) the oustanding variability of percentile gaps between and within regions. The percentile gap variation between regions emerges from the different living costs as mentioned above.

One important advantage of Lee´s methodology is that it takes into account spillover effects.[2] This fact is relevant for two main reasons: 1) some contracts are set as multiples of the minimum wage and 2) in 2005 the sector bargain was reinstated by the government and hence the minimum wage could be considered as the basis for negotiation. Despite Lee's treatment of the employment effect on the model, one possible limitation of this methodology is its capacity to account for it. The main problem is that this approach (like others including

[2] Flinn and Mabli (2008) provide a theoretical basis for the presence of spillover effects of the minimum wage.

Dinardo et al. decomposition) is based on observed wages. If we suppose that the competitive model applies and the minimum wage is set above the equilibrium wage, some employees will lose their jobs and therefore we will not observe their wages. In this context, what we observe indeed is a rightward shift of the wage density which could enhance spillover effects as Lee states.

This paper is relevant because the literature is not definitive about the impact of the minimum wage on wage inequality. For developed countries, the empirical evidence on the employment effects of the minimum wage is not unanimous. Card and Krueger (1994) and Dickens and Manning (2002) do not find negative effects of the minimum wage on employment in the US and the UK, respectively. The former authors consider that the standard competitive model may fail to predict labor market outcomes because it relies on a "number of simplifying assumptions". In addition, Manning (2003) argues that employers have monopsony power because of "frictions in the labor market," and questions whether the standard model of perfect competition properly predicts labor market outcomes. Recently, Addison, et al. (2008) find robust positive employment effects for the U.S. Retail-Trade Sector. In contrast to those findings, Neumark and Wascher (2007) review the existing literature for the US and other developed countries and find that there is greater evidence which supports the existence of negative employment effects -disemployment effects- on low-wage workers.

For some Latin American countries, the literature on this subject is quite mixed. For instance, Fajnzylber (2001) analyzes the case of Brazil for the period 1982-1997 using the Brazilian Monthly Employment Survey (longitudinal data). He finds employment elasticity of around -.10 for low-wage workers in the formal sector, and between -.25 and -.35 for low-wage workers in the informal sector. With the same survey, but considering a slight larger period 1982-2000, a different methodology and also considering the whole labor force, Lemos (2004) finds "small adverse effects on employment". Furthermore, Lemos (2005) finds employment elasticity from -.12 to .02 and from -.29 to .12 using OLS and IV, respectively. Neumark et al. (2006) realize a similar result to that of Lemos (2005) for the period 1996-2001, finding an estimated employment elasticity of -.07 for household heads and positive results for other family members. On the other hand, Lemos (2009) finds no evidence of employment effects in the formal and the informal sector. Bell (1997) analyzes the case of Colombia. Using time series data (Annual Industrial Survey 1980-1987), she finds an estimated employment elasticity of -.34. When she uses panel data (Minimum Wage Commission 1980-1987), the results range from -.24 to -.03 for skilled workers and from -.33 to -.14 for unskilled workers. Maloney and Nuñez (2004), using "panel employment data," obtain an estimated employment elasticity of -.15. The final research of this review is a study of Chile, conducted by Montenegro and Pagés (2004) using "repeated cross-section household surveys" (1960-1998) for Santiago. They find negative employment effects for young and unskilled workers, but positive effects for women.

Furtado (2005) analyzes the Uruguayan case for the period 1986- 2001 by estimating employment elasticities. Using a cointegration vector, she does not find robust employment effectss arguing that the national minimum wage is a useless redistributive tool. This result is also in line with the findings of González and Miles (2001). Moreover, Kristensen and Cunningham (2006) develop a minimum wage ranking for Latin American and Caribbean countries (adjusted by USD PPP) for 1998. Of 19 countries, Uruguay is in the last position of this ranking. This could be another explanation for the absence of employment effects. So, although the zero employment effect hypothesis´ seems to be reasonable for Uruguay, further research on this issue is required.

To carry out this research we construct panel data at the Department level using the National Household Survey from 1996 to 2009 and we focus on males to avoid selection issues. First, we estimate Lee´s model by Ordinary Least Squares (OLS) as he does in his research paper. As this estimate is probably biased because of a spurious correlation between the percentile gap and the relative minimum wage we go one step further, implementing an IV estimation method. In order to do so, we obtain data of the wage percentiles between 1996 and 2009 by Department from the Social Security records. The IV method enables us to mitigate endogeneity which could arise due to simultaneity. Additionally, we estimate a semiparametric linear partial modelling following Yatchew (1998). In the OLS case, we find that the increase in the minimum wage contributes to the reduction of wage inequality. Nevertheless, using intrumental variables and a semiparametric estimator the latter result tends to disappear.

The result of absence of effect, could be explained by several factors. For instance, despite the substantial rise in the minimum wage, it was previously set in a very low level relative to other Latin American countries, as Kristensen and Cunningham (2006) state, and to the average wage (in 1996 the ratio of minimum wage to average wage was around 15%, while in 2009 it was 30%). Also, the minimum wage policy depends on the level of enforcement. Regarding this issue, we observe that the level of compliance declines when the minimum wage is reintroduced, and therefore to effectively apply this kind of policy, enforcement should also be enhaced. Finally, the net effect will depend on whether there are employment effects.

2 Methodology

With the purpose of identifying the effect of the minimum wage on the wage distribution we follow the methodology developed by Lee (1999). This research is an empirical application of Lee´s theoretical model, which was implemented for the US case in order to find out the contribution of the minimum wage to the increasing wage inequality observed during the eighties, adapted for the Uruguayan case. Specifically, he takes advantage of the variation in the wage distribution and the (federal) minimum wage across states to identify the effect of the minimum wage on "latent" wage dispersion – the wage dispersion that would have resulted in the absence of the minimum wage. Hence, this methodology allows us to answer the question: How would the wage dispersion evolve once we account for the impact of the minimum wage on the wage distribution? Despite the fact that in Uruguay the minimum wage is only set at national level, the wage distribution varies greatly throughout the different Departments of the country. Therefore, our identification strategy is based on wage differential across departments and time. Contrary to the US study, here we are interested in assessing the reintroduction of the minimum wage on the wage dispersion.

