Unintended Consequences of Childcare Regulation in Chile: Evidence from a Regression Discontinuity Design

Villena, Mauricio G. and Sanchez, Rafael and Rojas, Eugenio

Universidad Adolfo Ibáñez, Universidad Adolfo Ibáñez, University of Pennsylvania

21 November 2011

Unintended Consequences of Childcare Regulation in Chile: Evidence from a Regression Discontinuity Design*

Eugenio Rojas
University of Pennsylvania

Rafael Sánchez
Adolfo Ibañez University

Mauricio G. Villena
Adolfo Ibañez University

First Version: November 21^{st}, 2011
This Version: February 10^{th}, 2015

Abstract

In several countries governments fund childcare provision, but in many others it is privately funded as labour regulation mandates that firms have to provide childcare services. For this latter case, there is no empirical evidence on the effects generated by the financial burden of childcare provision. In particular, there is no evidence about who effectively pays (i.e. firms or employees) and how it pays (i.e. via wages and/or employment). This study is the first one to provide such evidence. Our hypothesis is that, in imperfect labour markets (e.g. oligopsonistic), firms will transfer childcare cost on to their workers. To analyze this, we exploit a discontinuity on childcare provision mandated by Chilean labour regulation. Our results suggest that firms transfer entirely the cost of childcare (nearly 100%) to their workers via lower wages (not only to female but also to male workers) and not through the alteration of the share of male workers within the firm. This is consistent with our finding that firms do not manipulate the threshold (number of female workers) because they avoid the burden by transfering the cost to their employees.

JEL Classification: H32, J08, J13, J18, J33, J42.
Key words: Childcare, Labour Regulation, Labour Tax, Gender, Female workers.

*We are indebted to the useful comments of Wiji Arulampalan, Mark Stewart, Sascha Becker, Sarah Brown, Luis Felipe Céspedes, Eduardo Fajnzylber, Alejandra Marinovic, Francisco Parro, Tomás Rau, Andrea Repetto and seminar participants at Adolfo Ibañez University, Warwick University and all the comments at the Latin American and the Caribbean Economic Association (LACEA) meetings in Mexico City. We thank the Chilean Budget Office for providing us access to the data. The data analysis was carried out in a secure server.

1 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] Child care policies were mainly discussed in order to strengthen the parent-child link without negatively affecting their labour market situation, in particular female labour market participation. This latter point is still a concern in many countries around the world. One of the examples is the Chilean case, as female participation is 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 Urzúa and Veramendi (2011)). On the other hand, there are studies that analyze the effects of childcare policies on females' labour 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 (i.e. pays) 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 (i.e. an incentive to avoid such regulation by manipulating the number of women hired). However, if firms are not paying someone else must do it (for example: workers). Thus, the objective of this study is to present, for the first time, 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 labour code establishes that the financial responsibility about childcare bears on firms. In particular, in its Article N^{o}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 that "it will be understood that firms fulfill this obligation if they pay the cost of a private childcare

[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 child care 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 in the US*". (http://www.socialwelfarehistory.com/programs/child-care-the-american-history/).

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

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 N^{o}206 states that female workers are granted with up to 1 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, Chilean regulation imposes, theoretically, an additional cost to firms as after a certain number of female workers, firms have to bear different costs such as childcare provision, potential productivity losses for the firm due to the time spent by the female worker feeding her child and in 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 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 (lower option in **Figure 1**). 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 simptoms that randomness at the threshold is not very credible (upper option in **Figure 1**). Because this issue is crucial we analize it extensively below.

For our study we use administrative data from the Unemployment Insurance system provided by the Chilean Ministry of Labour. We show that, even if the firm is the one who 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 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 transfering the cost to their employees.

To provide this empirical evidence is important as there are several countries who 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 2 describes the institutional background, its evolution and the economic incentives generated by it. In section 3 we present our empirical strategy while in section 4 we present the data and the summary statistics. Finally, section 5 displays our results and presents robustness checks for our estimates and section 6 concludes.

2 Institutional Background

The Article N^{o}203 of the Chilean Labour Code has a long history. In 1917 it was established for the first time a Law (N^o 3,185) focused on childcare. 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 activate 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, the Article N^{o}203 establishes that:

- Every firm with 20 or more female workers, regardless of their age and marital status, has to provide childcare facilities within the firm premises so that mothers can feed their children and leave them there while working.
- 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 N^{o}206 establishes that female workers are granted with up to 1 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 N^{o}203 must also fulfill the obligations established by Article N^{o}206.

