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Assessing the Distributive Effects of Minimum Wage*

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Abstract

This paper analyzes the role of Uruguay's sharp minimum wage increases after 2004 amidst the country's slight wage inequality decrease. We found that the minimum wage increase has contributed to the reduction of wage inequality for formal workers mainly. However, we also found a negative impact on employment outside the capital city, Montevideo, and observed a reduction in working hours. These results raise doubts about the effectiveness of minimum wage as a redistribution instrument in developing countries.

Keywords: minimum wage, wage inequality, instrumental variables, employment effect, difference in difference

JEL Classifications: J20, J31, J38

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I. Introduction

Wage inequality has long been a matter of governmental concern. One of policy makers' preferred tools to alleviate wage inequality is minimum wage legislation, which directly intervenes in the labor market. The rationale behind such policy is that a rise in the minimum wage could produce an increase in the wage of individuals in the lower segment of the earnings distribution and, therefore, decrease wage inequality.

In addition to affecting wage inequality, minimum wage policy could also affect several labor market features such as individual wages, employment, worked hours, and informality. In terms of employment, from a theoretical perspective, in the competitive supply-and-demand model, a minimum wage set above the market-clearing price will lead to an employment reduction (what is usually called the "employment effects" of the minimum wage). On the other hand, search and matching models do not predict job losses as a result of a minimum wage increase and, what is more, rent redistribution occurs in favor of the employee (Mortensen and Pissarides, 1994 and Boeri et al., 2008). Likewise, in a monopsonistic labor market, a minimum wage increase can create jobs (Burdett and Mortensen, 1998). Hence, the impact of minimum wage on employment depends on the model used.

In this context, the potential contribution of the minimum wage policy towards wage inequality reduction could be affected by the presence of the so-called employment effect. If there are employment effects of the minimum wage, then the effectiveness of this policy could be reduced or could even be a counterproductive instrument. Since the theoretical predictions are mixed, the existence of employment reductions because of the minimum wage is ultimately an empirical issue.

Therefore, most of the minimum wage literature is devoted to testing the employment effect hypothesis. Nevertheless, the evidence is not conclusive,¹ and analysis is required on a case-by-case basis.

¹ The literature on developed countries has focused mostly on the employment effect of minimum wage (e.g., Card and Krueger (1994), Dickens and Manning (2002), Manning (2003), and Addison et al. (2008)). The results are mixed. For some Latin American countries, the literature on this subject also pays more

In contrast to the abundance of employment effect literature, less is known about the impact of minimum wage on wage inequality from a theoretical perspective.² However, from an empirical perspective, in developed countries, a growing body of research has shown that the effect of minimum wage on wage inequality is not negligible. For instance, Autor, et al. (2014) found that the reduction of the minimum wage in the US has contributed to an increase in wage inequality.

One exception among developing countries is Brazil, as identified by Neumark et al. (2006), who found adverse effects of the minimum wage on inequality. In their study, the treatment variable is the percentage of individuals who three months earlier had wages below the contemporaneous minimum. One potential shortcoming in their methodology could be related to the endogeneity of the treatment variable because of the simultaneous determination of wages and the percentage of individuals below the minimum wage. Furthermore, Bosch and Manacorda (2010) uses instrumental variables to analyzed the contribution of Mexico's minimum wage decrease on its wage dispersion increase. In this context of minimum wage reduction, they found that minimum wage accounts for a considerable part of the increase in wage inequality.

To add to this body of research, this paper analyzes the impact of Uruguay's recent more than 100% minimum wage increase on wage inequality. In particular, we study whether the variation in the minimum wage (or the effective minimum wage) could explain the observed wage inequality patterns in the Uruguayan labor market. In other words, the aim of this paper is to discern whether there is a causal relationship between minimum

attention to the employment effect and is also quite mixed. For instance, Fajnzylber (2001) found a negative employment effect of the minimum wage in Brazil for the period 1982–1997. Furthermore, the effect was higher for informal workers than for formal ones. However, Lemos (2004) noticed “small adverse effects on employment” in Brazil between 1982 and 2000. Neumark et al. (2006), for Brazil between 1996 and 2001, found negative employment effects for the household head but positive effects for other family members. On the other hand, Lemos (2009) did not discover any evidence of employment effects in the formal and informal sectors. Bell (1997) as well as Maloney and Nuñez (2004) discerned negative employment effects in Colombia. Interestingly, in Chile between 1960 and 1998, Montenegro and Pages (2004) found negative employment effects for young and unskilled workers but positive effects for women.

² One notable exception is Dickens, Manning and Butcher (2012), who developed a model in which minimum wage has an impact on wage inequality.

wage and wage inequality. Our paper is relevant because of the scarcity of literature about the impact of minimum wage on wage inequality in developing countries whose labor markets present a great proportion of adult low-wage workers compared to developed countries.

Additionally, Uruguay is an interesting case study for the reason that the real minimum wage more than doubled within a five-year period. Hence, if there is any effect of minimum wage on inequality and other labor market outcomes, it is more likely to be visible in the Uruguayan case. To the best of our knowledge, this paper is the first to analyze the distributive impact of more than doubling the minimum wage. Moreover, we estimate its impact on employment, hours of work, wages, and informality.

To do so, we have analyzed the period from 1996 to 2011, a particularly interesting period because, during the nineties, the minimum wage policy was not aimed to reduce the observed wage dispersion, and its value remained almost constant, while after 2004 the minimum wage more than doubled (26% the yearly growth rate), and earning inequality dropped (around 5 points of the Gini index). These movements in minimum wage provide a good identification strategy, which is based on the variation of the relative minimum wage over time and across regions.

In order to analyze the impact of minimum wage on inequality, we adapted the methodology proposed by Lee (1999) to the Uruguayan context. Lee developed a model explaining the theoretical relationship between percentile gaps (for instance, the 10th–70th percentile gap) across states and over time as well as 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 enabled 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 minimum wage and, therefore, has the advantage of an additional source of minimum wage variation. Despite the fact that in Uruguay there is only a national minimum wage, we can still apply Lee's methodology because, as he states on page 991, footnote 15, "...all the variations in the effective minimum wage comes from variations in the states'

medians...”.³ Thus, our identification strategy is focused on two possible sources of variation: 1) that of the national minimum wage across time, which experienced great variability in recent years; and 2) the outstanding variability of percentile gaps among and within regions. The percentile gap variation among regions emerges from their different living costs.

One important advantage of Lee’s methodology is that it addresses spillover effects.⁴ This fact is relevant for two main reasons: 1) some workers’ 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 DiNardo et al.’s decomposition method) is based on observed wages. If we suppose that the competitive model applies and the minimum wage is set above the equilibrium wage, then some employees will lose their jobs and, therefore, we will not observe their wages. In this context, what we observe is, indeed, a rightward shift of the wage density, which could enhance spillover effects, just as Lee stated.

Providing that, during the nineties in Uruguay, there was no relationship between the minimum wage⁵ and the observed wage inequality and that, between 1996 and 2004, this relationship remained almost constant, we could treat the reintroduction of the minimum wage as a quasi experiment. We, thereby, exploited the latter jointly with the

³ Lee’s (1999) main estimates were based on the federal minimum wage without accounting for its variation across states. In addition, during the 1980s, each state’s minimum wage was similar to the federal minimum wage, so there is not a great amount of variation in this source.

⁴ Flinn and Mabili (2008) provided a theoretical basis for the presence of spillover effects of the minimum wage.

⁵ Gonzalez and Miles (2001) analyzed the effect of a 56% decrease in real terms of the minimum wage (4.7% of the yearly average) in the wage structure between 1986 and 1997. Following a non-parametric quantile regression approach, they concluded that the decline in the minimum wage did not explain the increase in wage inequality. Furthermore, they observed an upward movement of the lower conditional quantile, which implied a negative link between the lower tail of the distribution and the minimum wage. Therefore, for this period, there was no relationship between the minimum wage and the wage structure.

fact that the minimum wage might have had a differential effect on wages across regions. In other words, we used the relative minimum wage⁶ to distinguish between the regions that are more sensitive to the reintroduction of a minimum wage from those in which we could expect a negligible effect. In this context, we used a difference-in-difference setup as our empirical strategy to assess the impact of the reintroduction of a minimum wage on employment and other margins of adjustment that could have been affecting the effectiveness of the policy. This idea was borrowed from the US and UK literature about the employment effects of the minimum wage,⁷ in which researchers treated the introduction (or changes) of the minimum wage as an exogenous source of variation.

To conduct this research, we constructed panel data at the department level using the National Household Survey from 1996 to 2011, and we focused on males to avoid selection issues. Since the minimum wage could have had a greater impact on the informal labor market (which is known as “the lighthouse effect”),⁸ we applied our empirical strategies to the whole sample, considering formal and informal workers separately.

First, we estimated Lee’s model by Ordinary Least Squares (OLS), as he did in his research paper. As this estimate was probably biased because of a spurious correlation between the percentile gap and the relative minimum wage, we went one step further, implementing an IV estimation method. In order to do so, we obtained data of the 1996 to 2011 wage percentiles by department from the social security records. The IV method enabled us to mitigate endogeneity that could arise due to simultaneity (the division bias problem). In the OLS case, we found that the increase in the minimum wage

⁶ In this case, the relative minimum wage refers to the national minimum wage after its dramatic increase relative to a wage percentile (for instance, the 70th percentile) before the reintroduction of the minimum wage.

⁷ See footnote 1 for prior literature on this topic.

⁸ Maloney et Al. (2004) analyzed the empirical density of wages for informal workers and observed that, in many Latin American countries, there seems to be a spike surrounding the minimum wage. Moreover, Boeri et al. (2011), using a matching model, discovered, after a drastic minimum wage increase, an informal sector increase because of a “significant sorting and composition effect” between the formal and uncovered sectors. Finally, some recent empirical studies that applied a difference-in-difference approach found that, in developing countries, the informal sector is more sensitive to minimum wage changes (Dinkelman et al., 2012 and Khamis, 2013).

contributed to a reduction in wage inequality. Nevertheless, using instrumental variables, we found that the latter result tended to be smaller. Additionally, we found weak evidence of a negative impact on employment outside the capital city, Montevideo, and we observed a reduction in the worked hours.

To present everything in detail, the paper is organized as follows. In the next section, Section II, we briefly describe the minimum wage policy and wage inequality trends in Uruguay. Section III presents the methodology applied to disentangle the impact of minimum wage on wage inequality and the approach to measure its impact on labor market outcomes. In Section IV, we describe the data used and, in Section V, we present the results. Finally, Section VI offers a conclusion.

II. Minimum wage policy and inequality in Uruguay

Uruguay introduced a national minimum wage in 1969 in order to establish a wage floor for private workers over 18,⁹ with the exception of rural and domestic workers. These sectors have had specific minimum wages since 1978 and 1990, respectively, and their values were quite similar to the national one. The government has discretionary authority to set the national minimum wage's value and frequency by means of a decree. The normative wage does not set up any linkage between their adjustment and the inflation rate. In 1976, Uruguay ratified the International Labor Organization (ILO) convention about the mechanisms of how to set a minimum wage. This convention set guidelines to determine the value of the minimum wage and encourage the authorities to take enforcement measures so as to make its policy effective. However, it was not useful in terms of how to set and adjust the wage's amount.

