XIX

Volume XIX, Number 1, May 2016

Journal of Applied Economics

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UCEMA

Edited by the Universidad del CEMA
Print ISSN 1514-0326
Online ISSN 1667-6726

Journal of Applied Economics. *Vol XIX, No. 1 (May 2016), 1-40*

THE UNINTENDED CONSEQUENCES OF CHILDCARE REGULATION: EVIDENCE FROM A REGRESSION DISCONTINUITY DESIGN

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Submitted November 2014; accepted August 2015

In several countries governments fund childcare provision but in many others it is privately funded as labor regulation mandates that firms have to provide childcare services. For this later case, there is no empirical evidence on the effects generated by the financial burden of childcare provision. In particular, there is no evidence on who effectively pays (firms or employees) and how (e.g., via wages and/or employment). Our hypothesis is that in imperfect labor markets, firms will transfer childcare cost on to their workers. To analyze this, we exploit a discontinuity in childcare provision mandated by Chilean labor regulation.

JEL classification codes: H32, J08, J13, J18, J33, J42
Key words: childcare, labor regulation, labor tax, gender, female workers

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I. Introduction

Childcare policies started to be in the public debate at least since the 19th century, as the Industrial Revolution in part was fueled by the economic necessity of many women, single and married, to find waged work outside their home.[1] Childcare policies were mainly discussed in order to strengthen the parent-child link without negatively affecting their labor market situation, in particular female labor market participation. This later point is still a concern in many countries around the world. One of the examples is the Chilean case, as female participation is rather low (47%, INE 2010) relative to other OECD countries (57%, OECD 2010).[2]

Previous empirical literature on childcare policies can be classified into two main strands. On the one hand there are studies that analyze the effects of childcare policies on the development of cognitive abilities of children (see Baker, Gruber and Milligan 2005, Berlinski, Galiani and Gertler 2009, Berlinski, Galiani and Manacorda 2008, Bernal 2008, Carneiro, Loken and Salvanes 2008, Herbst and Tekin 2010 and Veramendi and Urzúa 2011). On the other hand, there are studies that analyze the effects of childcare policies on females' labor market participation and employment (see Baker, Gruber and Milligan 2005, Berlinsky and Galiani 2007, Betancor 2011, Blau and Tekin 2003, Cascio 2006, Encina and Martínez 2009, Gelbach 2002, Guzmán 2009, Jaumotte 2003, Schlosser 2011 and UNDP 2008).

To the best of our knowledge, there is no empirical evidence on who bears the financial burden of childcare regulation when it is not publicly funded. This is important as if it is indeed paid by firms then this legislation is a tax to female workers in the sense that is a disincentive to hire female workers. However, if firms are not paying someone else must do it (for example: workers). Thus, the objective of this study is to present evidence about who bears the financial burden (i.e., firms or employees) of childcare. In order to do this, we exploit Chilean childcare regulation where the labor code establishes that the financial responsibility about

[1] See for example *The history of child care in the U.S.* where it is pointed out that "To draw attention to the need for childcare and to demonstrate "approved methods of rearing children from infancy on," a group of prominent New York philanthropists at the 1893 World's Columbian Exhibition in Chicago went on to found the National Federation of Day Nurseries (NFDN), the first nationwide organization devoted to this issue, in the US ". (http://www.socialwelfarehistory.com/programs/child- care-the-American-history).

[2] Actually, Chile has one of the lowest rates of female participation among OECD countries, only above Mexico, Turkey and Italy (OECD 2010).

childcare bears on firms. In particular, Article 203 states that “every firm with 20 or more female workers, regardless of their age and marital status, has to provide childcare facilities within firm premises so that mothers can feed their children and leave them there while working”. It also states “it will be understood that firms fulfill this obligation if they pay the cost of a private childcare facility”. This article also establishes that the employer will also have to pay for the transport costs of the female worker, in case the childcare facility is located outside of the firm. Additionally, Article 206 states that female workers are granted with up to one hour within the day to feed their children (if the childcare facility is located outside of the firm there is a time extension regarding the time spent traveling from the firm to the facility), which is considered as a worked hour. Currently these regulations involve children between 6-24 months old only.

Therefore, theoretically Chilean regulation imposes an additional cost to firms since, after a certain number of female workers, firms have to bear different costs such as childcare provision, potential productivity losses due to the time spent by the female worker feeding her child and on occasions the transport costs to the childcare facility. In order to explore if firms are indeed bearing these costs, we exploit the discontinuity given by Chilean regulation to compare wages of workers just above and just below the threshold given by the regulation using a regression discontinuity (RD) design (Hahn, Todd and van der Klaauw 2001, Imbens and Lemieux 2008, Lee 2008, Lee and Lemieux 2010). If for the former wages are lower, it could imply that firms are transferring the costs to their workers. If firms do not transfer all the cost, and males and females are substitutes, there should be an employment composition effect as it would be more convenient to relatively hire more males. Thus, we should observe some degree of manipulation of the female/male employee ratio and/or other symptoms that randomness at the threshold is not very credible. Because this issue is crucial we analyze it extensively below.

For our study we use administrative data from the Unemployment Insurance System provided by the Chilean Ministry of Labor. We show that, even if the firm is the one that theoretically (legally) bears the financial cost of childcare, at the end who pays the “childcare bill” (nearly 100% of it) are workers through lower wages. Also, we do not find any evidence of manipulation of the forcing variable in any of the ways we used to check the internal validity of the RD. Therefore, both sides of the story points to the same conclusion: firms do not manipulate the threshold (number of female workers), because they avoid the burden by transferring the cost to their employees.

To provide this empirical evidence is important, as there are several countries that have systems where the employer is the responsible for childcare provision. Among them are: Argentina, Brazil, Bolivia, Chile, Costa Rica, Ecuador, Guatemala, Honduras, Nicaragua, Paraguay and Venezuela. Furthermore, to learn from this experience is also important as there are a series of countries where there are mixed systems (such as Denmark, France and Panama) or where legally there is no private childcare responsibility (as Cuba, El Salvador and the United States), thus, in case they want to modify their childcare policies, they may learn what are the effects of changing their system to a privately funded childcare policy such as the Chilean case. This study is organized as follows. Section II describes the institutional background, its evolution and the economic incentives generated by it. Then, in Section III we provide a theoretical analysis of the Chilean childcare regulation by studying the behavior of the firm when confronting the decision of whether or not to hire the 20th female worker, which implies additional labor costs. In Section IV we present our empirical strategy while in Section V we present the data and the summary statistics. Finally, Section VI displays our results and presents robustness checks for our estimates and Section VII concludes.

II. Institutional background

Article 203 of the Chilean Labor Code has a long history. In 1917 Chile established for the first time a law focused on childcare (Law 3,185). This law established the employer's obligation of childcare provision within the firm, if the firm had more than 50 female workers. In 1931, a modification on the 1917 Law was introduced. This modified the threshold of female workers who activates the obligation from 50 to 20. Later, in 1981, a new modification was introduced in order to allow firms to provide childcare by paying an external private childcare provider (authorized by JUNJI).[3]

Since then, Article 203 establishes that: (i) Every firm with 20 or more female workers, regardless of their age and marital status, has to provide childcare

[3] Where JUNJI refers to "Junta Nacional de Jardines Infantiles" (National Organization of Public Childcare Centers). JUNJI is a state institution in charge of providing early childhood education to economically disadvantaged children.

facilities within the firm premises so that mothers can feed their children and leave them there while working; (ii) It will be understood that firms fulfill this obligation if they pay the cost of a private childcare facility.

This Article also states that in case the childcare facility provided by the employer is outside of the firm, the employer will have to pay the transport costs that the female worker incurs. Additionally, Article 206 determines that female workers are granted with up to one hour within the day to feed their children (if the childcare facility is located outside of the firm there is a time extension regarding the time spent traveling from the firm to the facility), which is considered as a worked hour. Hence, all of the firms that are affected by Article 203 must also fulfill the obligations established by Article 206.

Currently, Article 203 of the Labor Code holds for a few firms. However, it affects a great proportion of female dependent workers. Given the data supplied by the Chilean Ministry of Labor, in October 2010, only 3% of firms in Chile (around 9,300) have 20 or more female workers. Nevertheless, these few firms concentrate more than 71% of the dependent female workers, which make the childcare costs faced by these firms quite high.

It is important to mention that, if firms do not fulfill their obligation, there is a penalty that reaches 70 UTM (*Unidad Tributaria Mensual*) per employee, amount that is equivalent to approximately US$4,400 in 2015 US dollars. Given this, the number of firms that do not fulfill their obligations is very low. For example in 2011, only 118 firms were detected in this fault, according to information provided by the Chilean Ministry of Labor.

Finally, thus far, in Chile private childcare benefits only apply to female workers.

III. A theoretical model of childcare regulation

In this section we provide a theoretical analysis of the Chilean childcare regulation by studying the behavior of the firm when confronting the decision of whether or not to hire the 20th female worker, which implies additional labor costs. In other words, given the discontinuous nature of this policy, we study the behavior of the firm at the margin.

In particular, we assume an imperfect labor market characterized by monopsony power, i.e., the firm is not a price-taker in the labor market, in order to develop a model of wage discrimination which allows us to provide predictions of female/male wage differences, under the assumption that the firm is otherwise unconstrained (Manning 2003; Ransom and Oaxaca 2010).