The first step of this methodology is to establish the formal relationship over time and across Departments between the observed wage dispersion measured by the difference between percentiles of the (log) monthly wage distribution (for instance, the 10th - 70th percentile gap) and the "effective minimum wage" (following the example, (log) monthly minimum wage – 70th percentile). In addition, we also have to consider the linkage between the "latent" wage dispersion and the relative minimum wage.The connection among these three measures depends on the assumption about spillover and disemployment effects. Without considering both of these effects, which is the simplest scenario, the relationship can be modeled as follows,

$$w_{it}^{pth} - w_{it}^{70th} = \begin{cases} (w_{it}^{pth} - w_{it}^{70th})' & if \quad \left(mw_t - w_{it}^{70th}\right) < (w_{it}^{pth} - w_{it}^{70th})' \\ \\ \left(mw_t - w_{it}^{70th}\right) & if \quad \left(mw_t - w_{it}^{70th}\right) \geq (w_{it}^{pth} - w_{it}^{70th})' \end{cases} \tag{1}$$

where the term $w_{it}^{pth} - w_{it}^{70th}$ represent the observed wage inequality (or percentile gap) in Department i and in time t, while the term $(w_{it}^{pth} - w_{it}^{70th})'$ represents the latent wage inequality also in Department i and in time t. Finally, the relative minimum wage is denoted as $\left(mw_t - w_{it}^{70th}\right)$. As the minimum wage only varies across time it is only indexed with the letter t. The mechanism is similar to the one observed in a censored model. In the first case, where the relative minimum wage is less than the latent wage inequality, the observed percentile gap is equal to the latent wage inequality. In other words, the relative minimum wage is rather low compared to the "latent" wage distribution and therefore is not relevant in the determination of wages. This probably occurs in high-income Departments. On the other hand, the second line in equation (1) states that when the "latent" wage inequality is less than the relative minimum wage, the observed wage inequality equals the relative minimum wage. This fact is expected in low-income Departments since we observe a sort of bite in the wage distribution of those Departments around the minimum wage, as we will see in the next section.

When we introduce some refinements to the model and allow the presence of spillover effects, it will be appropriate to change the first line of equation (1) in the following way: $w_{it}^{pth} - w_{it}^{70th} = g\left(mw_t - w_{it}^{70th}\right) \quad if \quad \left(mw_t - w_{it}^{70th}\right) < (w_{it}^{pth} - w_{it}^{70th})'$. In this case, if the first inequality of equation (1) holds, the observed wage inequality is an increasing function of the relative minimum wage, reflecting that the latter affects the wage distribution despite being below the latent wage inequality, but this effect tends to disappear as the effective minimum wage increases. In our case, the spillover effects assumption is quite reasonable since, as we mentioned, the minimum wage in some cases is based on some contracts and sector bargains.

Regarding the employment effect, Lee discuss how its presence could affect the model. Since the analysis is based on observed wages, when a person loses his job due to the employment effect, we lose an observation because we do not observe his/her salary anymore. Thus, this fact could be associated with a shift in the wage percentiles which could be modeled in a similar way as spillovers and therefore, could lead to an "overestimation of true spillover effects." In the most realistc scenario, we might expect the presence of both effects.

Up to this point, the censored model represented in equation (1) is not yet estimable. It is necessary to figure out a parameterization which describes properly the model presented above. Lee expresses the observed wage inequality as a function of the relative minimum wage and the latent wage inequality. That is, $(w_{it}^{pth} - w_{it}^{70th})' = f(w_{it}^{pth} - w_{it}^{70th}, mw_t - w_{it}^{70th})$. Then our second step is reduced to parameterize the latter function, taking into account that there are different ways to do so. For instance, Lee (1999), Autor, Manning and Smith (2010) and Bosch and Manacorda (2010), state the following linear relationship: $(w_{it}^{pth} - w_{it}^{70th})' = (w_{it}^{pth} - w_{it}^{70th}) - [(mw_t - w_{it}^{70th}) + (mw_t - w_{it}^{70th})^2]$. In our case, the data does not support the quadratic term. We try the inclusion of a quadratic term in our estimation but in all cases it was not statistically different from zero. In the US case, which is studied in Lee (1999) and in Autor, et al. (2010), their analysis is based on the 50 States (in some cases fewer). Bosch et al. (2010) study the Mexican case using as the unit of analysis the different municipalities, working with about 63 municipalities. In our case, we have 19 Departments and thus it turns out to be difficult to capture a quadratic effect. In summary, we fit the following parametrization: $(w_{it}^{pth} - w_{it}^{70th})' = (w_{it}^{pth} - w_{it}^{70th}) - (mw_t - w_{it}^{70th})$.

One important issue which we also need to address in this approach is election of the percentile of reference. In the illustration of the model above we select the 70th percentile. The question that arises is: why we should choose the 70th percentile instead of other wage percentiles? For example, Lee justifies the use of the median wage in the US case because he finds evidence which supports the idea that the median wage is not affected by the minimum wage. However, and as we previously mentioned, the spillover effects hypothesis probably holds and therefore the median wage could not be an adequate choice. Hence, we opt for the 70th percentile as the reference wage (which is more similar to the Mexican case).