In that sense, despite observing recurrent increments in nominal terms, when considering the wage's evolution in real terms from its introduction until 2004, we observed a downward trend (Figure 1). In particular, during the 1969–1995 time frame, the downward trend was more pronounced, while it remained almost constant in the following years until 2004. In general, the national minimum wage was not being used

⁹ In 1975, a minimum wage was established for workers under 18; its value was set at 75% of the national one, but it was only in force until 1985.

with a redistributive purpose. In contrast, and mainly at beginning of the 1990s, the government used it as a policy instrument to reduce its expenditure, since some social security payments such as income tax, social health insurance, unemployment insurance, and pensions were indexed to the national minimum wage. Moreover, Kristensen and Cunningham (2006) developed a minimum wage ranking for Latin American countries and the Caribbean (adjusted by USD PPP) for 1998. Of 19 countries, Uruguay is in the last position of this ranking. Those latter features could explain the absence of causality between the minimum wage and wage inequality that Gonzalez and Miles (2001) found in their research.

In 2005, the government introduced the *Base de Prestaciones y Contribuciones* (BPC) to index social security variables. Therefore, the national minimum wage began to be used as a redistributive tool. Additionally, the statutory minimum wage has increased dramatically since 2005. Between 2004 and 2011, the real minimum wage increased almost 200%, in real terms, but it has not reached the initial level. In Figure 2, we have computed the minimum wage relative to the mean (and the median), and we have observed that it jumped from 20% in 2004 to around 50% in the subsequent year. Therefore, after 2004, the national minimum wage was reintroduced as a redistributive policy and was ultimately an important feature in the labor market.

We should note that, in Uruguay, the mechanism to set salaries and the minimum wage is independent. In practice, during the 1970s, salaries depended on the bargaining between employees and employers. When democracy was reinstated in 1985, negotiation was conducted by a tripartite body of members of the state, employers, and employees (one possible alternative that is considered by law), establishing minimum salaries for every sector. In 1991, the government eliminated the tripartite negotiation. In 2005, the sector bargaining was reinstated by the government.

Wage inequality, however, fluctuated during the 1990s without showing a clear trend. However, starting in the 2000s, we observed two periods. The first one, which continued to the mid-2000s, was characterized (as in most Latin American countries) by a trend towards inequality (see the top panel of Figure 3). Moreover, the bottom panel of Figure 3 shows that the gap between the top and bottom percentiles grew in this period. In the second period, we observed a considerable decrease in inequality measures by using the Gini index and the percentile top-bottom percentile gap. The upward trend tended to

reverse, and the wage distribution tended to shrink. However, when we analyzed the evolution of the percentile gap in the bottom plot for informal workers, we observed the opposite patterns. That is, the wage distribution tended to shrink during the 2000s, and, after 2005, tended to present an upward trend. The latter analysis suggests that wage inequality can evolve differently for informal workers than for formal ones.

During this last period, the minimum wage sharply increased. However, at the same time, other policies such as conditional cash transfer programs as well as health and tax reforms could potentially explain the change in inequality in recent years. Therefore, our research could be considered an assessment of the isolated contribution of the new minimum wage to wage inequality together with other market outcomes. In other words, we investigated the effectiveness of the recent increase of the minimum wage as a redistributive tool.

III. Empirical strategy

a) Impact on inequality (without employment effects)

For the purpose of identifying the effect of the minimum wage on wage distribution, we have followed the methodology proposed by Lee (1999). This research is an empirical application of Lee's technical approach, which was implemented for the US in order to determine the contribution of minimum wage to the increasing wage inequality observed during the 1980s, adapted for the Uruguayan case. Specifically, Lee takes advantage of the variation in the wage distribution relative to the minimum wages 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 following 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 Uruguay's minimum wage is only set at the national level, the wage distribution varies greatly throughout the different departments of the country (as we will see later in the Data section). Then, that enables us to identify the minimum wage effect separately from the aggregate time effects. Furthermore, while Lee, in his main estimates, uses the federal minimum wage and not the state ones, all of the sources of variation in his study come from differences in the wage distribution across states.¹⁰ Thus, our identification strategy is based on the 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 had to consider the link between the latent wage dispersion and the relative minimum wage. The connection among these three measures depends on the assumption about spillover and

¹⁰ Page 1000, Table I, Panel A. In addition, during the 1980s, the federal minimum wage and the state minimum wages were nearly similar in each state, as shown in Appendix 3 in his research.

disemployment effects. Without considering both of these effects, which is the simplest scenario, we can model the relationship as follows:

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

where the term $w_{it}^{pth} - w_{it}^{70th}$ represents the observed wage inequality (or percentile gap) in department i and at time t , while the term $(w_{it}^{pth} - w_{it}^{70th})'$ also represents the latent wage inequality in department i and at time t . Finally, the relative minimum wage is denoted as $(mw_t - w_{it}^{70th})$. As the minimum wage only varies across time, it is only indexed with the letter t . This mechanism is similar to the one observed in a censored model. In the first case, in which 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 is appropriate to change the first line of equation (1) as follows:

$w_{it}^{pth} - w_{it}^{70th} = g(mw_t - w_{it}^{70th}) \text{ if } (mw_t - w_{it}^{70th}) < (w_{it}^{pth} - w_{it}^{70th})'$. 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 contracts and sector bargaining.

Regarding the employment effect, Lee discussed how its presence could affect the model. Since the analysis was based on observed wages, when a person lost his/her job due to the employment effect, we lost an observation, because we did 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 realistic 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 determine a parameterization that describes properly the model presented above. Lee expressed the observed wage inequality as a function of the relative minimum wage and the latent wage inequality:

$(w_{it}^{pth} - w_{it}^{70th})' = f(w_{it}^{pth} - w_{it}^{70th}, mw_t - w_{it}^{70th})$. Thus, our second step is reduced to parameterizing the latter function, taking into account that there are different ways to do so. In that sense, we followed Lee (1999) as well as Autor et al. (2014), who stated the following linear relationship:

$$(w_{it}^{pth} - w_{it}^{70th}) = (w_{it}^{pth} - w_{it}^{70th})' + \beta_1^{pth} (mw_t - w_{it}^{70th}) + \beta_2^{pth} (mw_t - w_{it}^{70th})^2 + u_{it}^{pth}.$$

That is, the observed wage gap depends linearly on the latent wage inequality, the relative minimum wage, and its square.

One important issue that also needs to be addressed in this approach is the election of the percentile of reference so that the first line in equation (1) holds. In other words, the main identifying assumption of the model is that the reference wage percentile cannot be affected by the minimum wage. In the illustration of the model above, we selected the 70th percentile. We chose this percentile instead of other wage percentiles based on the following considerations. First, Lee justified the use of the US's median wage because he found evidence supporting the idea that the median wage is not affected by the minimum wage. However, as we previously mentioned, the spillover effects hypothesis probably holds and, therefore, the median wage could not have been an adequate choice for our empirical application. Hence, as we did not have evidence regarding this issue, we opted to present our estimates using the 60th, 70th, and 80th percentiles as the

reference wages (which is more similar to the Mexican case (Bosch and Manacorda, 2010)).

Finally, we relaxed Lee's assumption, which stated that the latent wage dispersion is equal across departments, letting the latter vary across departments through the inclusion of department fixed effects and year effects in the specification. Then, the equation to be estimated can be formally set as follows,

$$(w_{it}^{pth} - w_{it}^{70th}) = \alpha_i^{pth} + \lambda_t^{pth} + \beta_1^{pth}(mw_t - w_{it}^{70th}) + \beta_2^{pth}(mw_t - w_{it}^{70th})^2 + u_{it}^{pth} \quad (2),$$

where i represents the department unit, 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 minimum wage that 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-varying 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 parameters of interest are β_1^{pth} and β_2^{pth} , which measure the effect of the relative minimum wage on the percentile gap ($pth - 70th$). As we are interested in the marginal effect, we computed $\beta_1^{pth} + 2\beta_2^{pth}\overline{mw}$, in which \overline{mw} is the average of the relative minimum wage. For instance, if $p=10$, then the latter formula captures the effect of the relative minimum wage on the percentile gap $(w_{it}^{10th} - w_{it}^{70th})$, and so forth. We estimated equation (2) for $p=10, 20, 30, 40, 50, 60, 80$, and 90 . The estimation of equation (2) for the top percentiles (e.g., 80th and 90th percentiles when the reference wage is the 70th percentile) represents a robustness check, since we do not expect that the minimum wage has an impact on the upper tail of the wage distribution. If the latter happens, then our main identifying assumption is being violated. Stated differently, the marginal effect for the upper percentiles had to be statistically equal to zero for us 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 gap¹¹:

$$(w_{it}^{pth} - w_{it}^{70th}) = \alpha_i^{pth} + \lambda_t^{pht} + \beta_1^{pth}(mw_t - w_{it}^{70th}) + \beta_2^{pth}(mw_t - w_{it}^{70th})^2 + x_{it}'\phi^{pht} + u_{it}^{pth} \quad (3),$$

where x_{it}' is a vector of control variables that vary across department and over time. Equation (3) is our parameterization of model (1). Our objective was 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 predictions are the kind that the model produces.

There are two important assumptions in Lee's model. The first one is the independence between wage levels and wage dispersion by region. The second one is measurement error in variables.

With respect to the first one, Figure 4 shows that the dispersion in the upper part of the wage distribution does not vary across regions. The different plots show the kernel density of the relative (log) monthly salary by income region.¹² We divided the departments according to income into three groups: 1) high income, which includes the departments of Canelones, Colonia, Maldonado, Montevideo, Paysandú, and Rocha; 2) medium income, which includes the departments of Durazno, Florida, Salto, San Jose, Soriano, Tacuarembó, and Treinta y Tres; and 3) low income, which includes Artigas, Río Negro, Cerro Largo, Lavalleja, Rivera, and Flores. To the right of Figure 4 is the (log) monthly wage relative to the median for the high-income region, and we did not observe

¹¹ Additionally, we also included department-specific time trends to allow departments to follow different trends due to other factors that are unrelated to the effective minimum wage.

¹² We used the Epanechnikov kernel function and the Sheather-Jones (SJ) plug-in bandwidth. Our concern here was to detect if the minimum wage represented a feature in the labor market, which is why we chose the SJ plug-in. Dinardo et al. (1996) used it to estimate the actual and counterfactual (log) wage density.

any bite around the minimum wage in either year (apart from informal workers in 2011), which is not a striking feature in a high-income region labor market. In the medium-income region, a slight bite appears when we consider all workers, but the minimum wage in 2011 is closer to the mean (and there is a pronounced bite for informal workers). Finally, on the left, we observe that, in 2011, the minimum wage is relevant for the (log) monthly wage and could be related to a support effect.

The second important assumption of Lee's model concerns the estimation that arises from the possibility of spurious positive correlations between the observed percentile gaps and the effective minimum wage, which could emerge due to a sampling error and the fact that the 70th percentile is in both sides of equation (3), which Autor et. al. (2014) refer to the "division bias problem," citing Borjas (1980). It could be that no relationship exists between these 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. Consequently, attempting to solve this issue, Lee used 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 errors. Moreover, Autor et. al. (2014) showed formally that imposing other criteria does not entirely solve this problem and that this source of bias remains.