Monopsony power can be exercised by any employer that faces an upward sloping labor supply curve, that is, the firm can hire more workers only by increasing the wage (Ashenfelter et al. 2010).[4] The upward sloping labor supply function implies that the wage is an increasing function of employment (the inverse supply curve). Formally, let us assume that the firm only has two inputs of production: female workers, E_f, and male workers, E_m. For simplicity, suppose the firm's capital stock is fixed so that we can effectively ignore the role of capital in the model and write the production function as $f(E_f, E_m)$. We also assume that the labor supply function faced by the firm is given by $E = S(w)$ with $S(w) > 0$. It is easier to derive the model using the inverse supply function, that is, the function that defines the wage that the firm must pay to attract a particular number of workers, or $w = s(E)$ with $s' > 0$.

The firm's profit maximization problem is then given by:

$$\max_{E_f, E_m} \pi_i = pf(E_f, E_m) - w_m E_m - (w_f + \tau)E_f, \tag{1}$$

where p is the price of a unit of output, w_m and w_f are the wage rates for male and female workers respectively. Here we model the childcare regulation that affects the labor costs of firms with 20 or more female workers as a tax, implying that the wage of females in these firms is now given by $w_f + \tau$.

Hence, the first-order conditions to this maximization problem are given by:

$$\frac{\partial \pi_i}{\partial E_m} = p\frac{\partial f(E_f^*, E_m^*)}{\partial E_m} - w_m - E_m^* \frac{\partial w_m}{\partial S}\frac{\partial S}{\partial E_m} = 0, \tag{2}$$

$$\frac{\partial \pi_i}{\partial E_f} = p\frac{\partial f(E_f^*, E_m^*)}{\partial E_f} - w_f - \tau - E_f^* \frac{\partial w_f}{\partial S}\frac{\partial S}{\partial E_f} = 0. \tag{3}$$

[4] A single employer in a nominally competitive labor market can have monopsony power over his current workforce if workers bear a cost of job change, pecuniary or non-pecuniary (Ashenfelter et al. 2010).

Defining $\sigma_m = \frac{w_m}{E_m^*}\frac{\partial E_m}{\partial w_m}$ and $\sigma_f = \frac{w_f}{E_f^*}\frac{\partial E_f}{\partial w_f}$ as labor supply elasticities of male and female workers respectively, these equations can be rewritten as:

$$p\frac{\partial f\left(E_f^*, E_m^*\right)}{\partial E_m} = w_m\left(1 + \frac{1}{\sigma_m}\right), \tag{4}$$

$$p\frac{\partial f\left(E_f^*, E_m^*\right)}{\partial E_f} = w_f\left(1 + \frac{1}{\sigma_f}\right) + \tau. \tag{5}$$

Note that if the firm were perfectly competitive, the labor supply elasticities would equal infinity, and the condition in equation (4) reduces to the standard result that the wage must equal the value of marginal product, not so in equation (5) given the tax levied on firms with 20 or more female workers.

In order to explore in more detail the determinants of the values of marginal products of female workers, E_f and male workers, E_m, we use the CES production function which assumes a constant percentage change in factor proportions due to a percentage change in marginal rate of technical substitution (that is, a doubling of all inputs doubles output). Particularly, the CES functional form is useful in this context because it allows for a wide array of possibilities that describe the extent of substitution between female workers and male workers. Hence, we define:

$$f\left(E_f, E_m\right) = \left(aE_f^r + (1-a)E_m^r\right)^{\frac{1}{r}}, \tag{6}$$

where a is a share parameter and $r = \frac{s-1}{s}$, where s is the elasticity of substitution, which represents the ratio of the two inputs with respect to the ratio of their marginal products allowing us to measure the substitutability between the two inputs, i.e., how easy it is to substitute female workers, E_f, for male workers, E_m.

The parameter r is less than or equal to one (and can be negative). If $r = 1$, it is easy to see that the CES production function is linear, and that is the case where female and male labor are perfectly substitutable (so that the isoquants are straight lines). It can be shown that if r goes to minus infinity, the isoquants associated with the CES production function become right-angled isoquants, so that there is no substitution possible between female and male labor. The elasticity of substitution between female and male is defined by $\frac{1}{1-r}$. Then, if $r = 1$, the elasticity of substitution goes to infinity (perfect substitution), and if $r = -\infty$, the elasticity of substitution goes to zero (perfect complements).

Using equation (6) we get: $\frac{\partial f\left(E_f^*,E_m^*\right)}{\partial E_m} = (1-a)E_m^{r-1}\left(aE_f^r + (1-a)E_m^r\right)^{\frac{1-r}{r}}$ and $\frac{\partial f\left(E_f^*,E_m^*\right)}{\partial E_f} = aE_f^{r-1}\left(aE_f^r + (1-a)E_m^r\right)^{\frac{1-r}{r}}$, which replacing into equations (4) and (5) produce:

$$w_m = \frac{p\sigma_m(1-a)E_m^{r-1}}{(\sigma_m+1)\left(aE_f^r + (1-a)E_m^r\right)^{\frac{r-1}{r}}}, \tag{7}$$

$$w_f = \frac{\sigma_f\left(apE_f^{r-1} - \tau\left(aE_f^r + (1-a)E_m^r\right)^{\frac{r-1}{r}}\right)}{(\sigma_f+1)\left(aE_f^r + (1-a)E_m^r\right)^{\frac{r-1}{r}}}. \tag{8}$$

From equations (7) and (8) we can derive the ratio of female to male wages as follows:

$$\frac{w_f}{w_m} = \frac{(\sigma_m+1)\sigma_f\left(apE_f^{r-1} - \tau\left(aE_f^r + (1-a)E_m^r\right)^{\frac{r-1}{r}}\right)}{p\sigma_m(\sigma_f+1)(1-a)E_m^{r-1}}. \tag{9}$$

From equation (9) the following proposition can be inferred:

Proposition 1: *In an imperfect labor market characterized by monopsony power, a childcare regulation that affects the labor costs of firms with 20 or more female workers implies the following ratio of female to male wages, which defines the optimal fraction of female to male labor for firms with 19 female employees planning to hire an additional worker:*

$$\frac{w_f}{w_m} = \frac{(\sigma_m+1)\sigma_f\left(apE_f^{-\frac{1}{s}} - \tau\left(aE_f^{\frac{s-1}{s}} + (1-a)E_m^{\frac{s-1}{s}}\right)^{\frac{1}{1-s}}\right)}{p\sigma_m(\sigma_f+1)(1-a)E_m^{-\frac{1}{s}}}. \tag{10}$$

From Proposition 1, it transpires that the ratio of female to male wages depends upon the labor supply elasticities of male and female workers, σ_m and σ_f, the elasticity of substitution between female and male labor, s, the proportion of female and male workers used by the firm, a, the price of a unit of output, p, and the tax levied on firms with 20 or more female workers, τ.

This basic result allows for a variety of different equilibria. For example, a particular case in our model is the situation in which female and male labor are perfectly substitutable, that is $r = 1$ and the labor supply elasticities of male and female workers are equal, $\sigma_m = \sigma_f$. To simplify the analysis let us also assume that the share of female and male labor is the same, $a = \frac{1}{2}$. Hence, equation (9) becomes: $\frac{w_f}{w_m} = \left(\frac{p}{2} - \tau\right)/\frac{p}{2} < 1$, which implies that the tax on female labor will affect the behavior of the firm with 19 female workers which will in turn adjust the optimal fraction of female to male workers given the change in relative wages. In this case, given that a firm with monopsony power faces an upward sloping labor supply curve, that is, the firm can hire more workers only by increasing the wage, the higher relative wage for males implies hiring a higher proportion of males, substituting female workers with male workers, in order to avoid the higher costs associated with female labor imposed by the policy, not hiring the 20th female worker. Consequently, in this case this regulation implies that for the firm to increase its scale of production it will be more convenient to change the optimal combination of inputs, implying a change in the composition of its labor force with a direct impact on employment levels and as a result will imply a concentration of firms with a maximum of 19 female workers.

Nevertheless, in order to get this result we assumed that female and male labor were perfectly substitutable. From equation (9), it is easy to show that whenever $r \neq 1$ this result will depend on the level of substitutability between female and male labor and the size of the tax burden levied on the firm with 20 or more female workers. In fact, performing the same previous analysis but allowing for $r \neq 1$, the optimal condition for $w_f = w_m$ becomes: $\frac{p}{2}\left(E_f^{r-1} - E_{fm}^{r-1}\right) = \tau\left(\frac{E_f^r + E_m^r}{2}\right)^{\frac{r-1}{r}}$, which mainly depends upon the values of r and τ. In this context, it can be noted that the closer the value of to 1 the lower the difference between w_f and w_m, being even possible to obtain $w_f > w_m$. From this analysis it can be inferred that the strategy of substituting female workers with male workers, to avoid the change in relative prices implied by the policy (not hiring the 20th female worker) is not necessarily optimal when considering the situation in which female and male labor are not perfectly substitutable. In this case an alternative strategy for the firm can be to hire the 20th female worker and pay the additional cost associated while maintaining the optimal ratio of male to female workers, either by affording the additional cost the firm itself or by imposing the additional costs upon their workers (male and female) by lowering salaries altogether.

It is precisely in this context that we want to contribute to the literature by empirically testing the effect of this policy on wages, studying in particular who effectively pays (firms or employees) and how (e.g., via wages and/or employment).