Finally, we relax Lee´s assumption which states that the latent wage dispersion is equal across Departments, letting the latter vary across Departments by the inclusion of Department fixed effects and year effects in the model. Then, the equation to be estimated can be formally set as follows,

$$w_{it}^{pth} - w_{it}^{70th} = \beta^{pth}(mw_t - w_{it}^{70th}) + \lambda_t^{pth} + \alpha_i^{pth} + u_{it}^{pth} \qquad (2)$$

where i represents the unit which is Departments, t is the year, $w_{it}^{pth} - w_{it}^{70th}$ is the observed percentile gap between the pth percentile and the 70th percentile of the wage distribution for Department i and year t, $(mw_t - w_{it}^{70th})$ is the effective minium wage which varies across Departments and over time, λ_t^{pth} and α_i^{pth} are the year effect and the Department fixed effect when choosing the pth percentile, and u_{it}^{pth} is a Department time-varing error for the pth percentile (distributed independently across Departments and time and hopefully independently of λ_t^{pth} and α_i^{pth}). This regression is structured to capture the effects of aggregate factors and Department specific responses to aggregate factors. The parameter of interest is β^{pth} which measures the effect of the relative minimum wage on the percentile gap (pth - 70th). For instance, if p=10 the parameter β^{10th} captures the effect of the relative minimum wage on the percentile gap $w_{it}^{10th} - w_{it}^{70th}$, and so on. We estimate equation (2) for p=10, 20, 30, 40, 50, 60, 80 and 90. The estimation of equation (2) for the 80th and 90th percentile represents a robustness check since we do not expect that the minimum wage has an impact on the top percentiles. Stated differently, both coefficents β^{80th} and β^{90th} have to be statistically equal to zero so as to be confident about our estimates.

An additional robustness check is the inclusion in equation (2) of control variables by Department in order to control by other factors that could affect the percentile gap. Moreover, we also include a general trend.[3] Formally,

$$w_{it}^{pth} - w_{it}^{70th} = \beta^{pth}(mw_t - w_{it}^{70th}) + x_{it}'\phi^{pth} + \gamma^{pth}trend + \lambda_t^{pth} + \alpha_i^{pth} + u_{it}^{pth} \qquad (3)$$

where γ^{pth} $trend$ is a general time trend (associated with the pth percentile) and x_{it}' is a vector of control variables which vary across Department and over time. Equation (2) and (3) are our parametrization of model (1). Our objective is to mimic Lee´s censoring model by estimating these equations and then observing whether predictions can shed light on the contribution of the minimum wage to wage equality. The model predicts that when $(mw_t - w_{it}^{70th})$ increases the percentile gap $w_{it}^{pth} - w_{it}^{70th}$ will be similar to the former and when $(mw_t - w_{it}^{70th})$ decreases the percentile gap $w_{it}^{pth} - w_{it}^{70th}$ will approximate to the latent wage inequality. These are the kinds of predictions that the model produces.

One of the major concerns in the estimation of the above equations arises from the possibility of spurious positive correlations between the observed percentile gaps and the effective minimum wage which could emerge due to sampling error and the fact that the seventh percentile is in both sides of equation (2) and (3), which Autor, et al. (2010) refers to the "division bias problem" citing Borjas (1980). It could be that there is no relationship between those measures but because of measurement errors, estimation could incorrectly find a positive and statistically significant effect. These sources of bias have to be mitigated in order to avoid misleading estimates. So, attempting to resolve this issue, Lee uses a trimmed mean, which is the wage mean excluding the bottom and top 30 percent of the sample by year and state, to compute the relative minimum wage. One possible drawback of this strategy is arbitrariness in the exclusion of percentages at the top and bottom. Additionally, as we expect spillover effects, we focus on the 70th percentile and thus we have to impose other criteria of sample exclusion which will also be arbitrary and suffer from sampling error. Moreover, Autor et. al. (2010) show that this does not entirely solve this problem and thus this source of bias remains.

Therefore, one possible solution is to estimate equations (1) and (2) using the IV method (in Autor et al., 2010 and Bosch et al., 2010) the authors also address this sampling error issue by using IV). In this context, our variable to be instrumented is the effective minimum wage and our instrument will be the effective minimum wage but constructed using the 70th percentile of the wage distribution of the Social Security records. That is, the instrument

[3] Another possibility is to include Department specific time trend to allow Departments to follow different trends due to other factors that are unrelated to the effective minimum wage. However, in this case we have not an appropiate time span length so as to account for the effect of specific Deparment trends.

is the same measure but it comes from other sources of information. The strategy of using external information to account for measurement error is common practice when the data is available. For instance, Card (1996) employs external information to adjust his estimates in his research on the effect of unions on wages.

In both equation (2) and (3) we state that the wage dispersion (the dependent variable) is linearly affected by the effective minimum wage and thus imposing an specific parameterization. Therefore, we will test if the latter assumption holds by not placing any particular functional form and using nonparametric techniques to estimate a general function. In this context, we estimate a semiparametric regression model developed by Yatchew (1998). Then, we set the following partial linear model,

$$w_{it}^{pth} - w_{it}^{70th} = f(\hat{v}_{it}) + x_{it}'\phi^{pth} + \gamma^{pth} trend + \lambda_t^{pth} + \alpha_i^{pth} + u_{it}^{pth} \tag{4}$$

in where $\hat{v}_{it}$ are the predicted values from the first stage regression and $f(\cdot)$ is the function which is estimated nonparamterically. The rest factors are set parametrically. After the estimation of equation (4), we test the null hypothesis of parametric specification of f against the nonparametric alternative hypothesis as described in Lokshin (2003).

3 Data

In order to undertake this research we use the yearly Uruguayan National Household Survey (Encuesta Continua de Hogares, ECH) from 1996 to 2009, which is conducted by the National Statistical Office of Uruguay (Instituto Nacional de Estadística, INE). The ECH has been the main source of socio-economic information about Uruguayan households and their members at the national level since 2006, when it started to include rural areas. Prior to this year, the ECH only covered urban areas of the country. So as to have a comparable sample throughout the different years, our sample unit is the capital city of each Department which represents around 80% of the total labor force in the Department, and therefore is representative of the whole work force in each of them. Then, we refer to our data as a panel at the Department level.