Therefore, one possible solution is to estimate equation (3) using the IV method. Autor et al. (2014) and Bosch and Manacorda (2010) also addressed the division bias by using IV. In our context, the variable to be instrumented is the effective minimum wage, with our instrument being the effective minimum wage but constructed using the 70th percentile of the wage distribution of the social security records. That is, the instrument is the same measure, but it comes from other sources of information. The intuition here arises from the fact that we do not have arguments to believe that the sampling error from those different sources of information is correlated. The strategy of using external information to account for measurement error is a common practice when the data is

available. For instance, Card (1996) employed external information to adjust his estimates in his research on the effect of unions on wages.

b) Employment effect and other margins of adjustment

As we previously mentioned, Lee's methodology does not account for the employment effect (and other possible effects in related outcomes). Therefore, in order to address this issue, we used an alternative approach based on the idea that the introduction (or changes) in the minimum wage provide an exogenous source of variation in the wage distribution across departments. That is, we used the fact that the minimum wage affects the wage distribution differently across regions (as we observed in Figure 4). Similarly to the empirical strategy explained above, we used the relative minimum wage to distinguish regions that are more sensitive to changes in the minimum wage (for instance, low-income regions) from those in which we could expect a negligible effect (high-income regions). In this case, the measure of the relative minimum wages was computed as the average minimum wage after its reintroduction in 2005 minus the pre-2005 average of the 70th percentile by department. This latter measure, which we labeled as "Intense," provided the intensity of the treatment, and it varies at the department level. Once this variable was computed, the following step was analyzing how employment (and other outcomes such as worked hours, wages, and informality) varied in regions with different treatment intensity before and after the reintroduction of the minimum wage. This quasi-experimental approach, usually known in the treatment evaluation literature as the difference-in-difference estimator, leads us to the following equation:

$$y_{idt} = \alpha_0 + \alpha_1 Post_t + \alpha_2 Intense_d + \alpha_3 Post_t * Intense_d + \phi X'_{idt} + u_{idt} \quad (4),$$

where y_{idt} is the outcome variables (in this case employment, worked hours, log hourly wage, and informality) for individual i , at department d , and at year t ; $Post_t$ is a dummy variable that takes the value of one in the years after the reintroduction of the minimum wage and zero otherwise; $Intense_d$ varies across departments (as we mentioned earlier, it is useful to distinguish departments that are sensitive to minimum wage change from those who are not); $Post_t * Intense_d$ is the interaction of the last two variables; X'_{idt} represents the control variables for individual i , at department d , and at year t ; and,

finally, u_{idt} is the error term, which varies across individual, department, and year. Our parameter of interest is α_3 , and it captures the causal effect of the recent sharp increase observed in the minimum wage on several labor market outcomes such as employment.

One of the major concerns of this strategy is the fact that the error term u_{idt} could be divided into a component that varies across states and others that vary at the individual level. In order to consider this error structure in the estimation of the standard error of our main estimator, we applied the commonly used robust-clustered standard errors at the department level. The problem that immediately arose is the fact that we have 19 departments, which means a small number of clusters for making a reliable inference. To mitigate this econometric issue, we used two approaches that are often used in applied research: the 1) block-bootstrap and 2) the two-step estimators proposed by Donald and Lang (2007).

Another important concern is that, since several factors—for example, social policies, the cash transfer program, and the health and tax reforms that were introduced after 2005—could have confounded our estimates. Therefore, we conducted two robustness checks: 1) performing a placebo test, which entails changing the year of the introduction of the minimum from 2005 to any previous year (for instance, 2000); 2) estimating equation (4) for public employees, which are not considered in the minimum wage policy. If, for this subsample, we found that α_3 is statistically different from zero, our strategy would not have been working properly.

IV. Data

In order to undertake this research, we used the yearly Uruguayan National Household Survey (*Encuesta Continua de Hogares*, ECH) from 1996 to 2011, which is conducted by the National Statistical Office of Uruguay (*Instituto Nacional de Estadística*, INE). We focused on the latter period for two reasons: 1) data constraints (as we explain below, the data from the social security records was available only for this period); 2) our focus on the reintroduction of the minimum wage, which is the main aim of this research.

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. To have a comparable sample throughout the different years, we defined our sample unit as urban areas of more than 5,000 inhabitants of each department, which represents more than 80% of the total labor force in the department and, therefore, is representative of the whole work force in each.

Moreover, the selected sample is composed of male wage earners between 14 (the 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 service sectors, we did not exclude them because 1) we only consider urban areas, so there is a negligible proportion of rural workers whose minimum wage is similar to the national minimum wage and because 2) the minimum wage in the domestic service sector is set just above the national minimum wage, thus not creating an important difference between the two (see Furtado (2005) for a similar discussion). We excluded the public sector because the national minimum wage is not relevant for those workers. Finally, we also excluded the first and the ninety-ninth percentiles to avoid outliers.

The ECH has information on the net monthly salaries, social security, and income taxes of each household member, from which we constructed the monthly salary percentiles by department. We have 19 departments and a time period of 16 years; hence, as we aggregated the data by department, our sample size became 304. Therefore, we refer to our data as a panel at the department level.

We merged this data with the information about the monthly minimum wage, which is set by the government and usually changes slightly two times per year, so we took the latest value in each year.

In Table 1, we present some summative statistics of several variables for the selected sample period. Between 1996 and 2004, the different percentile salary gaps (e.g. 10th–70th percentile gap) tended to increase. When we compared 2004 with 2005 (the year in which the minimum wage was reintroduced), we observed a decline in the salary gaps. By the end of the analyzed period, apart from the 10th–70th percentile gap, they continued to decrease.

Figure 5 presents the evolution of the 10th, 20th, 80th, and 90th percentiles relative to the 70th throughout the 1996–2011 period, which arises from a regression of each percentile gap (which varies across department and time) on department and year dummies weighted by the number of observations in each department. As we observed in the lower plot, the ninth percentile increased to a peak in 2002, and then it fluctuated until 2005, after which it declined, increasing again during the last year of the period. A similar but more attenuated pattern was followed by the 80th percentile. Related to the 20th percentile gap, it almost shows an opposite pattern. What is interesting is that this percentile gap shows an upward trend after the increase of the minimum wage in 2005.

As for the effective minimum wage, it increased from -1.95 to -1.13 between 1996 and 2011 (see Table I). We also constructed an additional indicator, the minimum wage average or (median) monthly wage ratio, in order to explain the rise in the minimum wage related to the average and median wage. These ratios increased throughout the period. Specifically, between 1996 and 2011, the ratio almost doubled when we considered the average wage and increased by fifty percent when examining the median wage (see Figure 2). 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 had a ratio of just over 0.70 and 0.50, respectively, as Kristensen and Cunningham (2006) observed. They also found that, in 1998, the Uruguayan minimum wage was one of the lowest in the region. Based on these facts, one can argue 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. However, we have tested this hypothesis.

Another interesting labor market feature, which emerged from our observation of Table I, is that the percentage of workers below the minimum wage grew sharply from 1% to 5%. This fact 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 Nuñez (2004) as well as Kristensen and Cunningham (2006) noted that, for many Latin American nations, the minimum wage has a potential impact on both the formal (or covered) sector and the informal (or non-covered) sector. Moreover, they argued that the minimum wage seems to have a stronger effect on the latter than on the former sector. This phenomenon, usually called the “lighthouse effect,” occurs when minimum wage is

relevant for the informal sector (where minimum wage law does not apply). Additionally, in a recent paper, Khamis (2009) found that minimum wage has stronger effects on the informal labor market, in which workers experience more considerable wage increases than on the formal labor market.

In this research, we defined an informal worker as a person who has paid work but has no access to social security. Under this definition, the proportion of informal workers decreased from 36% in 1996 to 18% in 2011. We also observed 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. Neumark (2008) stated that, when analyzing data from developing countries, “enforcement of and compliance with minimum wage laws is often erratic.”

Finally, we observed that the average age in our sample is approximately 35 and that the average education level increased by one year during the 1996–2011 period.

As we mentioned earlier, we also used social security data obtained from the Social Security Office (*Banco de Previsión Social*, BPS). BPS is a state office in charge of pensions, social benefits, employment insurance, and social security tax collection. Employers are responsible for paying the social security tax, which is calculated using the nominal salary. As a result, the BPS has the salary records of employees from the entire formal labor market. The office provided us with a panel set that includes the percentiles by department for the years between 1996 and 2011. In Table 1, we also present statistics of the percentile salary gaps in the social security records. Using the BPS data, overall, we observed the same pattern as when using the ECH data. Finally, we also observed that our instrument—that is, the effective minimum wage constructed using the 70th percentile of the social security records—increased until 2005 and fell afterwards.

V. Results

a) Wage inequality

Table 2 and Figure 6 present our OLS estimates of equation (2) and equation (3) (which correspond to columns 1 and 2, respectively), in addition to adding time trend effects by department (column 3) for the different percentile gaps using the ECH data. For the

different percentiles of reference, we found a statistically significant effect of the relative minimum wage on the 10th percentile through the 60th percentile of the wage distribution. From the visual inspection of Figure 6, we also observed that this positive effect declined through the wage distribution, primarily when we considered higher percentiles. This result suggests the presence of spillover effects. In other words, the impact of the minimum wage extended to almost the 60th percentile. Interestingly, we did not find statistically significant effects for the top percentile gaps (80th and 90th) as we had expected from the model. Another striking point is that the coefficient increased in magnitude for all the percentiles when we considered a general trend and controlled variables by city in column (3) of each percentile of reference. As previously indicated, these results could be spurious because of the division bias problem.

In Table 3 (Figure 7), we present the estimates of the impact of the relative minimum wage on wage inequality using instrumental variables.¹³ First, in this case, the results are sensitive to the election of the percentile of reference and to the specification of the equation. In terms of the latter, when we consider the full sample without controls and with controls, we found no significant effect at the 1% level (in most of the cases) when we set the reference wage as the 60th or 70th percentile. However, when we included control variables and a department trend, the effect became significant except for the 10th percentile gap in column (3). This gap can be explained by non-compliance with the minimum wage law. It is important to note 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 in Table 3.¹⁴ Moreover, we included the p-value of the instrumental variable of the first stage regression. When considering the

¹³ As mentioned above, the estimations were conducted using yearly data. Additionally, we estimated equations (2) and (3) using quarterly data. The results went in the same direction, but, in this case, the effect appeared to be statistically significant in both cases with and without control variables by city and general trends. Nevertheless, it is necessary to highlight that when using quarterly panel data, additional issues like seasonality arise; what is more, the measurement error problem tends to increase.

¹⁴ The Kleibergen-Paap test of weak identification is commonly used when the assumption of i.i.d. errors is no longer valid, as in our case. In addition, we used the practical rule that the Kleibergen-Paap statistic should be above 10 in order not to have weak identification problems.

80th percentile as a reference percentile, the picture changed. In the latter case, we observed that the relative minimum wage contributed to the reduction of the wage gap up to the 70th percentile (column 1 and 2) and up to the 50th percentile when we used controls and time trends by department. Not finding significant coefficients above the p70 provides evidence for the strategy of identification used.

Figure 7 reaffirms what we observed in Table 3. That is, the estimated coefficient was around zero not only when we did not take into account the control variables but also when we included it and used the 60th and the 70th percentiles as the reference ones, while we found evidence of a slight effect when including time trends by department. Finally, the plots at the bottom, those for which the 80th percentile was the reference variable, we observed some statistically significant effects after the 10th percentile, which decreased until it vanished around the 60th.

In Tables A.1 and A.2 (see the Appendix), we show the estimations for formal and informal workers separately. In the estimation using only formal males, we found a similar situation. Nevertheless, there is clearer evidence of the impact of the minimum wage on the lower tail of the earning distributions. That is, when looking at the different specifications and considering different percentiles of reference, we observed that the minimum wage contributed towards a reduction in the wage inequality mainly in the lower tail of the wage distribution. As for spillover effects, the evidence is mixed. That is, for some specifications, the minimum wage had an impact on the 10th percentile through the 60th percentile.

To put these findings in perspective, multiplying the implied change in the minimum wage relative to the 7th decile between the beginning and the end of the period from Table 1 (+0.61) by the IV estimate for the most saturated specification in Table 3 (and for $p_{th}=70^{th}$), row 1, column 6 (+0.563) this gives an effect of the minimum wage in the ratio between the bottom decile and the seventh decile of around 34 log points over 16 years which seems to a sizeable effect. Following the previous calculation but only considering Formal workers (Table A.1., row 1 and column 6), the results leads to a greater reduction, 44 log points over 16 years.