IV. Empirical strategy

The way Article 203 operates allows us to use the discontinuity generated when a firm moves from 19 to 20 female workers. This is because from that point it is mandatory for firms to provide childcare services (inside or outside the firm premises). The existence of this rule makes it possible to identify the impact of this regulation on the desired outcomes.

We will refer from now on as "treatment" when Article 203 is activated (i.e., a firm has 20 or more female workers). In this way, let us call y_{i1} the variable of interest (e.g., wages) for individual i if she receives the treatment (i.e., works in a treated firm) and y_{i0} otherwise. Thus, an individual will be treated if she works in a firm with 20 or more female workers.

Let us call d_i the treatment variable for worker i, defined as follows: $d_i = \begin{cases} 1 \ if \ N_i \geq 20 \\ 0 \ if \ N_i < 20 \end{cases}$, where N_i is the number of female workers in the firm of worker i. Thus, we can estimate our model as follows:

$$y_i = f(N_i) + \varphi \cdot d_i + z_i'\gamma + u_i, \tag{11}$$

where u is an error term such that $E(u/d,z) = 0$ and $f(N_i)$ is a smooth function of the number of female workers in the firm (to allow for non-linearities between the outcome and the forcing variable). Additionally, we include variables that may affect the dependent variable, denoted by vector z_i.

A. Parametric versus non-parametric

When there is a model such as the one presented above, the previous literature use two approaches for the estimation: parametric and nonparametric (see Hahn, Todd and van der Klaauw 2001, Imbens and Lemieux 2008 and Lee and Lemieux 2010 for a detailed discussion). One of the advantages of the parametric approach is that it is more efficient when the functional form is correct. However, if the functional form is incorrect our results will be biased.[5] A disadvantage of the parametric approach is that it provides estimates of the regression function over all values of N_i, while the RD design focuses on local estimates of the regression function at the cutoff point (Lee and Lemieux 2010).

In the non-parametric case, kernel regressions or local linear regressions can be used. Both are local methods as they used data around the cutoff point to estimate the effect of the policy change on the desired outcome. However, kernel regression presents a boundary problem when applied in a RD design. This is because we are estimating a point effect at a boundary which implies that kernel regression will be a weighted average of one-sided data points which will generate a systematic bias in the estimates (see Hahn, Todd and van der Klaauw 2001 for a formal derivation of the bias). A solution to this problem has been suggested by Hahn, Todd and van der Klaauw (2001), who proposed to use local linear regression to reduce the importance of the bias.[6]

As Lee and Lemieux (2010) pointed out, it is advisable to use both approaches (parametric and non-parametric) when estimating the smooth function as neither of these two alone presents the supreme solution regarding functional form problems. Therefore, the econometrician should see them more as complements than substitutes.

The discrete nature of our assignment variable (number of female workers) has implications on the specification choice. Lee and Card (2008) states that in this case the conditions of the non-parametric estimation methods are not met, which implies that the model is not non-parametrically identified. The reason for this is that even with an infinite amount of data, there would be no data in a region in an "arbitrarily" small neighborhood around the cutoff point. Consequently, Lee and Card (2008) suggest "one must use regressions to estimate the conditional expectation of the outcome variable at the cutoff point by extrapolation". Thus, the parametric approach should be used for estimation.

In a more recent article, Lee and Lemieux (2010) point out that the discreteness of the assignment variable does not introduce important econometric

[5] For example, if the data suggest a nonlinear model when we estimate a linear one, results might suggest a discontinuity when in reality is just a nonlinear movement of the data.

[6] Hahn, Todd and van der Klaauw (2001) show that the remaining bias is of an order of magnitude lower, and is comparable to the usual bias in kernel regression at interior points.

complications for the parametric estimation, provided that this variable is not too coarsely distributed (as in our case).[7] As suggested by Lee and Card (2008), if the polynomial function is correct, then least squares inference is appropriate.

Given this, we use the parametric approach as our baseline case. However, and as the distinction between when a running variable is discrete and when it is continuous for practical terms is somehow always arbitrary (as strictly speaking the running variable is always discrete), we also estimate the model using the non-parametric approach for comparison purposes.

B. The model

Our parametric specification is presented in the equation: $y_i = \delta + \sum_{j=1}^{p} \kappa_j (N_i - 20)^j + \varphi \cdot d_i + z_i' \gamma + u_i$ and the estimated parameters are given by $\left(\hat{\delta}, \hat{\varphi}, \hat{\gamma}, \hat{\kappa}\right) = \operatorname{argmin}_{(\delta,\varphi,\gamma,\kappa)} \sum_{i=1}^{n} \left(y_i - \delta - \sum_{j=1}^{p} \kappa_j (N_i - 20)^j - \varphi \cdot d_i - z_i'\gamma\right)^2$, where p is the maximum degree of the polynomial introduced in the specification, $f(N_i)$ is $\sum_{j=1}^{p} \kappa_j (N_i - 20)^j$, where κ_j is a parameter that quantifies the effect on the outcome of the j^{th} power of the deviation $(N_i - 20)$. In this case the treatment is captured by the parameter $\hat{\varphi}$.[8]

On the other hand, our nonparametric specification is estimated using local linear regressions (see Fan 1992, Hahn, Todd and van der Klaauw 2001 and Imbens and Lemieux 2008) on both sides of the discontinuity point. Thus, the estimated parameters of this specification are:

$$\left(\hat{\delta}^+, \hat{\mu}^+, \hat{\gamma}^+\right) = \operatorname{argmin}_{(\delta^+,\mu^+,\gamma^+)} \sum_{i=1}^{n} \left(y_i - \delta^+ - \mu^+(N_i - 20) - z_i'^+ \gamma^+\right)^2 K\left(\frac{N_i - 20}{h}\right) I(N_i \geq 20) \quad (12)$$

$$\left(\hat{\delta}^-, \hat{\mu}^-, \hat{\gamma}^-\right) = \operatorname{argmin}_{(\delta^-,\mu^-,\gamma^-)} \sum_{i=1}^{n} \left(y_i - \delta^- - \mu^-(N_i - 20) - z_i'^- \gamma^-\right)^2 K\left(\frac{N_i - 20}{h}\right) I(N_i < 20) \quad (13)$$

[7] Additionally, Lee and Lemieux (2010) point out that the discreteness of the assignment variable simplifies the problem of bandwidth choice when graphing the data as "one can simply compute and graph the mean of the outcome variable for each value of the discrete assignment variable".

[8] Where $\hat{\varphi}$ is the degree of pass through of the childcare cost from the firm to its workers.

where μ is a parameter that quantifies the effect on the outcome of the deviation $(N_i - 20)$, K, is a kernel function and h is the bandwidth. The variable $I(\cdot)$ is an index function that takes the value 1 when the condition in the brackets takes place and 0 otherwise. The treatment effect is the difference of the linear predictions at the discontinuity point of the right and left local linear regressions. Hence, the treatment effect for the nonparametric specification will be given by the parameter $\hat{\varphi} = \hat{\delta}^{+} - \hat{\delta}^{-}$.

The kernel function used is the triangular kernel.[9] This is because, as Cheng, Fan and Marron (1997) demonstrate, the triangular kernel has Asymptotic Mean Square Error minimizing properties for boundary estimation problems.[10] For the selection of the bandwidth, there are two traditional methods: (1) ad hoc methods and (2) data driven methods such as cross validation methods (Ludwig and Miller 2007).[11] We use the data driven approach, in particular Ludwig and Miller's method (LM) for our baseline estimation as it is more appropriate than other methods when the data is discrete. However, we also estimate the model with the Imbens and Kalyanaraman (2012) approach. Both methods give similar but large bandwidths.[12] For this reason we also re-estimate the model with smaller bandwidths in the sensitivity analysis section. As it will be clear, results are very similar in all the specifications. For a matter of organization, we present the baseline results with the LM method leaving all the other results in the sensitivity analysis section.

V. Data summary statistics

We use cross section data from the Chilean Unemployment Insurance system for October 2010, provided by the Ministry of Labor. This database considers information about individuals who are affiliated to this system, since its origins in October 2002, or found a dependent job in the private sector after that date.[13]

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[9] Where the triangular kernel is: $K(u) = (1 - |u|)1_{\{|u| \leq 1\}}$

[10] Other kernels could also be used, however the choice of kernel typically has little impact in practice (Lee and Lemieux 2010).

[11] For more details see the Appendix.

[12] This is to be expected given the discrete nature of the data.

[13] This insurance system started in October 2002 and currently more than 94% of dependent workers are affiliated to the system. The Unemployment Insurance excludes independent and public sector workers.

Table 1 presents the distribution of female and male workers and firms by number of female workers within the firm (less than 20 and 20 or more of them). As outlined above, we see that female workers tend to concentrate in firms with 20 or more of them (almost 72% are working in firms with this characteristic) while the distribution of male workers is relatively homogeneous among these categories. When analyzing the number of firms in both groups we see that nearly 97% of the firms have less than 20 female workers. However, this distribution of firms tends to be something inherent to the Chilean economy, where approximately 90% of the firms have less than 20 workers (males and females) according to information provided by the Chilean Ministry of Labor.