Moreover, the selected sample is composed of male wage earners between 14 (minimum legal working age) and 60 years old. Despite the fact that the government sets a different monthly minimum wage for the rural and domestic sectors , we do not exclude them because: 1) we only consider urban areas, so there is a negligible proportion of rural workers and their minimum wage is similar to the national minimum wage; 2) the minimum wage in the domestic sector is set just above the national minimum wage, thus there is not an important difference between the two (see Furtado 2005 for a similar discussion). We keep out the public sector because the national minimum wage is not relevant for those workers. Finally, we also exclude the first and the ninty-ninth percentiles to avoid outliers.

The ECH has information on monthly salaries net of social security and income taxes of each household member, from which we construct the monthly salary percentiles by Department. We have 19 Departments and a time period of 14 years and hence our sample size is 266. We merge this data with the information about the monthly minimum wage which is set by the government and usually changes slightly two times during one year and so we take the lastest value in each year.

In Table 1 we present some summary statistics of several variables in 1996, 2004, 2005 and 2009. Between 1996 and 2004, the different percentile salary gaps (e.g. 10th - 70th percentile gap) tend to increase. When we compare 2004 with 2005 (year in which the minimum wage was reintroduced, we observe a decline in the salary gaps. By the end of the analyzed period, apart from the 10th - 70th percentil gap, they continue decreasing.

Figure 1 (bottom panel) presents the evolution of the 20th, 70th and 90th percentile relative to the median throughout the period 1996-2009, which arises from a regression of each percentile gap (which vary across Department and time) on Department and year dummies weighted by the number of observations of each Department. As we observe in the lower plot, the ninth percentile increases reaching a peak in 2002, then it fluctuates until 2005 and after that it declines, increasing again during the last year of the period. A similar but more attenuated pattern is followed by the 70th percentile. Related to the 20th percentile gap, it almost shows an opposite pattern. What is interesting is that this percentile gap shows a upward trend after the increase of the minimum wage in 2005.

Concerning to the effective minimum wage, it increases from -1.910 to -1.272 between 1996 and 2009 as we observe in Table 1. We also construct an additional indicator like the minimum wage - average or (median) monthly wage ratio - in order to account for the rise in the minimum wage related to the average and median wage. These ratios increase throughout the period. Specifically, between 1996 and 2009, the ratio almost doubles when we consider the average wage and increases fifty percent when considering the median wage. Despite the remarkable rise in the minimum wage, it is still far from the median as well as from the mean. For instance, in 1998 Paraguay and Colombia has a ratio of just over 0.70 and 0.5, respectively, as Kristensen and Cunningham (2006) observe. They also find that in 1998 the Uruguayan minimum wage was one of the lowest in the region. Based on these facts one can argue (and also assume) that there is no employment effect of the minimum wage as a result of a minimum wage increase or if there is, it probably is negligible.

Another interesting labor market feature, which emerges from the observation of Table 1 is that the percentage of workers below the minimum wage grows sharply - this could be related to compliance and enforcement issues. A different explanation is that in developing countries the informal labor market represents around one fourth of the total labor market. Nevertheless, Maloney and Nuñes (2004) and Kristensen and Cunningham (2006) point out that for many Latin American nations the minimum wage has a potential impact on both the formal (or covered) sector and also on the informal (or non-covered) sector. Moreover, they argue that the minimum wage seems to have a stronger effect on the latter than on the former sector. This phenomenon is usually called the "lighthouse effect" and it occurs when minimum wage is relevant for the informal sector (where minimum wage law does not apply). Additionally, in a recent paper Khamis (2009) finds that minimum wage has stronger effects on the informal labor market, where workers experience considerable wage increases, than on the formal labor market.

In this research we use the definition of informality elaborated by the International Labour Organization (Organización Internacional del Trabajo, OIT) in the 15th International Conference of Labour Statisticians (1993), which considers informal workers those who work in the domestic sector, unpaid household members, private wage earners working in a firm with less than five employees and self employed workers (excluding administrative, professionals and technicians). Between 1986 and 2000, the ECH provides information on the size of workers firm. Since 2001, the question about the firm´s size is discrete: 1) 1 employee; 2) between 2 and 4 employees; 3) between 5 and 9 employees; 4) between 10 and 49 employees; and 5) more than 50 employees. Therefore, we can identify small companies of 4 or less workers.

As our sample only includes private employees, informal workers are defined as those who work in small firms (four or less employees) and workers in the domestic sector. The proportion of informal workers rises between 1996 and 2004 and after that it declines from 25% in 2004 to 18.5% in 2009. Below the minimum wage, 65% and 44% are in the informal labor market in 1996 and 2009, respectively. Therefore, compliance could tell part of the increment in the proportion of workers below the minimum wage. We also observe that our sample is composed mainly of full time workers. Below the minimum wage, the proportion of full time workers decreases as is commonly expected. However, this proportion increases from 1996 to 2009 from 35% to 51%. Neumark (2008) states that when analyzing data of developing countries he finds that "enforcement of and compliance with minimum wage laws is often erratic."

Finally, we observe that the average age is around 35 and that education increases almost one year during the 1996-2009 period.

As we mentioned earlier, we also use Social Security data which was obtained from the Social Security Office (Banco de Previsión Social, BPS). BPS is a state office which is in charge of pensions, social benefits, employment insurance and collecting the social security tax. Employers are responsible for paying the social security tax which is calculated using the nominal salary. Then, the BPS has the salary records of the employees for the whole formal labor market. The office provided us with a panel set that includes the percentiles by Department and between 1996 and 2009. In Table 1 we also present statistics of the percentile salary gaps of the Social Security records. Using the BPS data, overall, the same pattern is observed as when using the ECH data. Finally, we also observe that our instrument, that is, the effective minimum wage constucted using the 70th percentile of Social Security records, increases until 2005 and after that it falls.