On the other hand, the effect of the relative minimum wage on wage inequality tended to disappear for the case of informal workers. In this last case, we seem to have weak

identification problems. To overcome this problem, we estimated models (1) and (2) using the 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 tended to under-reject the null hypothesis of absence of effect; we also applied the Anderson-Rubin test to perform a robust inference (the results are not shown but are available upon request). The results do not change.

For Figure 8, we graphed the IV estimates of model (2) for the 10th percentile gap (taking the 80th percentile as the reference one) and for all males in 1996 and in 2011, which are weighted by the number of observations by department. For 1996, we observed a flat relationship between the 10th relative percentile and the relative minimum wage, as was expected, since the minimum wage has been reaching its lower level ever since. Despite the fact that the minimum wage increased considerably in 2011, there was not a clear positive slope in our estimates. However, the 2011 estimates were closer to the 45° line. A problem could have arisen because of the absence of a linear relationship between the percentile gap and the effective minimum wage, which could have biased our estimates. Lee also included the square of the effective minimum wage. In our case, we also included a quadratic term, but it was not statistically significant.

b) Labor market outcomes

Following a difference-in-difference approach, as explained above, we have shown in Table 4 the estimation of the impact of the minimum wage on employment, worked hours, wages, and informality. Our coefficient of interest was the one associated with the interaction of the “Post” and the “Intense pth,” which is labeled as “Post * Intense pth.” We followed a similar strategy as above and then constructed the variable intensity using different percentiles of reference in order to check the robustness of our results. Using the full sample, we did not observe any impact on employment. That is, our results suggest that there is no employment effect. However, we estimated a negative impact of worked hours (a reduction of around -4.0 hours at the 1% level), a positive one on wages (an increment in 0.2 in logs at the 1% level), and a reduction of informality (of

around 6% and at the 5% level).¹⁵ We also conducted the same regression analysis but added control variables (the results are not presented here) such as years of education, age squared, marriage indicator, children indicator, dummies to control for industry effects, and if attending an educational institution. The results did not change.

We also estimated the impact of the minimum wage without considering Montevideo, the capital city in which half of the country's population resides. In this case, we observed a negative impact on employment (a just over 10% at the 5% level), on worked hours (around 7 hours at the 5% level), and a positive effect on wages (0.2 in logs and at the 1% level). We did not observe an effect concerning informality. These results were in line with the fact that wages were lower and informality was greater when we did not include the capital city. Interestingly, when considering only informal workers the coefficients were higher in absolute values than before.¹⁶

In order to check the robustness, we considered alternative approaches related to the inferences applied in this analysis. For Table A.4 (see the appendix), we first used the Donald and Lang methodology to make inferences in the context of a small number of clusters. We only used this technique for the sample not including the capital city, because this method requires a similar number of observations in each of the clusters (and Montevideo has a greater size in terms of observations compared to the other departments). In this case, we found very slight evidence of employment effects at the 10% level; hence, the effect of the minimum wage on employment seemed to vanish. As for the other variables, the results did not change. Additionally, we used a block bootstrap approach as an alternative to the prior inference method. In this case, we also did not find employment effects. In addition, the negative effect of the minimum wage on worked hours was statistically significant at the 10% level and only in one case (that is, using the 60th percentile as the reference wage). Results concerning to wages remained unchanged.

¹⁵ We also estimated this equation with the Donald and Lang (2007) two-step estimator and the bootstrap estimate for standard errors. The results are similar, and they are available from the authors upon request.

¹⁶ Results available upon request from the authors.

Finally, we performed two placebo tests to be sure that we were estimating the impact of the minimum wage on income inequality. First, we performed a placebo test, which entailed changing the year of the introduction of the minimum wage from 2005 to a previous year (2000); second, we estimated equation (4) only for public employees who are not covered under the minimum wage policy. Because we did not find coefficients statistically different from zero, our strategy was working properly.¹⁷

¹⁷ Results available upon request from the authors.

VI. Conclusions

Our empirical application aimed to shed light on the contribution of Uruguay's recent sharp minimum wage increase on the country's slight decline in wage inequality. We isolated the impact of the minimum wage on wage inequality for other social policies that potentially could have impacted our findings. To estimate the impact of the minimum wage on inequality, we used data from the urban areas of Uruguay between 1996 and 2011. To handle the joint determination of wages and the minimum wages, we estimated the model using an instrumental variable estimation strategy.

We found that the minimum wage increase had a significant impact on wage inequality, but mainly for formal wage workers. In other words, more than doubling the minimum wage had an effect on lower-income individuals. Despite the minimum wage being a relevant feature for informal workers, as we observed using kernel plots, the gap between the top and the bottom percentile shows that it evolves according to different patterns, just as when we considered the distribution for the whole sample. A possible explanation for the lack of effect on informal workers could be related to the low level of compliance (as we observe in Figure 4 a great mass of density falls below the minimum wage in the case of informal workers in 2011). We also observed a reduction in hours of work for the whole country, which confirmed the hypothesis that the minimum wage effects operate through other margins of adjustment. Additionally, we found a negative impact on employment outside the capital city, Montevideo. That is, we observed some slight evidence of employment effects that is traditionally related to the competitive supply-and-demand model.

Finally, we put these results in the context of some recent theoretical developments in this field. For instance, our results are in line with the theoretical prediction of Boeri et al. (2011). That is, we found that wages from informal workers increased and that informality was reduced, which could be related to the fact that low-skill workers shifted to the formal sector. In addition, Dickens et al. (2012) developed a theoretical framework to rationalize empirically the lack of employment effect together with a significant reduction of wage inequality, which they observed in the US and UK. Our

findings can be considered to be in line with the latter theoretical development; however, it is important to note that, first, despite finding slight employment effects, the minimum wage could affect other relevant variables such as worked hours (as we observed); second, in developing countries where there are dual labor markets, the minimum wage policy also affects the reallocation of human resources between the formal and the informal sectors; finally, despite our results suggesting an effect of the minimum wage on wage inequality, minimum wage does not seem to be a relevant instrument for addressing wage inequality reduction in the informal sector. The latter features also have to be integrated into a theoretical framework and, therefore, further research.

Ultimately, these results raise doubts about the effectiveness of minimum wage as a redistribution instrument in developing countries.

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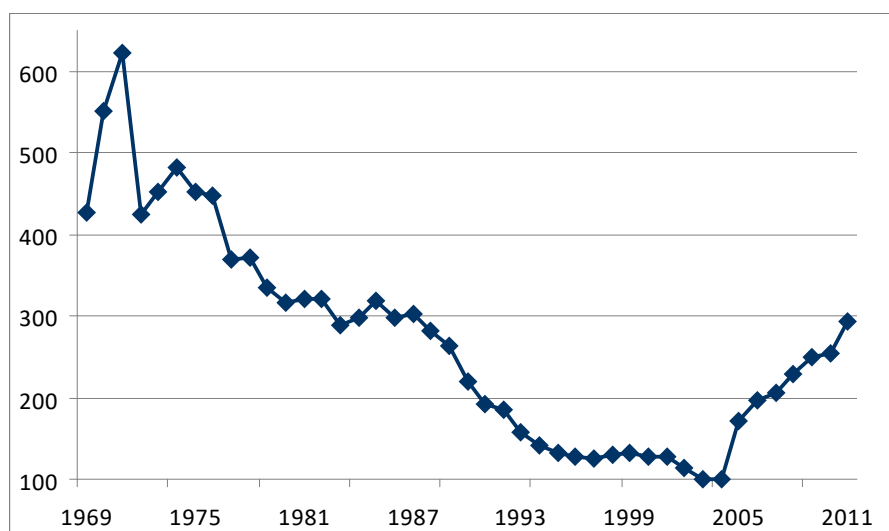
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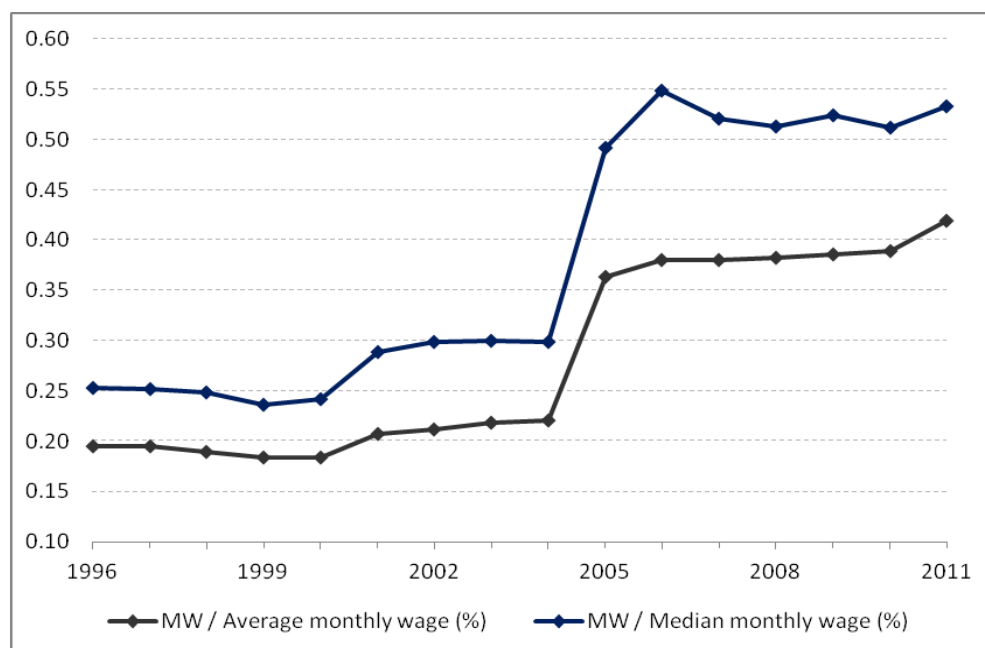
Figures

Figure 1. Historical Real Minimum Wage (2004=100)