Table 1. Distribution of workers and firms by number of female workers

Type of Firm	Female workers: number(%)	Male workers: number(%)	Firms: number(%)
Less than 20 female workers	475,234 (28.1%)	1,430,388 (50.6%)	287,136 (96.8%)
20 or more female workers	1,217,994 (71.9%)	1,391,281 (49.4%)	9,358 (3.2%)
Total	1,693,228	2,821,669	296,494

Since our main focus is related to the financial side of childcare regulation, we separate the sample into three sub-samples: fertile age female workers, non-fertile age female workers and male workers. Regarding the first group, we examine the economic sectors where women with these characteristics are more concentrated. Table 2 presents the distribution of fertile female workers across different type of industries.[14] As can be seen, three types of industries (commerce, financial services and social services), concentrate nearly 80% of the fertile female workers. The same pattern is observed for non-fertile age female workers as according to our data, 81% of them are also concentrated in these industries (19% in commerce, 17% in financial services and 45% in social services). Hence we focus on these industries.[15]

[14] Women who work and are aged between 18 and 49 years are considered as fertile female workers. This definition follows the one provided by the National Institute of Statistics (INE).
[15] Given the high dispersion observed in the data, we deleted those individuals at the highest and lowest 5% of the wages.

Table 2. Distribution of fertile age female workers by type of industry

Type of Industry	Female Workers	% of the Total
Agriculture, hunting, forestry and fishery	61,333	4.8%
Mines and quarry	9,592	0.8%
Manufacture	95,801	7.5%
Electricity, gas and water	3,585	0.3%
Construction	34,884	2.7%
Commerce	288,208	22.6%
Transport, storage and communications	53,960	4.2%
Financial and business services	268,824	21.0%
Communal, personal and social services	461,526	36.1%

Note: Not all female workers in the database present type of industry.

In this section we present the summary statistics of the dataset used. Also, in order to give support to the validity of our estimation procedure, we present a graphical analysis of our variables (as suggested by Imbens and Lemieux 2010). Table 3 presents the summary statistics for fertile female workers (aged between 18 and 49 years old), separated by size of the firm used in our dataset.[16] We see that on average fertile female workers are similar in observables to their peers who work in firms with less than 20 women.

Table 3. Descriptive statistics for fertile age female workers

Variable	Less than 20 female workers	More than 20 female workers	15-19 female workers	20-24 female workers
Log Wage	12.4	12.5	12.62	12.63
	(0.57)	(0.65)	(0.59)	(0.60)
Age	34.1	33.3	33.24	33.34
	(8.30)	(8.20)	(8.21)	(8.20)
Commerce	0.43	0.24	0.36	0.32
	(0.49)	(0.43)	(0.48)	(0.47)
Financial and Business Services	0.25	0.25	0.21	0.21
	(0.43)	(0.43)	(0.41)	(0.41)
Communal, Personal and Social Services	0.30	0.50	0.42	0.46
	(0.46)	(0.50)	(0.49)	(0.50)
Number of observations	226,258	690,308	29,779	20,577

Note: Mean of the variables is presented. Standard deviations in parentheses.

[16] This separation was only based on the numbers of female workers, thus no constraint was imposed on the number of male workers.

Tables 4 and 5 present the summary statistics for non-fertile age female workers (aged between 50 and 60 years old) and male workers, separated by size of the firm respectively. For the case of non-fertile age female workers we observe that the trend is similar to the case of fertile female workers, which also coincides with the case of men. Tables 4 and 5 also present descriptive statistics of observations around the threshold, for non-fertile age female workers and male workers respectively. This will be important below, as balanced covariates are an indirect check that the assumption of randomness at the threshold implicit in a RD analysis is more credible.

Table 4. Descriptive statistics for non-fertile age female workers

Variable	Less than 20 female workers	More than 20 female workers	15-19 female workers	20-24 female workers
Log Wage	12.3	12.6	12.57	12.60
	(0.55)	(0.67)	(0.54)	(0.59)
Age	54.8	54.7	54.77	54.69
	(3.77)	(3.70)	(3.87)	(3.83)
Commerce	0.41	0.15	0.33	0.24
	(0.49)	(0.35)	(0.47)	(0.42)
Financial and Business Services	0.24	0.18	0.19	0.17
	(0.43)	(0.38)	(0.39)	(0.37)
Communal, Personal and Social Services	0.33	0.66	0.48	0.60
	(0.47)	(0.47)	(0.50)	(0.49)
Number of observations	44,195	113,145	4,363	3,23

Note: Mean of the variables is presented. Standard deviations in parentheses.

Table 5. Descriptive statistics for male workers

Variable	Less than 20 female workers	More than 20 female workers	15-19 female workers	20-24 female workers
Log Wage	12.57	12.75	12.81	12.81
	(0.57)	(0.64)	(0.60)	(0.61)
Age	39.3	37.2	37.55	37.37
	(11.7)	(11.7)	(11.34)	(11.38)
Commerce	0.41	0.28	0.42	0.43
	(0.49)	(0.45)	(0.49)	(0.50)
Financial and Business Services	0.35	0.31	0.35	0.30
	(0.47)	(0.46)	(0.48)	(0.46)
Communal, Personal and Social Services	0.23	0.40	0.22	0.27
	(0.42)	(0.49)	(0.42)	(0.44)
Number of observations	527,968	672,157	44,463	32,62

Note: Mean of the variables is presented. Standard deviations in parentheses.

Finally Table 6 presents the summary statistics of the database used in the analysis of employment composition (share of male employment within the firm), which is carried out by firm and not by worker, as before. Following Lemieux and Milligan (2008), we restrict our sample to the case of firms with more than 5 and less than 35 female workers, since there are systematic differences between the firms (and its workers) with 6 to 34 female workers and those with up to 5 female workers and more than 35 of them. We see that firms with 20 or more female workers have a slightly greater proportion of male workers within their labor force composition and that these firms are more concentrated (relative to the ones with less than 20 female workers) in the communal, personal and social services industry. Table 6 also presents descriptive statistics for firms that are near the cutoff.

Table 6. Descriptive statistics for firms

Variable	Less than 20 female workers	More than 20 female workers	15-19 female workers	20-24 female workers
Share of Male Workers (%)	0.40	0.41	0.40	0.42
	(0.27)	(0.23)	(0.24)	(0.24)
Commerce	0.42	0.30	0.36	0.31
	(0.49)	(0.46)	(0.48)	(0.46)
Financial and Business Services	0.25	0.21	0.22	0.22
	(0.43)	(0.41)	(0.41)	(0.42)
Communal, Personal And Social Services	0.33	0.49	0.42	0.46
	(0.47)	(0.50)	(0.49)	(0.50)
Number of observations	14,349	2,637	2,253	1,221

Note: Mean of the variables is presented. Standard deviations in parentheses.

When regression discontinuity design is used as a method of estimation, the previous literature (Imbens and Lemieux 2008 and Lee and Lemieux 2010) suggests a series of tests on the variables used. The idea is that these checks allow us to see how robust is the internal validity of our design, in the sense of how credible our results could be. These checks consist of verifying:

a) If there exists a discontinuity in the dependent variables (in our case, wages).

b) If there exist discontinuities in control variables (in our case, age and type of industry).

c) If there is a discontinuity in the density of the running variable (in our case, the number of female workers in the firm).

The first test, in (a), should suggest a discontinuity in the variable of interest, otherwise our estimation may conclude that there are no significant effects. If there is no effect here, it is unlikely that we will find effects with the econometric specification. The tests in (b) are important as they check if the covariates present discontinuities or not. If they do, it is is unclear if the discontinuity in the dependent variable that is attributed to the policy change is instead due to a discontinuity in the covariates. Furthermore, the smoothness of the covariates makes the continuity assumption of the expected potential outcomes more plausible (as discussed below). Finally, the test in (c) allows us to check if agents (in our case firms and workers) do or do not manipulate the running variable. This is important because if there was manipulation (i.e., a discontinuity in the density at the threshold), it would imply that agents just above the threshold are not necessarily similar to those just below the threshold and this, as Lee and Lemieux (2010) pointed out, would imply that the existence of a treatment being a discontinuous function of an assignment variable would not be sufficient to justify the validity of an RD design. Furthermore, discontinuous rules may generate incentives, causing behavior that would invalidate the RD approach. We check for discontinuities through graphical inspection and formally test for the existence of a discontinuity of the assignment variable by using the test proposed in McCrary (2008).[17]

This later issue is crucial in the RD context because as long as there is imprecise manipulation of the forcing variable, local randomization will hold, which is what we need in order to correctly estimate the counterfactual (as it ensures the continuity assumption about the expected potential outcomes). Despite its importance, imprecision of control of the forcing variable will often be nothing more than a conjecture, but thankfully it has testable predictions such as indicated above by tests (b) and (c). Therefore, these two tests are crucial for the internal validity of our empirical strategy as they allow us to test that the predictions of local randomization holds.