Our identification strategy is based on variability across Departments and time. Lee has two sources of variation. First, each state has its own minimum wage, and the second is that Lee observes that the minimum wage is more or less binding according to the level of income of each state. In order to illustrate how the identification strategy could work properly with our data, we plot the variation of the 10th - 70th percentile gap in Figure 2. As we can see, each dot represents a Department percentile gap and the line is a nonparametric fit. We observe an interesting variability of our data across and within departments.

In addition, in Figure 3 we plot the kernel density of the relative (log) monthly salary by income region.[4] Depending on the income we generate three groups: 1) high income group which includes the Departments of Canelones, Colonia, Maldonado, Montevideo, Paysandú and Rocha; 2) medium income group which includes the Departments of Durazno, Florida, Salto, San José, Soriano, Tacuarembó and Treinta y Tres; and 3) low income group which includes Artigas, Río Negro, Cerro Largo, Lavalleja, Rivera and Flores. In the top panel of Figure 3 we have the (log) monthly wage relative to the median for the high income region and we do not observe any bite around the minimum wage in either year, which is not a striking feature in a high income region labor market. In the medium income region there is also no bite but the minimum wage in 2009 is closer to the mean. Finally, in the lower panel we observe that in 2009 the minimum wage is relevant for the (log) monthly wage and could be related to a support effect. In Figure 4, in where we also add an histogram to the

[4]We use the Epanechnikov kernel function and the Sheather-Jones (SJ) plug-in bandwidth. Our concern here is to detect if the minimum wage represents a feature in the labor market and that is the reason why we choose the SJ plug-in. Dinardo, et al. (1996) use it to estimate the actual and counterfactual (log) wage density.

kernel density estimation, we observe some sort of bit in the level of the minimum wage in the case of the low income region.

4 Results

Table 2 presents our OLS estimates of equation (2) and (3) for the different percentiles gap using the ECH data and the Social Security records (BPS data) for the whole sample and also separating between formal and informal workers in the case of the ECH sample. Using the first source of data (the ECH), we find a statistically significant effect of the relative minimum wage on the 10th percentile through the 60th percentile and the coefficent declines when we consider higher percentiles. This result suggets the presence of spillover effects. Interestingly, we do not find statistically significant effects for the top percentiles gap (80th and 90th) as we expect in the model. Another striking point is that the coefficent increases in magnitude for all the percentiles except for the 10th percentile when we consider a general trend and controls variables by city in column (2). Moreover, the effective minimum wage has a positive and statistically significant effect on the 80th - 70th percentil gap which could be explained by the sources of endogeneity that bias the OLS estimates. Overall, the same picture arise when separately estimate equation (2) and (3) for formal and informal workers. However, in this latter case the sources of bias appear to be greater than when we consider the full sample. Using the BPS data, the results are overall quite similar. However, we observe a greater effect on the 30th, 40th and 50th percentile in the two specifications and negative but not statistically significant effects on the 80th percentile gap. As previously indicated, this result could be spurious because of the "division bias" problem.

In Table 3 we estimate the impact of the relative minimum wage on wage inequality using instrumental variables.[5] First, we consider the full sample and we find that the effective minimum wage has a significant impact on the 10th, 20th, 40th and 60th percentile gap at the 5% level. For instance, the β^{10th} is equal to 0.603. When we include a general trend and also control variables by city, this effect tends to decline in magnitud and in the level at which they are statistically significant except for the 10th percentile gap. It is important to point out that our instrument is highly correlated with the endogenous variable (the effective minimum wage), as we can see in the weak identification test of Kleibergen-Paap presented

[5] As mentioned the estimations are carried out using yearly data. Additionaly, we also estimate equation (2) and (3) using quarterly data. The results go in the same direction but in this case the effect appears to be statistically significant in both cases with and without control variables by city and general trend. Nevertheless, it is necessary to point out that when using quarterly panel data additional issues arise like seasonality and what is more, the measurement error problem tend to increase.

in Table 3.[6] Moreover, we include the p-value of the intrumental variabel of the first stage regression.

In the second case, that is, the estimation using only formal males we find a similar picture. However, the effect of the relative minimum wage on wage inequality tend to disappear. The first stage continue being appropiate to carry out an IV procedure. We also try using only informal workers but we do not find any effect for the different specifications. In this last case, we seem to have weak identification problems. So as to overcome this problem, we estimate model (1) and (2) using limited information maximum likelihood (LIML) estimator which seems to perform better than the conventional IV estimator when using a weak instrument. In addition, as in the presence of weak instrument we tend to under-reject the null hypothesis of absence of effect, we also apply the Anderson-Rubin test to perform robust inference (which is not showed in Table 3). Results do not change.

In Figure 5 we graph the IV estimates of model (2) for the 10th percentile gap and for all males in 1996 and in 2009, which are weighted by the number of observation by Department. In 1996, we observe a flat relationship between the 10th relative percentile and the relative minimum wage as is expected since the minimum wage has been reaching its lower level ever since. Despite the fact that the minium wage increases considerably, in 2009 there is not a clear positive slope in our estimates. However, the 2009 estimates are closer to the 45° line. A problem could arise because of the absence of a linear relationship between the percentile gap and the effective minimum wage which could bias our estimates. Lee also includes the square of the effective minimum wage. In our case, we also include a quadratic term but it is not statistically significant.