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

Currently, the Article N^{o}203 of the Labour Code affects a few firms. However, it affects a great proportion of female dependent workers. Given the data supplied by the Chilean Ministry of Labour, 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. Some descriptive statistics are shown in **Table 1**.

Finally, it is important to mention that if firms do not fulfill their obligation the penalty reaches 70 UTM per employee.[4] 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 Labour.

3 Empirical Strategy

The way Article N^{o}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 the Article N^{o}203 is activated (i.e. 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:

$$d_i = \begin{cases} 1 & \text{if} \quad N_i \geq 20 \\ 0 & \text{if} \quad N_i < 20 \end{cases}$$

where N_i is the number of female workers in the firm of worker i. Thus, we can estimate our model as follows:

$$y_i = f(N_i) + \varphi \cdot d_i + z_i'\gamma + u_i \tag{1}$$

[4] Where UTM stands for *Unidad Tributaria Mensual* and it is a monthly inflation-indexed measure. Currently, 1 UTM is nearly US $82.

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.

3.1 Parametric versus Non-Parametric

When there is a model such as the one presented above, 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 that

[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.

"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) points out that the discreteness of the assignment variable does not introduce important econometric 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 comparision purposes.

3.2 The Model

3.2.1 Parametric Model

Our parametric specification is presented in the following 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:

$$(\hat{\delta}, \hat{\varphi}, \hat{\gamma}, \hat{\kappa}) = \text{argmin}_{(\delta,\varphi,\gamma,\kappa)} \sum_{i=1}^{n} \left(y_i - \delta - \sum_{j=1}^{p} \kappa_j (N_i - 20)^j - \varphi d_i - z_i' \gamma \right)^2$$

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]

[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 passthrough of the childcare cost from the firm to its workers.

3.2.2 Non-parametric Model

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)) in both sides of the discontinuity point. Thus, the estimated parameters of this specification are:

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

$$(\hat{\delta}^{-}, \widehat{\mu}^{-}, \hat{\gamma}^{-}) = \text{argmin}_{(\delta^{-}, \varphi^{-}, \gamma^{-})} \quad \sum_{i=1}^{n} (y_i - \delta^{-} - \mu^{-}(N_i - 20) - z_i'^{-}\gamma^{-})^2 K\left(\frac{N_i - 20}{h}\right) I(N_i < 20) \tag{3}$$

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 which 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) demonstrates, 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 (2011) approach. Both methods give similar but large bandwidth,[12] for this reason we also reestimate 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.

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

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

[11] More details in the appendix.

[12] As expected given the discrete nature of the data.

4 Data and Summary Statistics

We use cross section data from the Chilean Unemployment Insurance system for October 2010, provided by the Ministry of Labour. 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]

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 Labour.

Since our main focus is related to the financial side of childcare regulation, we separate the sample into three sub-samples: fertile female workers, non fertile female workers and male workers. Regarding the first group, we examine the economic sectors where women with this characteristics are more concentrated. **Table 2** presents the distribution of fertile female workers across different type of industries.[14] As it can be seen 3 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 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]

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 graphic analysis of the used 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.

[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.

[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 within the sample.

[16] This separation was only based on the number of female workers, thus it was not imposed any constraint on the number of male workers.

Tables 4 and **5** present the summary statistics for non fertile 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 female workers we observe that the trend is similar to the case of fertile female workers, which also coincides with the case of men. 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.

4.1 Graphical Analysis

When regression discontinuity design is used as a method of estimation, previous literature (Imbens and Lemieux (2008) and Lee and Lemieux (2010)) suggest 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 in:

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

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

(c) If there is a discontinuity on 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 on 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 covariates present discontinuities or not. If they do, it gets unclear the causality claimed from the policy change as the discontinuity found on the dependent variable is due to a discontinuity on the covariates and not to the policy change. Furthermore, the smoothness of the covariates make the continuity assumption of the expected potential outcomes more plausible (as discussed below). Finally, test (c) allow 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 were 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 generate 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 latter issue is crucial in the RD context because as long as there 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.

4.1.1 Test A

A.1. Firms with fertile and non fertile females and males:

In **Figure 2** we observe that there is a discontinuity on wages of female workers in firms with 19 relative to firms with 20 female workers.[18] Discontinuities on wages are also observed in non fertile female women and in men, as **Figure 3** and **Figure 4** show. These results suggest that firms transfer the cost of childcare not only to fertile female workers in the form of lower wages, but also to non fertile females and men as well. We will explore the magnitude of this transfer below.