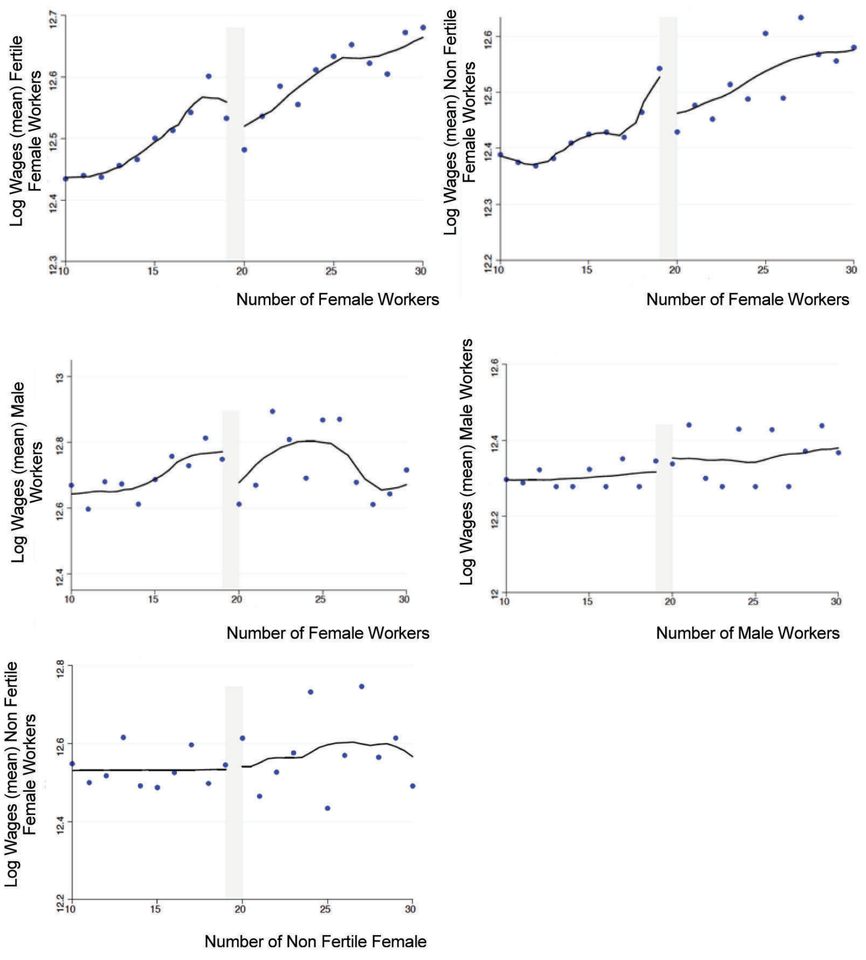
A. Discontinuity in the dependent variables

We observe that there is a discontinuity in wages of female workers in firms with 19 relative to firms with 20 female workers.[18] Discontinuities in wages are also observed in non-fertile age female women and in men. These results suggest that

[17] For more information on McCrary's (2008) test see the Appendix.
[18] For smoothing the data points, we consider local-mean smoothing.

firms transfer the cost of childcare not only to fertile female workers in the form of lower wages, but also to non-fertile age females and men as well. We will explore the magnitude of this transfer below (see Figure 1).

Figure 1. Characterization of log wages (mean) of the different type of workers

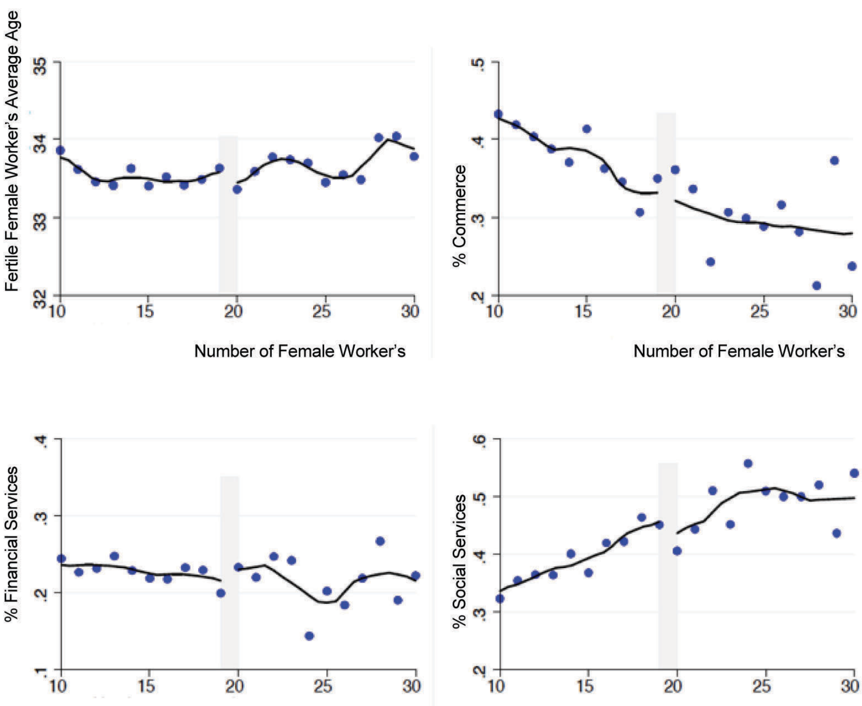


To further support our previous results, we apply again test (a) but now only to firms with male workers. As Article 203 of the labor code only applies to firms that have female workers, we should expect no discontinuity in those firms with only male workers and we observe exactly what we were expecting, this is that there are no effects on wages when we move from firms with only 19 male workers to firms with only 20 male workers. In order to study further our hypothesis, we analyze the behavior of firms with only non-fertile age female workers (aged 50-60). If our hypothesis is true, the firm should not expect any childcare expenditure and so there should be no discontinuity in wages. Our results are also presented in Figure 1 and suggest that, as expected there is no significant discontinuity at the threshold.

B. Discontinuity in control variables

Our next step is to test discontinuity in the covariates. They are: age and type of industry dummies. Figure 2 presents the result for fertile age female workers, and we found that there are no significant differences between both sides of the threshold. In particular we found point estimates of -0.12, 0.019, 0.02 and -0.04 for Age, Commerce dummy, Financial Services Dummy and Social Services Dummy respectively, but none of them were significantly different from zero.

Figure 2. Covariates of fertile female workers by number of female workers



Next, in Figures 3 and 4, we present the same graphical analysis but now for non-fertile age female workers and for male workers respectively. Results again suggest no significant discontinuities at the threshold. Non-significant point estimates for non-fertile age female workers were -0.06, -0.02, 0.004 and 0.02 for Age, Commerce dummy, Financial Services Dummy and Social Services Dummy respectively and for males were 0.02, 0.01, -0.02 and 0.002 respectively. All these are in line with what was suggested by the summary statistics presented in Tables 3 to 5 where covariates are balanced between both sides of the threshold making the assumption of local randomness more credible.

Figure 3. Covariates of non-fertile female workers by number of female workers

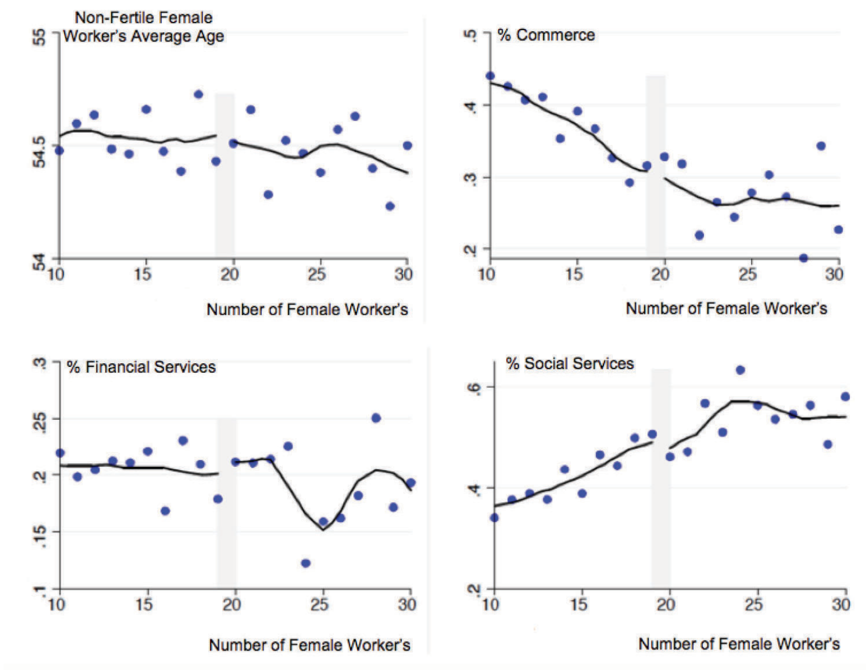
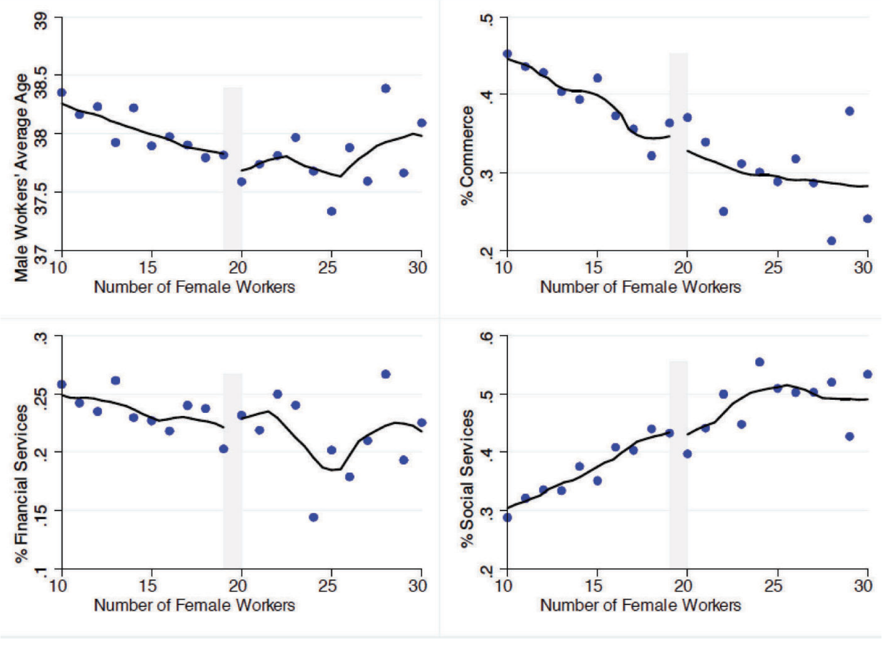