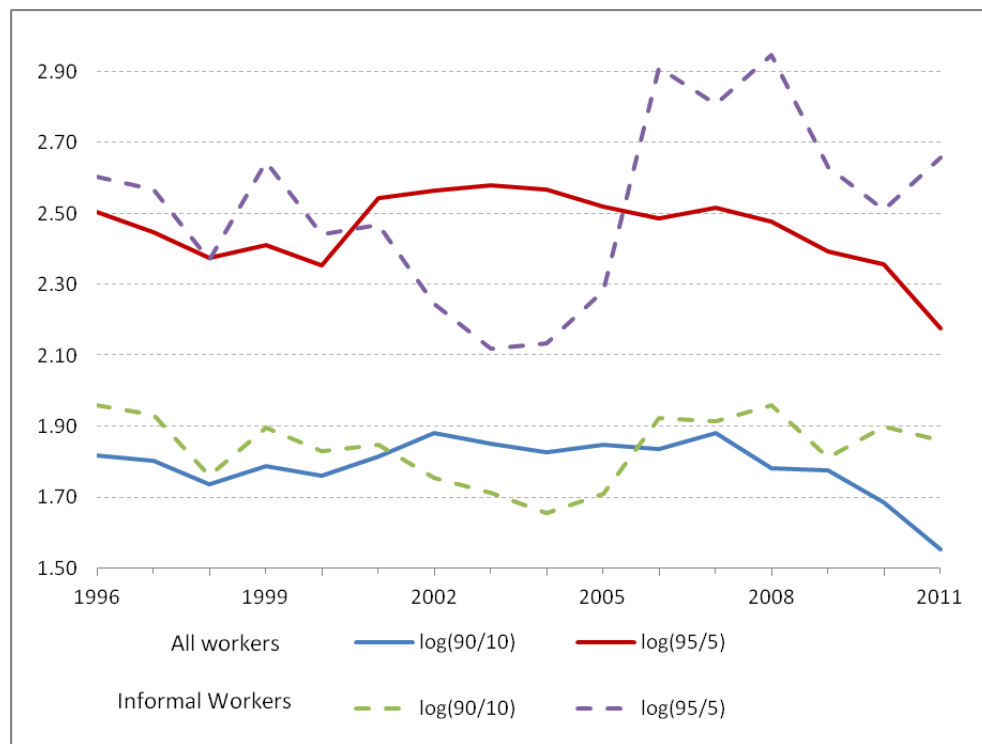
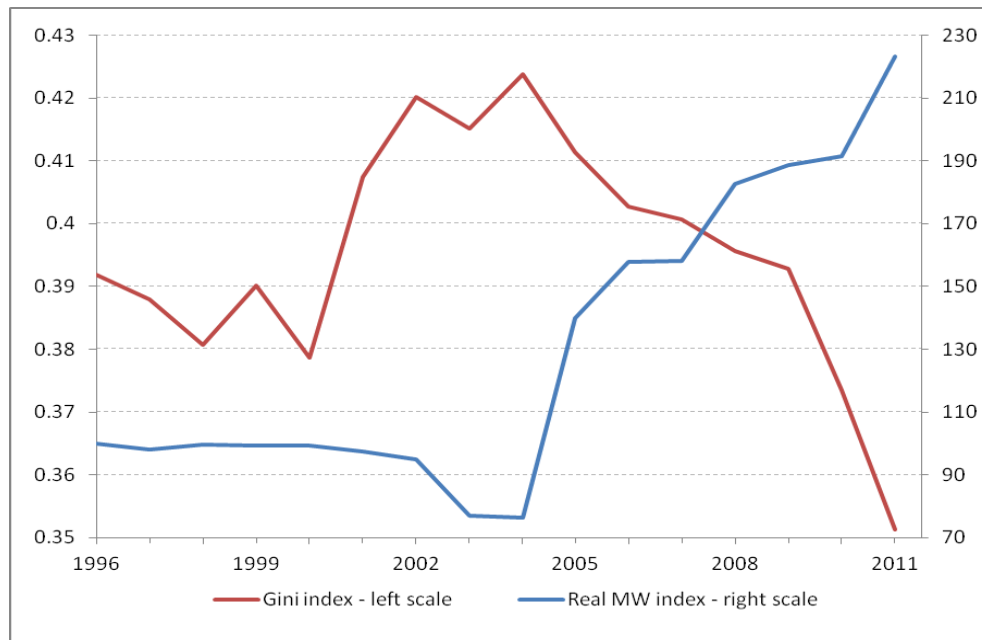
Source: National Statistical Office of Uruguay (Instituto Nacional de Estadística, INE).

Figure 2. National Minimum Wage Relative to the Mean and to the Median



Source: Author's calculation; ECH.

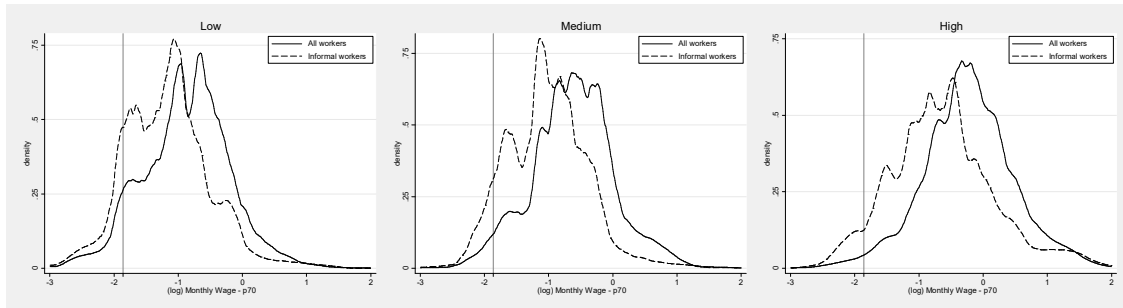
Figure 3. Trends in Earnings Inequality



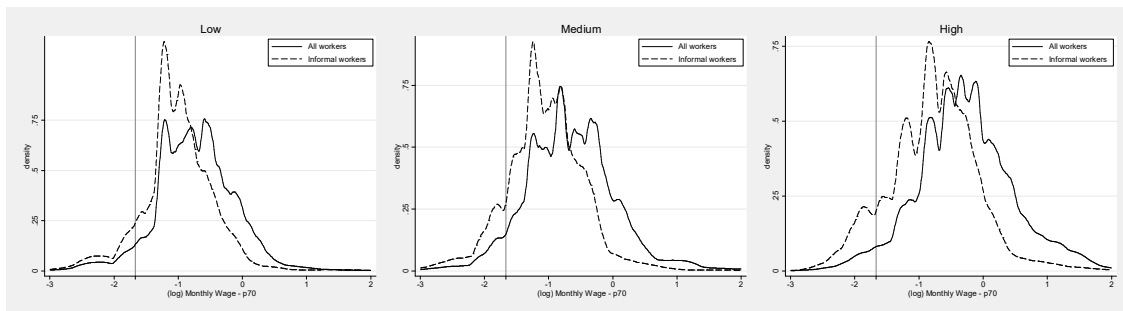
Source: Author's calculation; ECH.

Figure 4. Effective minimum wage variation within Departments.

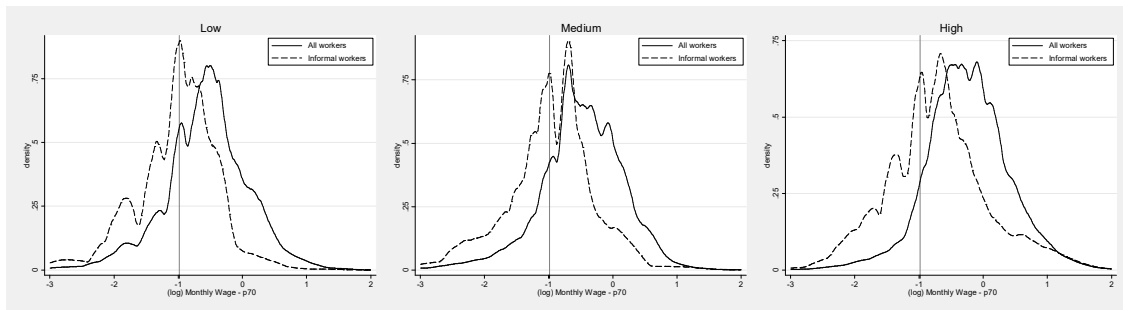
a. 1996



b. 2004



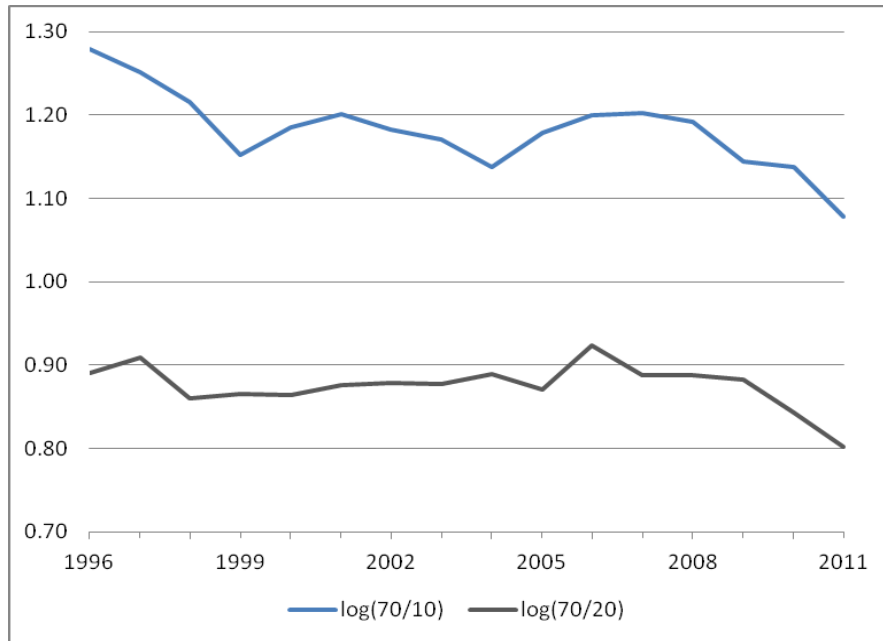
c. 2011



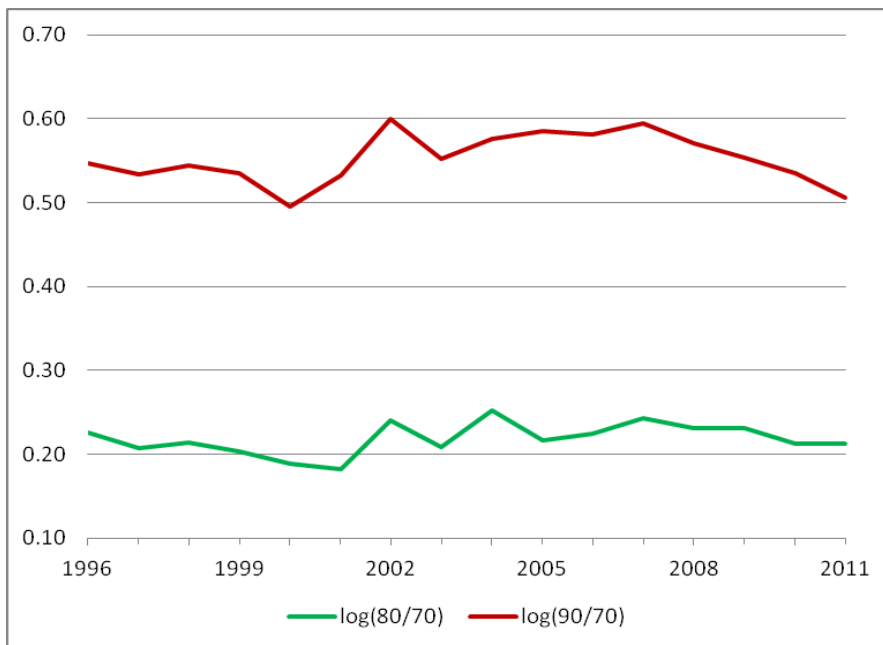
Source: Authors' calculation; ECH.

Figure 5. Evolution of the percentile gap.