In order to test the non-linear hypothesis, we estimate equation (4) using the semiparametric procedure developed by Yatchew (1998). This kind of strategy relaxes the assumption of imposing a linear or quadratic relationship on the percentile gap and relative minimum wage. On the other hand, we cannot estimate the parameter of interest β^{th} because of the non-parametric nature of this approach. In order to avoid the division bias problem we use the predicted value of the first stage regression as mentioned in the methodology section.

Figure 6 presents the nonparametric function that arise from estimating equation (4) for the different percentile salary gaps for the whole sample. At the same time, we plot the linear estimation which emerge from the IV estimates. As we observe in the different graphs, the nonparametric estimates seems to produce a similar result as in the linear case and thus, our

[6] The Kleibergen-Paap test of weak identificaiton is commonly used when the assumption of *i.i.d.* errors is no longer valid, as in our case. In addition, we use the rule-of-thumb that the Kleibergen-Paap statistic should be above 10 in order not to have weak identification problems.

parametrization seems to be quite reasonable. Interestingly, as we consider a higher relative percentile, the relationship tends to be flat and almost negative for the top percentiles. This results could be considered as an additional robustness check since it is doubtful to expect a positive relationship between top percentiles and the minimum wage.

In Table 4 we test the null hypothesis of linear parametrization against the nonparametric alternative. In almost all cases, we cannot reject the linear parametrization and therefore the linear specification fits the data similarly to the nonparametric specification.

5 Concluding Remarks

Our empircal application is aimed to shed light on the contribution of the recent sharply increase in the mimimum wage on the slight decline in wage inequality. Using an instrumental variable estimation we find that, overall, the boost of the minimum has no significant impact on wage inequality. This results could be explained by several facts: 1) the low starting level of the minimum wage; 2) the high economic growth and the low unemployment experience by the country in the last years; 3) compliance and enforcement of the minimum wage law. Finally, the Uruguayan experience shows that the minimum wage is not always effective as a redistribution instrument. One shortcoming of this study is that we do not take into account the potential disemployment effects of the mimimum wage. However, economic growth in Uruguay has been vigorous since 2003 and the unemployment rate at the end of the 2000s is in the lowest historical value.

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Table 1. Summary Statistics

ECH data	1996	2004	2005	2009
(log) monthly minimum wage (MW) - 1997 pesos	6.63	7.18	7.82	8.40
10th - 70th percentile gap	-1.23	-1.32	-1.29	-1.31
20th - 70th percentile gap	-0.93	-0.97	-0.95	-0.91
50th - 70th percentile gap	-0.34	-0.37	-0.36	-0.36
90th - 70th percentile gap	0.57	0.65	0.62	0.57
MW - 70th percentile gap	-1.91	-1.85	-1.28	-1.27
MW / Average monthly wage (%)	16	16	29	30
MW / Median monthly wage (%)	22	23	40	40
Workers below the MW (%)	2	5	10	11
Informal worker (%)	23	25	24	18
Informal workers below the MW (%)	65	48	53	44
Full time workers (%)	80	82	82	83
Full time workers below the MW (%)	35	47	43	51
Average age	34	36	36	36
Average education	9.0	9.9	10.0	9.9
Social security data	1996	2004	2005	2009
10th - 70th percentile gap	-1.64	-1.82	-1.63	-1.76
20th - 70th percentile gap	-0.94	-1.10	-0.87	-1.00
50th - 70th percentile gap	-0.37	-0.38	-0.35	-0.38
90th - 70th percentile gap	0.61	0.68	0.64	0.54
MW - 70th percentile	-1.28	-1.15	-0.63	-0.76

Sources: National Household Survey (ECH) and Social Security data.

Table 2. Impact of the minimum wage on wage inequality. OLS estimates								
	ECH data		ECH data- Formal		ECH data- Informal		Social Security data	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
p10-p70	0.434***	0.401***	0.389***	0.248***	0.390**	0.584***	0.378***	0.412***
	(0.127)	(0.117)	(0.108)	(0.086)	(0.140)	(0.128)	(0.104)	(0.106)
p20-p70	0.350***	0.378***	0.396***	0.330***	0.305***	0.498***	0.201*	0.236**
	(0.086)	(0.069)	(0.069)	(0.073)	(0.066)	(0.081)	(0.113)	(0.091)
p30-p70	0.285***	0.335***	0.344***	0.296***	0.264***	0.446***	0.743***	0.767***
	(0.058)	(0.057)	(0.054)	(0.076)	(0.061)	(0.073)	(0.053)	(0.048)
p40-p70	0.287***	0.324***	0.317***	0.295***	0.192***	0.323***	0.541***	0.556***
	(0.038)	(0.037)	(0.044)	(0.062)	(0.055)	(0.072)	(0.048)	(0.052)
p50-p70	0.186***	0.206***	0.274***	0.274***	0.167***	0.298***	0.410***	0.418***
	(0.036)	(0.041)	(0.038)	(0.051)	(0.054)	(0.068)	(0.039)	(0.035)
p60-p70	0.160***	0.175***	0.159***	0.176***	0.115***	0.188***	0.262***	0.280***
	(0.028)	(0.030)	(0.037)	(0.047)	(0.029)	(0.039)	(0.055)	(0.053)
p80-p70	0.033	0.070**	0.055**	0.120***	0.123***	0.191***	-0.052	-0.044
	(0.031)	(0.030)	(0.024)	(0.030)	(0.041)	(0.049)	(0.058)	(0.045)
p90-p70	0.005	0.113	0.058	0.219***	0.310***	0.373***	0.122	0.143
	(0.081)	(0.084)	(0.082)	(0.073)	(0.059)	(0.064)	(0.124)	(0.105)
Observations	266	266	266	266	266	266	266	266
City effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trend-controls		Yes		Yes		Yes		Yes
Adjusted R^2	0.427	0.510	0.520	0.576	0.162	0.224	0.788	0.882
Sample period	1996-2009							