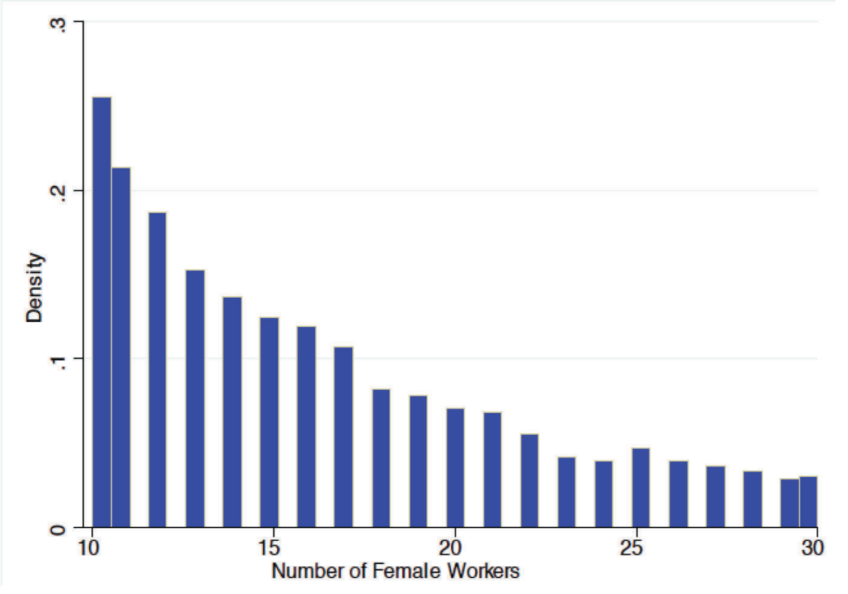
Figure 4. Covariates of male workers by number of female workers



C. Discontinuity in the density of the running variables

Finally, in Figure 5 we present the result for the test of discontinuities in the density of the number of the female workers in the firm. We observe that there are no significant discontinuities in the density of the running variable at the threshold. This suggests no evidence of manipulation from the agent's point of view. This is crucial as Lee (2008) formally show that one need not assume the RD design isolates treatment variation that is "as good as randomized"; instead, such randomized variation is a consequence of agents' inability to precisely control the assignment variable near the known cutoff.

Figure 5. Density of the firms by number of female workers



To further investigate the presence of manipulation of the assignment variable we follow McCrary (2008) who develops a density test.[19] Unfortunately, his test was developed for continuous assignment variables. However, as Lemieux and Milligan (2008) point out, the discrete nature of the assignment variable does not complicate further the analysis as it is straightforward to implement this test by estimating separately two local linear regressions (where we considered as dependent variables the fraction and log fraction of women below and above the threshold) and checking if there is statistical difference between the predicted outcomes at the discontinuity point.[20] Our results suggest that there is no evidence of manipulation of the assignment variable, supporting in this way our previous graphical analysis. In particular, the p-value for the fraction of women is 0.93 and

[19] For more details on McCrary's test see the Appendix.

[20] We use triangular kernel as suggested by McCrary (2008). Following Lemieux and Milligan (2008), we use a window of 10 female workers (i.e., from 15 to 25 female workers per firm). The weight of the observations linearly decreases from 1 in the threshold to 0 at 15 or 25 female workers.

0.90 for the log fraction of women. Hence we do not reject the null hypothesis of continuity.

As mentioned in Section III, the discrete nature of our data can introduce complications in the regression discontinuity analysis (Lee and Card 2008). However, Lee and Lemieux (2010) point out that the discreteness of the running variable (number of female workers in the firm) does not introduce important complications if this variable is not too coarsely distributed. As Figure 5 and the McCrary test show, this seems to be the case.

All tests support the internal validity of our identification strategy.[21] However a natural concern may appear. All the checks suggest no manipulation, but in theory firms might do it. As we will show in the results section below, firms do not manipulate the threshold because they are transferring the whole cost of childcare to their employees, hence they do not have incentives to do so.

VI. Results

In this section we present the results of our estimation on wages of fertile and non-fertile age females and males of the firm. Additionally, we perform a sensitivity analysis of our parametric and nonparametric estimates, in order to check their robustness. In particular, we consider different kernel functions and bandwidths and falsification tests.

A. Wages

Table 7 presents the results regarding the impact of Article 203 on fertile female workers' wages. In the Table it is possible to observe that wages on average decrease due to the treatment. The magnitude depends on the specification used (parametric or nonparametric). For the parametric case we see that the effect varies depending on the degree of the polynomial considered. For the case of the linear polynomial the effect is an average reduction of nearly -3.9% on monthly wages

[21] Additionally, in line with Lee and Lemieux (2010), we carried out nonparametric discontinuous regressions on the covariates. We did not find any significant discontinuity on the covariates, which support our previous results.

while in the case of a quadratic and cubic polynomial the effect is lower, -3.4% and -3.8%, respectively. When considering a quartic polynomial, the reduction is slightly larger than the linear case, -4.2%. We also see that all these estimates are statistically significant at 1%. For the nonparametric case we see that the estimation yields -4.0% (LM), which is also statistically significant at 1%. It is important to mention that, even after considering different polynomial degrees and different approaches (parametric and nonparametric), the results appear to be quite robust.

Table 7. Impact of Article 203 on log wages of different groups

Parametric specification	Fertile age females	Non-fertile age females	Males
Linear	-0.039***	-0.027*	-0.039***
Quadratic	-0.034***	-0.023*	-0.028***
Cubic	-0.038***	-0.035*	-0.029***
Quartic	-0.042***	-0.039*	-0.026***
Nonparametric	-0.040***	-0.038*	-0.040***

Note: ***, ** and* represent statistical significance at 1%, 5%, 10%, respectively.

Table 7 presents the estimates, through parametric and nonparametric specifications, for non-fertile age female workers and male workers who are in firms along with fertile age females, respectively. For the case of non-fertile age female workers we see negative effects ranging from -3.9% to -2.3% for the parametric specification, and -3.8% for the nonparametric one (LM), of Article 203 on wages but these effects seem to be less robust than the case of fertile female workers since most of the estimates are only statistically significant at 10%. This may be due to the considerably smaller sample size of non-fertile age females. In the case of male workers we also observe negative impacts of this Article on wages, where the effect varies between -3.9% to -2.6% in the parametric case and 4.0% (LM) in the nonparametric one. These results are statistically significant at 1%.

If we consider an average firm with 20 female workers we see that the reduction of wages due to Article 203 (along with Article 206) is nearly equivalent to the expected childcare cost. Hence, firms transfer nearly 100% of the total childcare cost on to their workers. For more details about this calculation see the Appendix.

In Section III, Proposition 1 states that in an imperfect labor market characterized by monopsony power, a childcare regulation that affects the labor costs of firms with 20 or more female workers implies a ratio of female to male wages which basically depends upon the labor supply elasticities of male and female workers, the elasticity of substitution between female and male labor and the tax levied on firms with 20 or more female workers. From this general model, two hypotheses were put forward. First, for the case in which female and male labor were perfectly substitutable and the labor supply elasticities of male and female workers were the same. In this case, our theoretical model predicted that the tax on female labor will affect the behavior of the firm with 19 female workers implying an increase in relative wages for males which in turn will entail hiring a higher proportion of males, substituting female workers with male workers, in order to avoid the higher costs associated with female labor imposed by the policy, not hiring the 20th female worker. Second, we analyzed the situation in which female and male labor were not perfectly substitutable. In this case, by contrast, our model showed that the strategy of substituting female workers with male workers, to avoid the change in relative prices implied by the policy (not hiring the 20th female worker) was not optimal. Here, in this case for the firm it can be best to hire the 20th female worker and pay the additional cost associated while maintaining the optimal ratio of male to female workers, either by affording the additional cost the firm itself or by imposing the additional costs upon their workers (male and female) by lowering salaries altogether.

This second hypothesis is the one corroborated by our empirical results, implying that the elasticity of substitution between female and male labor can be rather inelastic and therefore female and male labor are complements and not necessarily perfect substitutes. We also find that firms are transferring the cost to non-fertile age female workers and male workers as well.

Consistent with our theoretical framework, we explain these results as follows. In a competitive labor market, female and male workers who do not have children would be penalized in the above setting; therefore they would move to firms unaffected by the policy (i.e., those with less than 20 female workers) until wages equalize the gains. Nevertheless, in imperfect labor markets characterized by monopsony power, with given search costs, firms have the incentives to socialize the cost among all its workers and not only to transfer them to fertile female workers. This is because if the firm charges all the cost to a particular group, they will have higher incentives to search for another job. Instead if they spread the cost among all their workers, the decrease in the wage of each worker will be lower and thus the incentive to look for another job will be lower as well (all this given search costs). This market imperfection may be one explanation for workers stickiness (immobility).