A. 10th-70th & 20th-70th



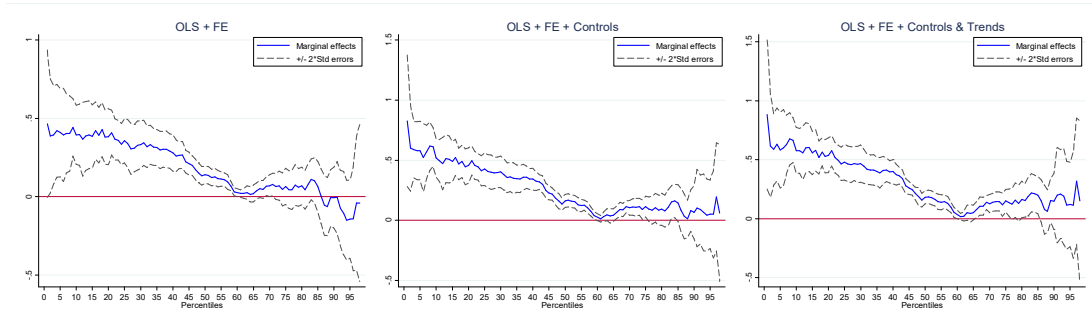
B. 90th-70th & 80th-70th



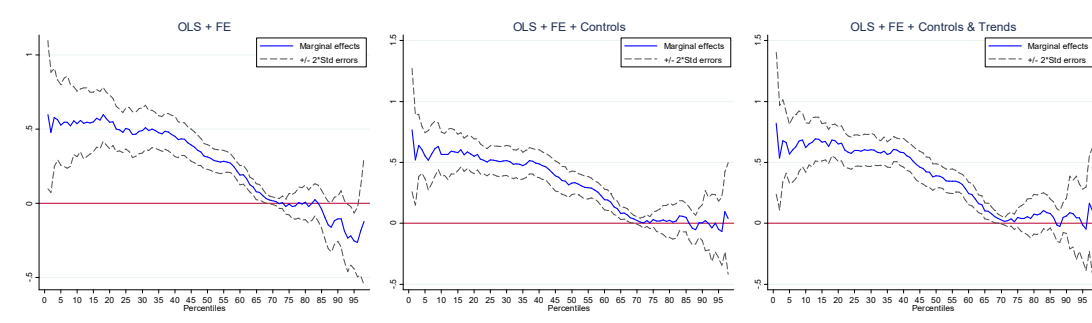
Source: Author's calculation; ECH.

Figure 6. OLS estimates

pth=60



pth=70



pth=80

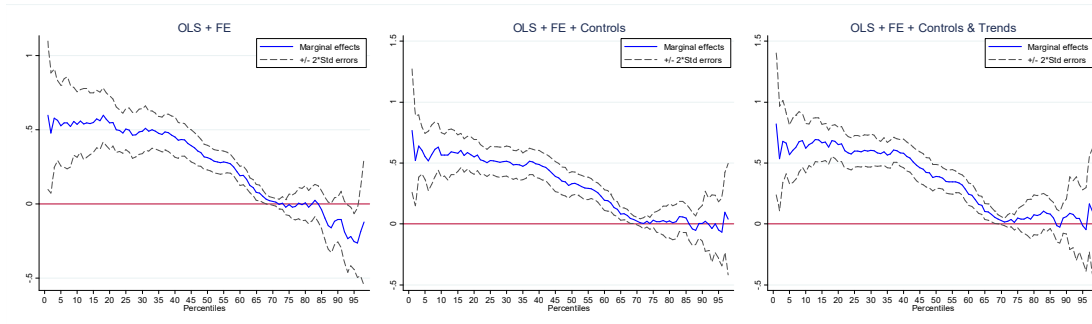
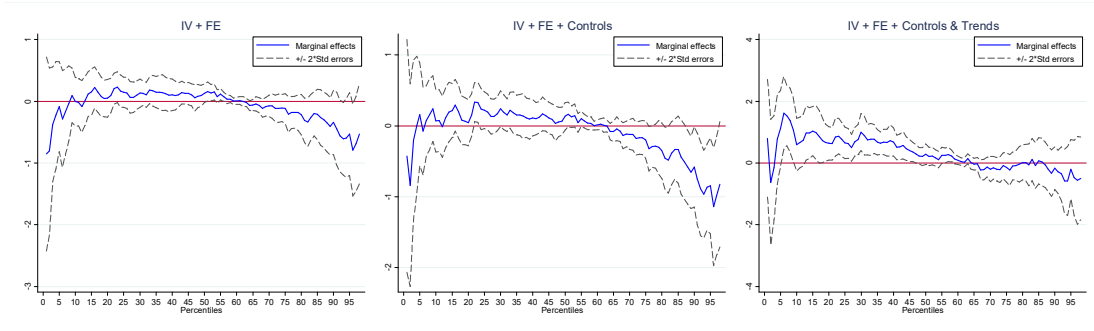
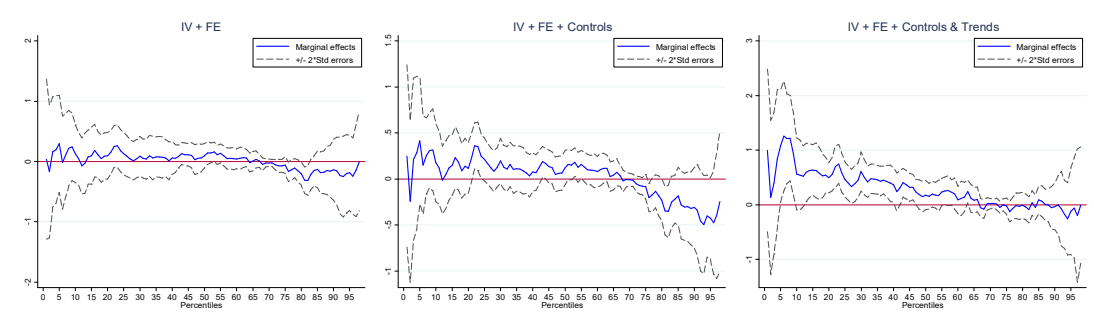


Figure 7. IV Estimates

pth=60



pth=70



pth=80

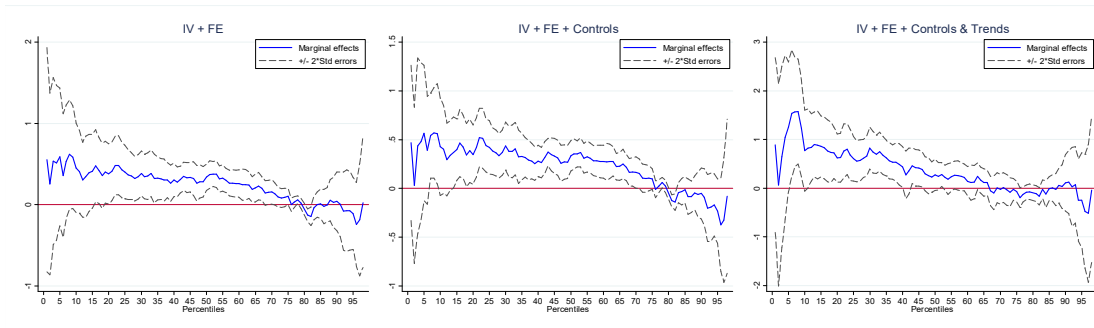
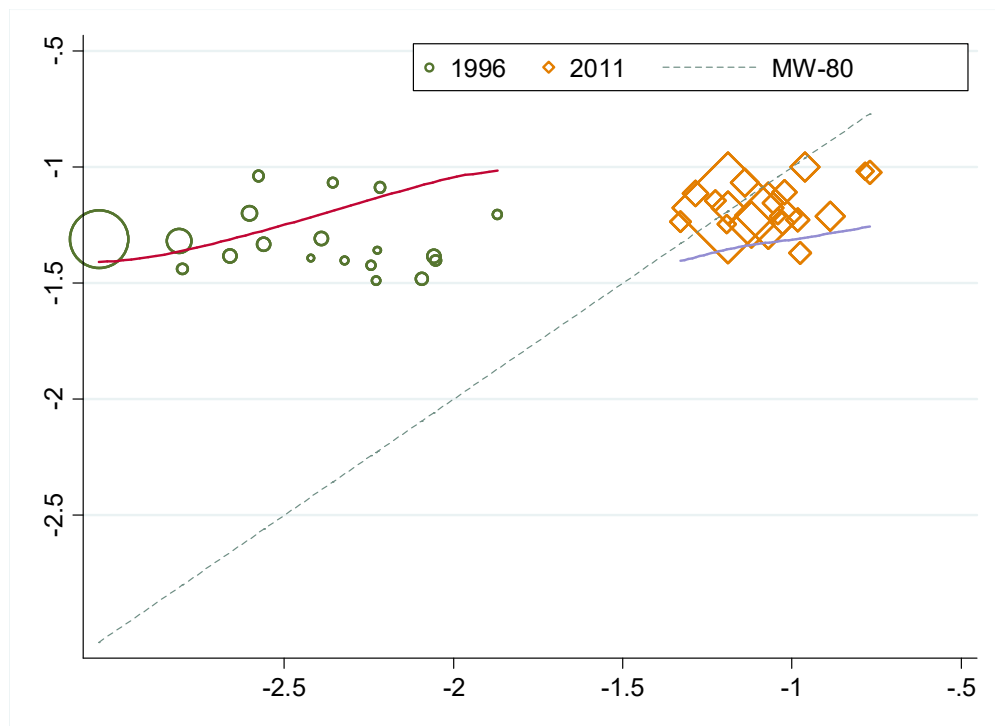


Figure 8. IV estimates of model (2) for the 10th percentile gap



Tables

Table 1. Summary Statistics of the Selected Sample

<i>National Household Survey</i>	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
10th - 60th percentile gap	-1.117	-1.085	-1.050	-0.995	-1.021	-1.018	-1.020	-0.992	-0.955	-1.004	-0.994	-1.015	-1.012	-0.946	-0.948	-0.895
10th - 70th percentile gap	-1.279	-1.251	-1.216	-1.153	-1.185	-1.201	-1.182	-1.171	-1.138	-1.178	-1.200	-1.202	-1.192	-1.145	-1.138	-1.078
10th - 80th percentile gap	-1.505	-1.459	-1.430	-1.357	-1.374	-1.383	-1.423	-1.380	-1.390	-1.396	-1.425	-1.445	-1.423	-1.376	-1.351	-1.291
MW - 60th percentile gap	-1.790	-1.802	-1.830	-1.840	-1.827	-1.691	-1.594	-1.607	-1.562	-0.995	-0.960	-1.037	-0.968	-1.002	-1.013	-0.950
MW - 70th percentile gap	-1.951	-1.968	-1.995	-1.998	-1.991	-1.874	-1.756	-1.786	-1.744	-1.169	-1.166	-1.224	-1.149	-1.201	-1.203	-1.132
MW - 80th percentile gap	-2.177	-2.176	-2.209	-2.202	-2.180	-2.056	-1.997	-1.995	-1.996	-1.387	-1.391	-1.466	-1.379	-1.433	-1.415	-1.346
Workers below the MW (%)	0.9	1	1	0.7	0.7	1	0.9	1.1	1	4.7	6.5	6.1	5.7	5.7	5	5
Informal worker (%)	36.1	35.9	34.9	34.6	35	31.8	31.3	34	36.1	34.3	34.1	30.7	29.1	22.1	21	18
Informal workers below the MW (%)	83.7	85.2	86.8	83.4	91.3	84.6	85.4	89.1	81	77.4	74.8	75.3	69.9	60.7	59	55
Full time workers (%)	68.2	68.5	69.2	68.5	68.1	70.6	70.4	70.6	71	70	68.7	69.3	69.7	70.3	71	72
Full time workers below the MW (%)	85.4	82.8	83	81.5	76.6	83.8	83.5	79.1	78.4	71	73	70.2	71.6	69.5	70	66
Average age	34.6	34.7	34.8	35.2	35.3	35.7	36.3	36.7	36.4	36.3	36.3	35.9	36.4	36.5	36.4	36.0
Average education	8.9	8.9	9.0	9.0	9.0	9.4	9.5	9.5	9.8	9.8	9.9	9.9	9.7	9.9	9.8	10.1
<i>Social Security Records</i>																
10th - 60th percentile gap	-1.424	-1.438	-1.449	-1.467	-1.480	-1.508	-1.574	-1.619	-1.614	-1.432	-1.401	-1.458	-1.515	-1.557	-1.577	-1.642
10th - 70th percentile gap	-1.641	-1.643	-1.636	-1.648	-1.657	-1.678	-1.750	-1.808	-1.806	-1.625	-1.591	-1.661	-1.722	-1.761	-1.784	-1.837
10th - 80th percentile gap	-1.907	-1.924	-1.916	-1.920	-1.936	-1.967	-2.041	-2.113	-2.107	-1.902	-1.841	-1.900	-1.963	-1.998	-1.998	-2.051
MW - 60th percentile gap	-1.079	-1.064	-1.047	-1.065	-1.050	-1.045	-0.984	-1.020	-0.988	-0.460	-0.474	-0.564	-0.478	-0.544	-0.630	-0.539
MW - 70th percentile gap	-1.296	-1.269	-1.235	-1.246	-1.226	-1.215	-1.160	-1.209	-1.180	-0.653	-0.665	-0.766	-0.685	-0.747	-0.837	-0.734
MW - 80th percentile gap	-1.561	-1.550	-1.514	-1.518	-1.506	-1.503	-1.452	-1.514	-1.480	-0.930	-0.915	-1.006	-0.926	-0.984	-1.051	-0.947