Note: Each row represents the marginal effects of the effective minimum wage on the respective percentile gap. Robust standard errors clustered at city level reported in parenthesis. All models include year effects. Controls by city include: average years of education, unemployment rate, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector(industrial, building, transport & communication, financial & services, others). All the regressions are weighted by the inverse of the number of observations by Department and year.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3. Impact of the minimum wage on wage inequality. IV estimates						
	All		Formal		Informal	
	(1)	(2)	(1)	(2)	(1)	(2)
p10-p70	0.603**	0.460*	0.456***	0.278*	0.052	-0.227
	(0.273)	(0.243)	(0.146)	(0.151)	(0.779)	(0.602)
p20-p70	0.354**	0.260**	0.246***	0.128	0.360	0.132
	(0.175)	(0.131)	(0.078)	(0.107)	(0.628)	(0.375)
p30-p70	0.175	0.110	0.176**	0.111	0.367	0.162
	(0.132)	(0.136)	(0.069)	(0.102)	(0.526)	(0.297)
p40-p70	0.179**	0.144*	0.119**	0.064	0.079	-0.001
	(0.075)	(0.080)	(0.058)	(0.074)	(0.315)	(0.227)
p50-p70	0.057	0.008	0.109*	0.066	0.044	-0.041
	(0.059)	(0.059)	(0.056)	(0.069)	(0.219)	(0.144)
p60-p70	0.120**	0.080*	0.038	0.040	0.117	0.060
	(0.053)	(0.049)	(0.050)	(0.057)	(0.130)	(0.090)
p80-p70	-0.016	-0.042	-0.022	-0.028	0.262	0.236
	(0.048)	(0.052)	(0.051)	(0.056)	(0.234)	(0.149)
p90-p70	-0.160	-0.201	-0.055	-0.015	0.204	0.249
	(0.145)	(0.131)	(0.183)	(0.168)	(0.226)	(0.186)
Observations	266	266	266	266	266	266
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Trend-controls		Yes		Yes		Yes
Kleibergen-Paan weak identification test	34.3	35.1	44.7	54.4	3.9	7.7
First Stage: Instrument p-value	0.000	0.000	0.000	0.000	0.063	0.012
Sample period	1996 - 2009					

Note: Each row represents the marginal effects of the effective minimum wage on the respective percentile gap. Robust standard errors clustered at city level reported in parenthesis. All models include year effects. Controls by city include: average years of education, unemployment rate, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector(industrial, building, transport & communication, financial & services, others). All the regressions are weighted by the inverse of the number of observations by Department and year.

* significant at 10 %; ** significant at 5 %; *** significant at 1 %.

Table 4. Yatchew (1998) Non-Parametric Test	
	V-Test Statistics
p10-p70	1.20
p20-p70	1.96*
p30-p70	0.31
p40-p70	0.39
p50-p70	0.06
p60-p70	1.74*
p80-p70	2.00**
p90-p70	3.43***
Observations	266

* significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1
Earnings inequality and mimimum wage trends