B. Employment composition

Table 8 presents the results of the effect of Article 203 on the share of male workers of the firm. We observe that there is not a statistically significant effect on this variable. This is the case for any specification used: quadratic, quartic polynomial, linear and cubic, for all cases the results are not significantly different from zero. For the non-parametric case, the point estimate is 2.7 (LM) percentage points but not statistically significant.

Table 8. Impact of Article 203 on the share of male workers in the firm

Parametric specification	Estimate
Linear	0.006
Quadratic	0.016
Cubic	0.014
Quartic	0.022
Nonparametric	0.027

Note: In the case of parametric specification clustered standard errors were used. For the nonparametric case the triangular kernel is used and the optimal bandwidth, chosen following Ludwig and Miller (2007), is $h^* = 5$.

These results are in the same line with those related to wages, where the firm tends to transfer almost entirely the childcare costs onto its workers, something that does not modify importantly the relative prices between males and females. This is because when firms cannot fully transfer the childcare cost to each of their female workers, then females become a more expensive input relative to male workers. If some degree of substitution exists between them, we should observe an increment in the relative share of male workers (relative to female workers) in the firm. This latter effect would not be necessarily true if firms were also transferring the childcare cost among male workers, which is the case.

C. Sensitivity analysis

As Imbens and Lemieux (2008) point out, estimates that are sensitive to the order of the polynomial (in the parametric case) and the kernel or bandwidth specification (in the non-parametric case) are not very credible. In this section we perform several estimations using different kernel functions, bandwidths and different slopes of the regression functions on both sides of the discontinuity of our parametric specifications, in order to check the robustness of our parametric and nonparametric estimates specification (the sensitivity to different order of the polynomial was shown above). Additionally, we perform falsification tests in order to validate our regression discontinuity design.[22]

Alternative kernels

The estimates of our nonparametric specifications presented in Table 7 consider the triangular kernel. This kernel function has special properties, as shown in Cheng, Fan and Marron (1997). In particular, this kernel has Asymptotic Mean Square Error minimizing properties for boundary estimation problems. In this section we use other kernel functions, such as the Epanechnikov and Biweight kernels, in order to test the robustness of our nonparametric specification.[23] The results of our estimations using these two kernel functions for wages of fertile age, non-fertile age female workers and men workers in Table 9 suggests that using a different kernel function specification does not affect the estimates in an important magnitude, where differences between the estimates using the triangular kernel barely differ from these ones.

Table 9. Impact of Article 203 on log wages of different groups with alternative kernels

Kernel effect	Fertile age females	Non-fertile age females	Males
Epanechnikov	-0.039***	-0.039***	-0.031***
Biweight	-0.040***	-0.036***	-0.038***

Note: ***, ** and* represent statistical significance at 1%, 5%, 10%, respectively. For the nonparametric case the triangular kernel is used and the optimal bandwidth, chosen following Ludwig and Miller (2007), is h* = 14.

We can conclude that the kernel specification chosen does not have an important effect on the estimates of our model. This result is aligned with what the related literature (Imbens and Lemieux 2008 and Lee and Lemieux 2010, for instance) says about conditions of consistent regression discontinuity estimations.

[22] We performed a sensitivity analysis for the size of the window considered (firms with more than 3 and less than 37 female workers, firms with more than 7 and less than 33 female workers, for example). Our estimates do not vary in a significant way. The results can be obtained upon request from the authors.
[23] The Epanechnikov kernel is $K(u)=\frac{3}{4}(1-u^2)1_{\{|u|\leq 1\}}$ and the Biweight kernel is $K(u)=\frac{15}{16}(1-u^2)^2 1_{\{|u|\leq 1\}}$.

Alternative Bandwidths

We present estimates using different kernel bandwidths. In particular, we consider a difference of +2, +1, -1 and -2 of the optimal bandwidth calculated according to Ludwig and Miller (2007). The results of our estimations are presented in Table 10.[24] We appreciate that for all outcomes, even after modifying the bandwidths, the estimates appear to be consistent. We do not appreciate important differences in our estimations, which suggests that our regression discontinuity design is well specified.

Table 10. Impact of Article 203 on log wages with alternative bandwidths

Outcome: Log Wage	Difference with optimal bandwidth			
	+2	+1	-1	-2
Fertile age females	-0.042***	-0.040***	-0.040***	-0.040***
Non-fertile age females	-0.040***	-0.039***	-0.036***	-0.035***
Males	-0.038***	-0.039***	-0.042***	-0.046***

Note: ***, ** and* represent statistical significance at 1%, 5%, 10%, respectively. The optimal bandwidth was chosen following Ludwig and Miller (2007) and we consider the triangular kernel in these estimations.

Although our bandwidth selection criteria follow Ludwig and Miller (2007), we obtain relatively large optimal bandwidths for the case of the effect of Article 203 on wages. Given this, we also consider lower bandwidths in order to test the robustness of our estimates.[25] Table 11 presents the RD estimates considering smaller bandwidths (6 to 13). We observe that no significant differences with our original estimates arise which supports the robustness of our specification.

[24] We consider the triangular kernel for these estimations.

[25] We also consider the Imbens and Kalyanaraman (2012) optimal bandwidth selection method. Although smaller than Ludwig and Miller (2007), we also obtain large optimal bandwidths with this technique (around 9 instead of 14). These big bandwidths make sense in our context, as the running variable is discrete.

Table 11. Impact of Article 203 on log wages of different groups (smaller bandwidths)

Bandwidth	Fertile age females	Non-fertile age females	Males
6	-0.033***	-0.057**	-0.075***
7	-0.041***	-0-046*	-0.089***
8	-0.043***	-0.043*	-0.085***
9	-0.043***	-0.039*	-0.072***
10	-0.043***	-0.037*	-0.065***
11	-0.042***	-0.032*	-0.054***

Note: ***, ** and* represent statistical significance at 1%, 5%, 10%, respectively. For the nonparametric case the triangular kernel is used and the optimal bandwidth, chosen following Ludwig and Miller (2007), is h* = 14.

Different slopes on both sides of the discontinuity

The baseline model defined above assumed that the slopes of the regression functions (of our parametric specifications) on each side of the discontinuity were the same, which can be a strong assumption in the case of Regression Discontinuity Designs. We present a sensitivity analysis for our estimations considering that these slopes may be different. The parametric model can be redefined as: $y_i = \delta + \sum_{j=1}^{p} \kappa_j (N_i - 20)^j + \varphi \cdot d_i + \sum_{j=1}^{p} \varsigma_j (N_i - 20)^j \cdot d_i + z_i'\gamma + u_i$, where the main difference with the specification defined in Section IV.B is the interaction of $\varsigma_j(\mathrm{N_i} - 20)^{\mathrm{j}} \cdot d_i$, which allows for different slopes on both sides of the discontinuity. Some of the results are shown in Table 12. We see, for example, that results for fertile age females suggest that considering different slopes do not introduce major alterations in our estimates in comparison with the original ones. Similar results hold for other groups.

Table 12. Impact of Article 203 on log wages of fertile age females (different slopes on both sides of the discontinuity allowed)

Polynomial	Fertile age females
Linear	-0.037***
Quadratic	-0.039***
Cubic	-0.041***

Note: ***, ** and* represent statistical significance at 1%, 5%, 10%, respectively.

Falsification tests

In this section we present falsification tests. In particular, we estimate our baseline model (20 female workers) considering different thresholds (17, 23 and 30 female workers). If the regression discontinuity design were well specified then we would expect a lack of statistical significance by the RD estimators. Before estimating, in order to make a valid RD analysis, we perform the McCrary (2008) test for the density of the assignment variable for the new threshold. Results indicate that a discontinuity on these variables is not observed.

Table 13 presents the results of our falsification tests for fertile age females' wages, non-fertile age females' wages and males' wages. We see that the estimates are not statistically significant for females (fertile and non-fertile ages) and male workers. These results show that our regression discontinuity design performs well as changing the threshold does not yield statistically significant estimates.

Table 13. Falsification test: effects of different thresholds on log wages of different groups

Polynomial	Threshold								
	Fertile age females			Non-fertile age females			Males		
	17	23	30	17	23	30	17	23	30
Linear	-0.002	-0.012	-0.019	-0.003	0.002	-0.01	0.24	-0.039	-0.029
Quadratic	-0.012	0.01	0.015	-0.009	0.022	0.016	0.007	0.002	0.055
Cubic	-0.003	0.026	-0.005	-0.009	0.031	0.018	0.026	0.012	0.064

VII. Concluding remarks

The previous literature on childcare has focused on two main strands: (i) those who analyze the effect of childcare policies on cognitive development of the child and (ii) those who study the effects of these types of policies on maternal labor supply. There is no empirical evidence on who bears the financial burden of childcare provision when childcare regulation mandates that firms have to provide that service. Thus, we present the first empirical study that analyzes who bears the financial burden of childcare provision. We exploit the discontinuity generated by Article 203 of the Chilean Labor Code, which mandates that firms with 20 or more female workers have to provide childcare. We explore its effects on wages using a regression discontinuity design.