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

**Table 2. Impact of the Minimum Wage on Wage Inequality. OLS Estimates using the National Household Survey (ECH).
Sample Period 1996 - 2011.**

	pth = p60			pth = p70			pth = p80		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
p10-pth	0.273*** (0.085)	0.415*** (0.076)	0.480*** (0.091)	0.456*** (0.092)	0.505*** (0.069)	0.589*** (0.083)	0.662*** (0.080)	0.659*** (0.059)	0.786*** (0.068)
p20-pth	0.313*** (0.079)	0.386*** (0.068)	0.462*** (0.069)	0.486*** (0.081)	0.493*** (0.055)	0.598*** (0.060)	0.642*** (0.065)	0.613*** (0.046)	0.718*** (0.052)
p30-pth	0.290*** (0.069)	0.377*** (0.056)	0.454*** (0.067)	0.467*** (0.079)	0.503*** (0.051)	0.604*** (0.062)	0.620*** (0.064)	0.627*** (0.045)	0.719*** (0.061)
p40-pth	0.263*** (0.058)	0.319*** (0.042)	0.397*** (0.045)	0.445*** (0.075)	0.475*** (0.053)	0.583*** (0.059)	0.605*** (0.066)	0.614*** (0.053)	0.720*** (0.066)
p50-pth	0.146*** (0.028)	0.161*** (0.030)	0.194*** (0.029)	0.332*** (0.050)	0.348*** (0.044)	0.414*** (0.050)	0.503*** (0.045)	0.514*** (0.044)	0.570*** (0.054)
p60-pth				0.207*** (0.034)	0.221*** (0.035)	0.263*** (0.042)	0.414*** (0.034)	0.433*** (0.036)	0.458*** (0.044)
p70-pth	0.039 (0.032)	0.055 (0.036)	0.082* (0.044)				0.256*** (0.031)	0.287*** (0.035)	0.279*** (0.038)
p80-pth	0.042 (0.056)	0.037 (0.059)	0.137* (0.070)	0.000 (0.048)	0.004 (0.053)	0.081 (0.068)			
p90-pth	-0.044 (0.098)	-0.025 (0.103)	0.117 (0.097)	-0.093 (0.077)	-0.016 (0.067)	0.103 (0.066)	-0.070 (0.059)	-0.013 (0.058)	0.041 (0.058)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time trend by department	No	No	Yes	No	No	Yes	No	No	Yes

N = 304. Each row represents the marginal effects (evaluated at the mean) of the effective minimum wage on the respective percentile gap. Panel data at the department level of male wage earners between 14 and 60 years old. Standard errors clustered at the department level reported in parenthesis. All models include year effects. Controls by department 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 number of observations by year-department.

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

Table 3. Impact of the minimum wage on wage inequality. IV estimates. Sample period 1996 - 2011.									
	pth = p60			pth = p70			pth = p80		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
p10-pth	-0.005 (0.194)	0.070 (0.220)	0.596 (0.429)	0.128 (0.238)	0.179 (0.211)	0.563* (0.329)	0.452 (0.275)	0.427* (0.250)	0.771* (0.417)
p20-pth	0.050 (0.153)	0.044 (0.163)	0.637** (0.269)	0.094 (0.193)	0.117 (0.140)	0.496*** (0.139)	0.380** (0.186)	0.345** (0.152)	0.619** (0.247)
p30-pth	0.132 (0.114)	0.243* (0.127)	1.001*** (0.300)	0.087 (0.165)	0.196 (0.122)	0.605*** (0.180)	0.384*** (0.138)	0.434*** (0.124)	0.823*** (0.216)
p40-pth	0.104 (0.126)	0.113 (0.128)	0.680*** (0.230)	0.059 (0.135)	0.077 (0.105)	0.363** (0.159)	0.304*** (0.102)	0.281*** (0.080)	0.436** (0.210)
p50-pth	0.131* (0.077)	0.137 (0.097)	0.286* (0.168)	0.098 (0.101)	0.125 (0.092)	0.177 (0.133)	0.339*** (0.081)	0.335*** (0.078)	0.275* (0.160)
p60-pth				0.044 (0.082)	0.081 (0.082)	0.088 (0.125)	0.261*** (0.084)	0.274*** (0.084)	0.142 (0.152)
p70-pth	-0.074 (0.086)	-0.122 (0.105)	-0.197 (0.203)				0.157** (0.076)	0.164** (0.081)	-0.021 (0.154)
p80-pth	-0.217 (0.163)	-0.350* (0.196)	0.017 (0.283)	-0.199** (0.095)	-0.230** (0.114)	-0.008 (0.119)			
p90-pth	-0.341 (0.261)	-0.580** (0.284)	-0.169 (0.346)	-0.136 (0.252)	-0.309 (0.217)	-0.032 (0.213)	0.043 (0.180)	-0.051 (0.131)	0.106 (0.290)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time trend by department	No	No	Yes	No	No	Yes	No	No	Yes
Angrist and Pischke first stage F statistic:									
Linear: (Min wage - pth)	5.647	3.289	7.738	4.663	3.268	6.224	4.274	2.872	7.061
Quadratic: (Min wage - pth) ²	11.279	6.579	38.158	11.406	7.450	24.152	12.339	7.545	32.167

N = 304. *Instruments*: effective minimum wage and effective minimum wage squared constructed using the Social Security Records. Each row represents the marginal effects (evaluated at the mean) of the effective minimum wage on the respective percentile gap. Panel data at the department level of male wage earners between 14 and 60 years old. Standard errors clustered at the department level reported in parenthesis. All models include year effects. Controls by department include: proportion of workers at primary school level, proportion of workers at the secondary school level, proportion of workers at tertiary education, unemployment rate, proportion of full time workers, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector (Manufacturing, Construction, Transportation and Warehousing, Finance and Insurance, Whole Sale and Retail Trade, Social Services). All the regressions are weighted by the number of observations by year-department.

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

Table 4. Impact of the Effective Minimum Wage on Labor Market Outcomes. Difference in Difference Estimator

	Employment			Worked hours			Wage			Informality		
	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80
a) Full sample												
Post	0.039*** (0.005)	0.039*** (0.005)	0.039*** (0.005)	0.285 (0.230)	0.281 (0.233)	0.277 (0.235)	0.071*** (0.015)	0.070*** (0.012)	0.069*** (0.009)	0.070*** (0.008)	0.070*** (0.007)	0.070*** (0.007)
Intense pth	0.003 (0.023)	0.001 (0.021)	-0.001 (0.018)	5.172*** (0.837)	4.782*** (0.765)	4.221*** (0.692)	1.117*** (0.020)	1.027*** (0.011)	0.907*** (0.021)	0.370*** (0.041)	0.340*** (0.036)	0.300*** (0.033)
Post * Intense pth	-0.028 (0.024)	-0.024 (0.022)	-0.018 (0.020)	-4.273*** (1.159)	-3.849*** (1.083)	-3.296*** (0.979)	0.446*** (0.041)	0.418*** (0.032)	0.379*** (0.024)	-0.060** (0.026)	-0.060** (0.022)	0.059*** (0.020)
Constant	0.886*** (0.004)	0.886*** (0.004)	0.886*** (0.004)	44.912*** (0.169)	44.914*** (0.161)	44.917*** (0.161)	4.009*** (0.006)	4.008*** (0.004)	4.008*** (0.009)	0.318*** (0.007)	0.318*** (0.008)	0.318*** (0.009)
N	179,149	179,149	179,149	163,115	163,115	163,115	154,984	154,984	154,984	163,115	163,115	163,115
Number of clusters	19	19	19	19	19	19	19	19	19	19	19	19
b) Without Montevideo												
Post	0.064*** (0.011)	0.069*** (0.012)	0.075*** (0.015)	0.984 (0.725)	1.279 (0.824)	1.593 (0.993)	-0.002 (0.016)	-0.010 (0.017)	-0.020 (0.018)	0.097*** (0.023)	0.097*** (0.025)	0.096*** (0.026)
Intense pth	0.060 (0.044)	0.068 (0.047)	0.071 (0.049)	4.986** (1.823)	5.319** (1.913)	5.405** (2.030)	1.024*** (0.029)	1.057*** (0.043)	1.054*** (0.063)	0.378*** (0.084)	0.399*** (0.084)	0.406*** (0.086)
Post * Intense pth	-0.113** (0.041)	-0.122** (0.043)	-0.126** (0.046)	-6.717** (2.456)	-7.191** (2.590)	-7.342** (2.817)	0.209*** (0.052)	0.217*** (0.057)	0.223*** (0.056)	0.036 (0.070)	0.032 (0.071)	0.022 (0.066)
Constant	0.869*** (0.009)	0.866*** (0.010)	0.862*** (0.013)	44.966*** (0.469)	44.751*** (0.534)	44.525*** (0.637)	3.981*** (0.010)	4.017*** (0.016)	4.057*** (0.028)	0.316*** (0.016)	0.300*** (0.017)	0.283*** (0.019)
N	88,547	88,547	88,547	80,431	80,431	80,431	76,321	76,321	76,321	80,431	80,431	80,431
Number of clusters	18	18	18	18	18	18	18	18	18	18	18	18

Standard errors clustered at the department level reported in parenthesis

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

Appendix

Table A.1. Impact of the Minimum Wage on Wage Inequality. IV Estimates. Sample Period 1996 - 2011. Formal Wage Earners

	pth = p60			pth = p70			pth = p80		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
p10-pth	0.505** (0.215)	0.629*** (0.178)	0.732* (0.381)	0.485* (0.286)	0.696*** (0.168)	0.715*** (0.213)	0.705*** (0.269)	0.863*** (0.182)	0.839** (0.343)
p20-pth	0.367** (0.175)	0.438*** (0.168)	0.658** (0.260)	0.282 (0.287)	0.388* (0.201)	0.479*** (0.164)	0.524** (0.226)	0.565*** (0.178)	0.622** (0.267)
p30-pth	0.233 (0.151)	0.248 (0.179)	0.621*** (0.233)	0.214 (0.252)	0.300 (0.186)	0.576*** (0.120)	0.400* (0.204)	0.438*** (0.167)	0.580** (0.234)
p40-pth	0.130 (0.087)	0.129 (0.126)	0.362* (0.213)	0.114 (0.192)	0.203 (0.148)	0.371** (0.152)	0.285 (0.177)	0.339** (0.154)	0.255 (0.318)
p50-pth	0.084 (0.080)	0.123 (0.108)	0.297** (0.134)	0.164 (0.131)	0.269** (0.115)	0.394*** (0.126)	0.297* (0.154)	0.364*** (0.121)	0.219 (0.252)
p60-pth				0.132 (0.096)	0.182** (0.088)	0.261*** (0.096)	0.226* (0.116)	0.266*** (0.096)	0.040 (0.265)
p70-pth	-0.079 (0.082)	-0.122 (0.120)	-0.180 (0.280)				0.067 (0.114)	0.068 (0.101)	-0.332 (0.268)
p80-pth	-0.184 (0.195)	-0.247 (0.220)	0.161 (0.251)	-0.052 (0.121)	-0.064 (0.110)	0.255* (0.136)			
p90-pth	-0.544** (0.229)	-0.592** (0.266)	-0.224 (0.408)	-0.101 (0.283)	-0.147 (0.209)	0.158 (0.231)	-0.021 (0.268)	-0.030 (0.208)	-0.054 (0.314)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time trend by department	No	No	Yes	No	No	Yes	No	No	Yes
<i>Angrist and Pischke first stage F statistic:</i>									
Linear: (Min wage - pth)	3,658	1,956	5,915	2,991	2,766	4,677	2,773	1,967	3,969
Quadratic: (Min wage - pth) ²	5,961	2,538	21,485	7,068	4,568	10,965	7,428	3,762	7,327

N = 304. *Instruments:* effective minimum wage and effective minimum wage squared constructed using the Social Security Records. Each row represents the marginal effects (evaluated at the mean) of the effective minimum wage on the respective percentile gap. Panel data at the department level of male wage earners between 14 and 60 years old. Standard errors clustered at the department level reported in parenthesis. All models include year effects. Controls by department include: proportion of workers at primary school level, proportion of workers at the secondary school level, proportion of workers at tertiary education, unemployment rate, proportion of full time workers, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector (Manufacturing, Construction, Transportation and Warehousing, Finance and Insurance, Whole Sale and Retail Trade, Social Services). All the regressions are weighted by the number of observations by year-department.