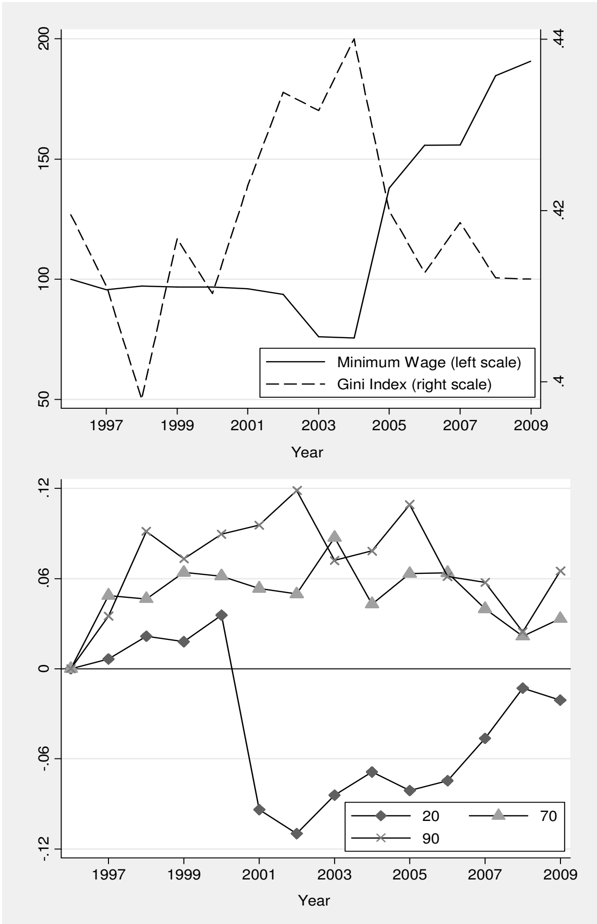

Figure 2
10th - 70th percentile gap variation within Departments

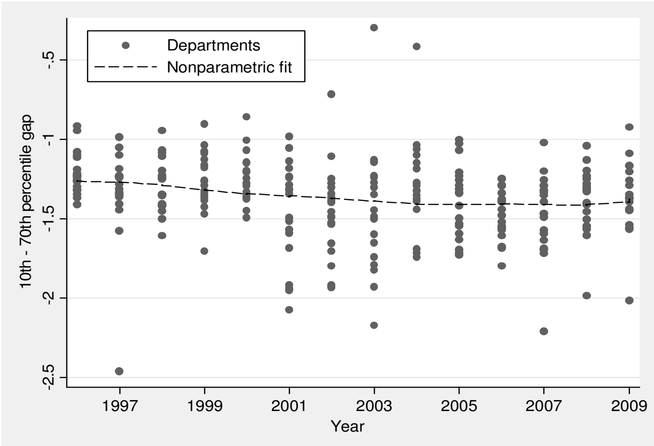

Figure 3
Log monthly wage density across regions between 1996 and 2009

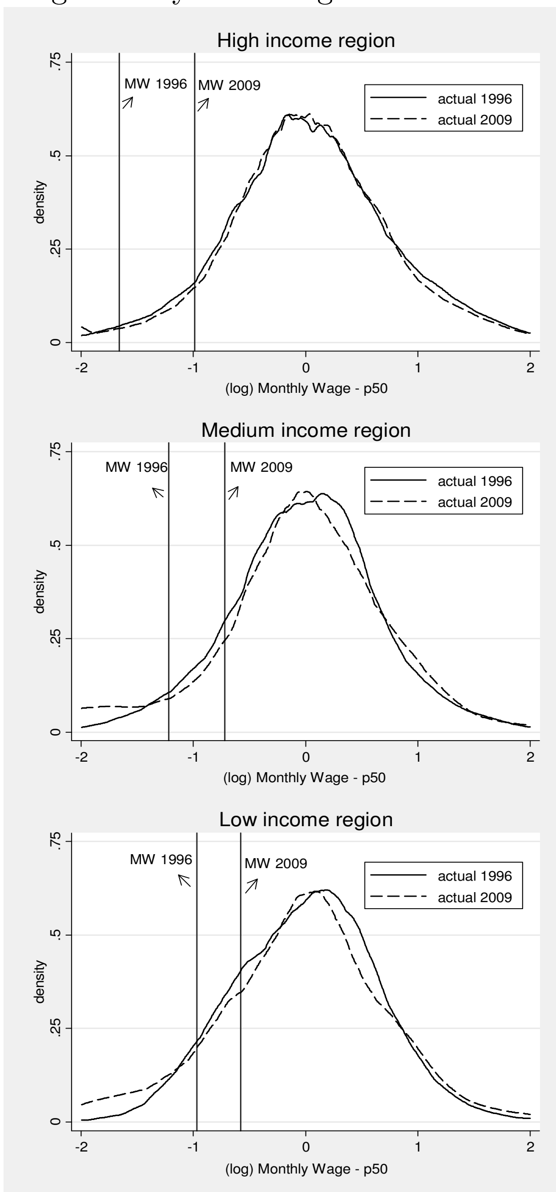

Figure 4
Histograms by Region

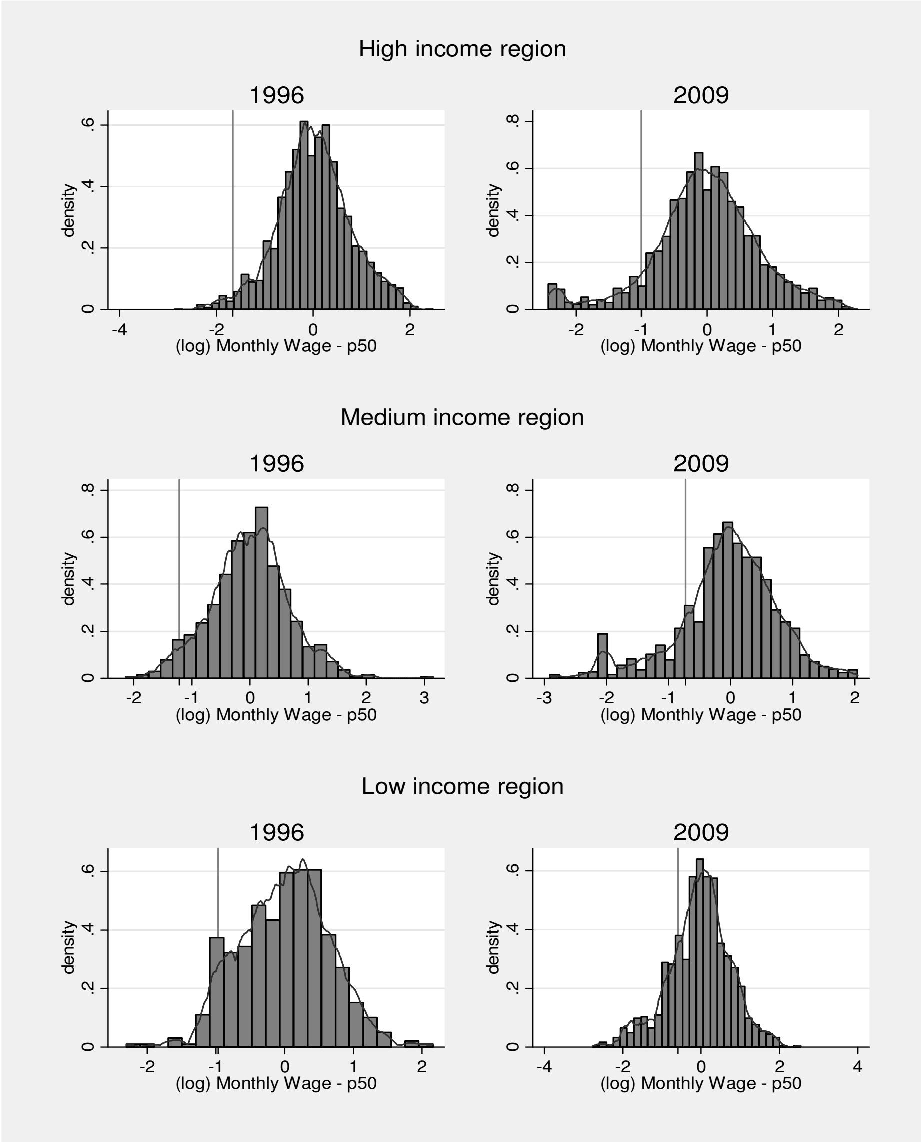

Figure 5
Latent inequality and minimum wage effect using IV estimates

Figure 6
Latent wage inequality and minimum wage effect using semiparametric technics