Article 203 theoretically imposes an additional cost on firms, which may result in different outcomes depending on who actually bears the cost (i.e., firms or employees). If firms do not transfer the cost on to their workers we should observe a disincentive to hire female workers in treated firms through a substitution of females by males, observing a change in employment composition between treated versus untreated firms (and hence a discontinuity of the share of female workers at the threshold). Hence firms will have all the incentives to manipulate the threshold in order to avoid the regulation. If firms can instead transfer the full cost to their workers then we should observe lower wages and no manipulation of the threshold, whether labor markets are competitive or not.[26]

Our empirical results seem to indicate that we are in the presence of a non-competitive labor market. In particular, we explain these empirical results by means of a simple model of an imperfect labor market characterized by monopsony power, in which the childcare regulation that affects the labor costs of firms with 20 or more female workers is modeled as a tax implying a ratio of female to male wages which depends on the labor supply elasticities of male and female workers, the elasticity of substitution between female and male labor and the tax levied on firms with 20 or more female workers. We argue that the strategy of substituting female workers with male workers, to avoid the change in relative prices implied by the policy (not hiring the 20th female worker) is not necessarily optimal when considering the situation in which female and male labor are not perfectly substitutable. In this case an alternative strategy for the firm can be to hire the 20th female worker and pay the additional cost associated while maintaining the optimal ratio of male to female workers, by imposing the additional costs upon their workers (male and female) by lowering salaries altogether. In a context of a non-competitive labor market characterized by monopsony power, with given search costs, firms have the incentives to socialize the cost among all its workers and not only to transfer them to fertile female workers. This is because if the firm charges all the cost to a particular group, they will have higher incentives to

[26] In a competitive labor market, female and male workers who do not have children would be penalized, so they would move to firms unaffected by the policy (i.e., those with less than 20 female workers) until wages equalize the gains.

search for another job. Instead if they spread the cost among all their workers, the decrease in the wage of each worker will be lower and thus the incentive to look for another job will be lower as well (all this given search costs). This market imperfection may be one explanation for workers stickiness (immobility).

Our empirical results show that Article 203 (along with Article 206) has a negative impact on the wages of all groups of workers (fertile age females, non-fertile age females and males). In fact, our findings suggest that firms transfer nearly 100% of the total childcare cost on to their workers, since the reduction of wages is nearly equivalent to the expected childcare cost when we consider an average firm with 20 female workers. We also observe that there is no significant change in the employment composition (relative prices between males and females remain unaltered once the threshold of 20 female workers is reached), which is consistent with the fact that firms do not have incentives to manipulate the threshold because they transfer almost all the cost on to their employees.

Overall, despite that legally the financial burden of Article 203 is imposed on firms, the final agents who carry the burden are the workers of affected firms. This result calls then to have in consideration the potential unintended consequences of childcare regulations. In a dynamic version of our model, Prada et al. (2015) obtain similar but slightly higher results.

Appendix

A. Leave one out cross validation bandwidth (Ludwig and Miller 2007)

The method for choosing the optimal bandwidth within the Regression Discontinuity framework is not indisputable. Ludwig and Miller (2007) present an alternative method for choosing the optimal bandwidth, which consists in a "leave-one-out" cross validation (CV from hereon) procedure. Traditional CV procedures may provide misleading results since they do not account for the discontinuity at the threshold and estimate a function in the interior of the support. Ludwig and Miller's (2007) alternative considers two estimations at each side of the threshold, which centers on boundary predictions. The procedure is the following:

(1) Given a bandwidth h we run separate regressions, leaving one observation out of the sample, on both sides of the threshold considering only observations that are within this bandwidth (i.e., the threshold minus the value of the running variable is, in absolute value, less or equal to the bandwidth).

(2) Using the estimates from both regressions, predictions of the dependent variable are computed (at each side of the threshold) for the observation that was left out of the sample.
(3) The difference between the predicted and observed dependent variable is computed.
(4) Repeating this exercise for each observation yields a complete set of differences between the predicted and observed dependent variable. The optimal bandwidth is the one that minimizes the mean square of this difference.

B. The McCrary (2008) discontinuity test

The use of regression discontinuity designs (RD) has become more popular in the last decade. Relatively low complex estimation techniques and relaxed identifying assumptions have made this possible. As Lee (2008) and McCrary (2008) point out, a core assumption of RD is the inability to alter the treatment assignment rule by individuals. A clear example of a violation of this assumption is the one presented in McCrary (2008). Suppose a doctor wishes to randomly assign patients a certain drug. In order to do so, the doctor assigns patients into two waiting rooms, A and B, where those in the first one will receive the drug and the others will receive a placebo. If individuals know the treatment assignment rule and they may undo the doctor's assignment, then we would expect for room A to be crowded. In this case, because of discontinuities of the assignment variable, the treatment effect estimated by RD will probably be far from a precise estimation, as Lee (2008) formally shows that if there were manipulation of this variable then there could be identification problems of the treatment effect.

McCrary (2008) proposes a formal test in order to analyze if there are discontinuities, at the cutoff, in the assignment variable. This test consists in two steps. First, construct a detailed gridded histogram of the assignment variable. Second, using local linear regressions, smooth the histogram on both sides of the cutoff of the assignment variable and test if there is a difference in the density of both sides (at the cutoff). This applies for the case of a continuous assignment variable.

In the case of a discrete assignment variable, like the one in this article (number of female workers), McCrary's (2008) test can also be applied. As Lemieux and Milligan (2008) show, it is necessary to run local linear regressions on both sides of the cutoff and test if the predicted outcome (fraction or log fraction of the assignment variable in the bins) of both sides is the same.

C. Calculations of childcare cost pass-through on to workers

In this section we present the calculations of the childcare cost transfer to workers by the firm, based on our regression discontinuity estimates. According to our database, in firms that belong to the commerce, financial services or social services industries and that count with 19 female workers, the average monthly wage for fertile female workers is $378,047 CLP (Chilean pesos), $415,575 CLP for non-fertile age female workers and $443,476 CLP for males.[27] The average firm with 19 female workers has 17 female workers, 2 non-fertile age female workers and 25 male workers. Considering a simple average of the parametric effects of Article 203 on wages and that the next female worker that the firm will hire is a fertile one, we have that the total monthly penalization on wages is $628,044 CLP. Table A1 resumes these calculations:

Table A1. Cost transfer calculations

Type of worker	Average wage (CLP)	Number in a firm with 20 females*	RD effect	Cost transfer (CLP)
Fertile female	$378,047	18	-3.8%	$258,584
Non fertile female	$415,575	2	-3.1%	$25,766
Male	$443,476	25	-3.1%	$343,694
Total				$628,044

Note: Average number of workers from firms with 19 female workers are considered. * We assume that in a firm with 19 female workers (17 fertile), the 20th female worker hired is a fertile one. The Regression Discontinuity (RD) effect considers a simple average of the estimated parametric effects.

According to the CASEN 2009 Survey, 13.9% of the working fertile females have a child aged between 6 and 24 months and hence are eligible for childcare provided by the employer.[28] Thus, nearly 2.5 fertile age female workers of the firm will require the childcare service.[29] The monthly cost of childcare is variable. Public childcare (JUNJI) cost nearly $191,000 CLP and private ones range from

[27] Currently (early May 2012), 1 US$ is nearly $500 CLP.
[28] Dependent working fertile age females from the private sector are considered.
[29] These results are obtained from: 13.9% (probability of having a child aged between 6 and 24 months) 18 (fertile age female workers).

$120,000 to $300,000, with an average that is near the public cost. Hence, the expected childcare cost for the employer is $477,500 (CLP).[30]

However, as stated in Articles 203 and 206, other type of expenditures must be paid by the employer. In particular, travel costs to the childcare facility, time travelled from the firm to the childcare facility and vice versa and time granted to the female worker for feeding her child, are indirect costs. At the moment this database was created (October 2010), the cost of public transport was $500 CLP.[31] Hence, the monthly cost of transportation that the employer has to pay for each mother is $22,000 CLP.[32] The cost associated to productivity losses for the firm due to the time spent by the mother feeding her child (1 hour) can be calculated as a fraction of monthly wages. This cost is approximately $47,256 CLP, one-eighth of the daily wage.[33] In the case of the time travelled, we assume that it takes to the mother 1 hour a day for getting from the firm to the childcare facility and vice versa. Thus, the cost is nearly $47,256 CLP. The incremental indirect cost that Article 203 generates is caused by the additional fertile female that we assume that the firm hires. Hence, the indirect costs totalize an amount of (considering the incremental fertile female) $594,012 CLP.[34] A summary of the total costs for the employer due to Articles 203 and 206 is presented in Table A2.

Table A2. Total costs due to Articles 203 and 206

Item	Cost (CLP)
Childcare	$477,500
Transport	$22,000
Productivity loss	$94,512
Total	$594,012

Note: The average number of female workers that will require childcare is considered.

We see that on average the employer transfers to its workers approximately 100% of the total childcare costs.

[30] This result is obtained from: 2.5 (number of female workers that will require childcare) $191,000 CLP (average childcare cost).
[31] This is the cost of Santiago's public transportation system, Transantiago.
[32] Assuming that females must travel twice a day, we have that $22,000=$500 (public transportation cost). 2 (trips in the day), 22 (average worked days in the month).
[33] 8 working hours a day is the maximum allowed by the Chilean Labor Code.
[34] Our analysis is incomplete since we do not have information of the number of firms that have childcare facilities within them and of the exact travel time.

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