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

Table A.2. Impact of the Minimum Wage on Wage Inequality. IV Estimates. Sample period 1996 - 2011. Informal Wage Earners.

	pth = p60			pth = p70			pth = p80		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
p10-pth	-2.484*	-1.603**	4.533	-3.608	-1.751	-0.889	-1.756	-1.089	-0.064
	(1.435)	(0.677)	(5.275)	(5.288)	(1.310)	(2.946)	(5.794)	(1.697)	(6.227)
p20-pth	-0.650	-0.506	-0.399	-2.089	-1.212	1.154	-0.644	-0.682	2.379
	(0.652)	(0.360)	(2.022)	(2.698)	(0.842)	(2.016)	(2.415)	(0.949)	(6.890)
p30-pth	-0.654	-0.443	2.506	-2.144	-0.959	-1.213	-1.585	-0.750	-2.574
	(0.552)	(0.310)	(2.563)	(3.432)	(0.779)	(2.454)	(4.973)	(0.991)	(12.882)
p40-pth	-0.058	-0.043	0.248	-1.273	-0.673	-0.505	-0.436	-0.387	-1.264
	(0.399)	(0.280)	(0.874)	(2.590)	(0.776)	(1.417)	(2.631)	(0.760)	(7.227)
p50-pth	-0.267	-0.056	0.567	-1.424	-0.592	-0.319	-0.730	-0.326	-0.435
	(0.347)	(0.179)	(0.674)	(2.905)	(0.681)	(1.184)	(3.428)	(0.780)	(4.595)
p60-pth				-1.463	-0.771	-0.369	-1.300	-0.650	-1.128
				(2.541)	(0.679)	(1.046)	(4.471)	(1.036)	(6.716)
p70-pth	0.564	0.545**	0.278				-0.179	-0.094	-1.129
	(0.366)	(0.252)	(0.518)				(1.382)	(0.481)	(5.809)
p80-pth	1.226*	0.944***	-2.152	0.737	0.298	1.491			
	(0.629)	(0.306)	(3.013)	(1.671)	(0.437)	(2.443)			
p90-pth	2.472*	1.881**	-7.724	1.469	0.629	4.505	-0.931	-0.228	3.240
	(1.289)	(0.945)	(9.214)	(3.671)	(1.021)	(7.636)	(2.750)	(0.677)	(15.236)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time trend by department	No	No	Yes	No	No	Yes	No	No	Yes
<i>Angrist and Pischke first stage F statistic:</i>									
Linear: (Min wage - pth)	1.688	3.084	0.582	0.205	1.898	0.409	0.119	1.222	0.201
Quadratic: (Min wage - pth) ²	3.488	5.771	14.188	1.153	7.954	8.413	7.429	27.449	0.248

N = 304. *Instruments*: effective minimum wage and effective minimum wage squared constructed using the Social Security Records. Each row represents the marginal effects (evaluated at the mean) of the effective minimum wage on the respective percentile gap. Panel data at the department level of male wage earners between 14 and 60 years old. Standard errors clustered at the department level reported in parenthesis. All models include year effects. Controls by department include: proportion of workers at primary school level, proportion of workers at the secondary school level, proportion of workers at tertiary education, unemployment rate, proportion of full time workers, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector (Manufacturing, Construction, Transportation and Warehousing, Finance and Insurance, Whole Sale and Retail Trade, Social Services). All the regressions are weighted by the number of observations by year-department.

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

Table A.3. Impact of the Minimum Wage on Wage Inequality. IV Eestimates. Sample Period 1996 - 2011. Without the Capital City (Montevideo)

	pth = p60			pth = p70			pth = p80		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
p10-pth	-0.356 (0.319)	-0.193 (0.316)	0.760 (0.618)	0.069 (0.278)	0.132 (0.220)	0.410 (0.377)	0.481 (0.362)	0.397 (0.293)	0.676 (0.505)
p20-pth	-0.170 (0.251)	-0.093 (0.245)	0.776 (0.474)	0.121 (0.195)	0.159 (0.132)	0.402* (0.221)	0.441* (0.256)	0.362** (0.181)	0.529 (0.350)
p30-pth	0.001 (0.203)	0.210 (0.195)	1.258*** (0.442)	0.089 (0.190)	0.223 (0.148)	0.442** (0.210)	0.407** (0.207)	0.435** (0.177)	0.661** (0.273)
p40-pth	0.054 (0.185)	0.041 (0.198)	0.823*** (0.301)	0.079 (0.147)	0.068 (0.130)	0.206 (0.187)	0.307** (0.156)	0.223* (0.128)	0.267 (0.308)
p50-pth	0.102 (0.087)	0.137 (0.124)	0.136 (0.175)	0.127 (0.079)	0.150 (0.091)	-0.025 (0.154)	0.351*** (0.092)	0.309*** (0.088)	0.060 (0.294)
p60-pth				0.055 (0.079)	0.095 (0.097)	-0.004 (0.156)	0.248*** (0.091)	0.239** (0.102)	0.058 (0.243)
p70-pth	-0.065 (0.112)	-0.155 (0.162)	-0.100 (0.256)				0.105 (0.084)	0.091 (0.084)	-0.009 (0.229)
p80-pth	-0.104 (0.174)	-0.249 (0.249)	0.266 (0.398)	-0.110 (0.086)	-0.119 (0.097)	0.001 (0.152)			
p90-pth	0.206 (0.345)	-0.140 (0.395)	0.613 (0.452)	0.229 (0.281)	0.016 (0.263)	0.396 (0.289)	0.254 (0.256)	0.140 (0.214)	0.728* (0.419)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time trend by department	No	No	Yes	No	No	Yes	No	No	Yes
<i>Angrist and Pischke first stage F statistic:</i>									
Linear: (Min wage - pth)	4.175	2.334	6.737	3.306	2.038	4.895	2.355	1.337	5.237
Quadratic: (Min wage - pth) ²	14.018	7.386	3.285	8.597	4.410	5.575	4.803	2.433	2.717

N = 288. *Instruments*: effective minimum wage and effective minimum wage squared constructed using the Social Security Records. Each row represents the marginal effects (evaluated at the mean) of the effective minimum wage on the respective percentile gap. Panel data at the department level of male wage earners between 14 and 60 years old. Standard errors clustered at the department level reported in parenthesis. All models include year effects. Controls by department include: proportion of workers at primary school level, proportion of workers at the secondary school level, proportion of workers at tertiary education, unemployment rate, proportion of full time workers, proportion of workers by age intervals (14-20, 21-30, 31-40, 41-50), proportion of workers by sector (Manufacturing, Construction, Transportation and Warehousing, Finance and Insurance, Whole Sale and Retail Trade, Social Services). All the regressions are weighted by the number of observations by year-department.
significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.4. Impact of the Effective Minimum Wage on Labor Market Outcomes. Difference in Difference estimator.

	Employment			Worked hours			Wage			Informality		
	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80	pth = p60	pth = p70	pth = p80
a) Using Donald and Lang + without Montevideo												
Post	0.057*** (0.014)	0.060*** (0.014)	0.063*** (0.015)	1.453** (0.626)	1.550** (0.649)	1.574** (0.692)	-0.041 (0.026)	-0.050 (0.030)	-0.058 (0.040)	-0.089*** (0.027)	-0.087*** (0.028)	-0.085** (0.032)
Intense pth	0.024 (0.030)	0.029 (0.030)	0.033 (0.029)	5.601*** (1.372)	5.593*** (1.356)	5.182*** (1.339)	-1.033*** (0.057)	-1.020*** (0.063)	-0.965*** (0.077)	0.369*** (0.059)	0.368*** (0.059)	0.344*** (0.062)
Post * Intense pth	-0.072 (0.043)	-0.076* (0.042)	-0.077* (0.041)	-7.043*** (1.940)	-6.933*** (1.917)	-6.371*** (1.893)	0.320*** (0.080)	0.330*** (0.089)	0.327*** (0.109)	-0.005 (0.083)	-0.013 (0.083)	-0.019 (0.088)
Constant	0.873*** (0.010)	0.871*** (0.010)	0.869*** (0.011)	44.422*** (0.443)	44.323*** (0.459)	44.291*** (0.489)	3.983*** (0.018)	3.999*** (0.021)	4.010*** (0.028)	0.331*** (0.019)	0.325*** (0.020)	0.322*** (0.023)
N	38	38	38	38	38	38	38	38	38	38	38	38
b) Block bootstrap standard errors												
Post	0.039*** (0.013)	0.039** (0.018)	0.039* (0.021)	0.292 (0.684)	0.284 (0.784)	0.278 (1.038)	-0.073** (0.036)	-0.071** (0.030)	-0.070** (0.028)	-0.069*** (0.022)	-0.069*** (0.021)	-0.070*** (0.025)
Intense pth	0.005 (0.044)	0.003 (0.048)	0.003 (0.052)	5.268*** (1.180)	4.686*** (1.307)	4.143*** (1.486)	-1.083*** (0.146)	-0.969*** (0.103)	-0.853*** (0.116)	0.344*** (0.102)	0.309*** (0.086)	0.274*** (0.106)
Post * Intense pth	-0.029 (0.049)	-0.024 (0.057)	-0.019 (0.061)	-4.608** (2.246)	-3.932 (2.484)	-3.320 (2.778)	0.441*** (0.120)	0.403*** (0.092)	0.358*** (0.082)	-0.053 (0.071)	-0.054 (0.062)	-0.051 (0.066)
Constant	0.886*** (0.010)	0.886*** (0.014)	0.886*** (0.017)	44.908*** (0.345)	44.913*** (0.370)	44.917*** (0.557)	4.011*** (0.042)	4.009*** (0.031)	4.009*** (0.039)	0.317*** (0.023)	0.318*** (0.020)	0.318*** (0.028)
N	179,149	179,149	179,149	163,115	163,115	163,115	154,984	154,984	154,984	163,115	163,115	163,115
Number of clusters	19	19	19	19	19	19	19	19	19	19	19	19

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