A.2. Firms with male workers only:

To further support our previous results, we apply again test (a) but now only to firms with male workers. As the Article N^{o}203 of the labour code only applies to firms that have female workers, we should expect no discontinuity on those firms with only male workers. Results are presented in **Figure 5**, 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.

A.3. Firms with non fertile females only:

In order to study further our hypothesis, we analyze the behaviour of firms with only non-fertile 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 on wages. Our results are presented in **Figure 6** and suggest that, as expected there is no significant discontinuity at the threshold.

[17] For more information on McCrary's (2008) test see the Appendix.

[18] For smoothing the data points we consider local-mean smoothing.

4.1.2 Test B

Our next step is to apply test (b) on the covariates. They are: age and type of industry dummies. **Figure 7** presents the result for fertile 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. Next, in **Figures 8 and 9,** we present the same graphical analysis but now for non fertile female workers and for male workers respectively. Results again suggest no significant discontinuities at the threshold. Non significant point estimates for non fertile 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 above (**Tables 3, 4 and 5**) where covariates are balanced between both sides of the threshold making the assumption of local randomness more credible.

4.1.3 Test C

Finally, in **Figure 10** we present the result for test (c). We observe that there are no significant discontinuities on the density of the running variable at the threshold. This suggests no evidence of manipulation from the agents point of view. This is crucial as Lee (2008) formally showed 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.

To further investigate the presence of manipulation of the assignment variable we follow McCrary (2008) who developed a density test.[19] Unfortunately, his test was developed for continuous assignment variables. However, as Lemieux and Milligan (2008) pointed 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

[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.

fraction of women is 0.93 and 0.90 for the log fraction of women. Hence we do not reject the null hypoythesis of continuity.

As mentioned in section 3, the discrete nature of our data can introduce complications in the regression discontinuity analysis (Lee and Card (2008)). However, Lee and Lemieux (2010) points out that the discreteness of the running variable (number of female workers in the firm) does not introduce important complications if this variables is not too coarsely distributed. As **Figure 10** and the McCrary test show this seems to be the case.

Overall, tests (a), (b) and (c) 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 may do it. As we will show in the results section below, firms do not manipulate the threshold because they are transfering the whole cost of childcare to their employees, hence they do not have incentives to manipulate.

5 Results

In this section we present the results of our estimation on wages of fertile and non fertile females and males of the firm. Additionally, we present 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.

5.1 Wages

Table 6 presents the results regarding the impact of the Article N°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 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

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

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.

Tables 7 and **8** present the estimates, through parametric and nonparametric specifications, for non fertile female workers and male workers who are in firms along with fertile females, respectively. For the case of non fertile 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 the Article N^{o}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 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 N^{o}203 (along with Article N^{o}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.

5.1.1 Explaining the Results

At the begining our hypothesis was that firms transfered the cost of childcare to fertile female workers due to asymetric information. Punishing those fertile female workers without children. This follows the same reasoning than the one on health insurance, where insurance companies have asymetric information on individuals (high and low risk individuals) and thus charge a unique premium, where high risk get a lower premium and low risk a higher premium than under perfect information. In our case firms do the same.

That hypothesis is corroborated by our results. However we also find that firms are transfering the cost to non-fertile female workers and male workers as well. A potential way to explain these further results is the following. In a competitive labour 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. However in imperfect labour markets 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 beacuse 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). This can be an interesting agenda for future research.

5.2 Sensitivity Analysis

As Imbens and Lemieux (2008) points 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 non parametric 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]

5.2.1 Alternative Kernels

The estimates of our nonparametric specifications presented in **up to Table 8** 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, non fertile female workers and men workers in **Tables 9, 10 and 11** suggest 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.

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 $K(u) = \frac{3}{4}(1-u^2)\mathbf{1}_{\{|u|\leq 1\}}$ and the Biweight kernel is $K(u) = \frac{15}{16}(1-u^2)^2\mathbf{1}_{\{|u|\leq 1\}}$.

5.2.2 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 and Ludwig and Miller (2007). The results of our estimations are presented in **Table 12**.[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.

Although our bandwidth selection criteria follows 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 if the robustness of our estimates.[25] **Tables 13**, **14** and **15** present 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.

5.2.3 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 follows:

$$y_i = \delta + \sum_{j=1}^{p} \kappa_j (N_i - 20)^j + \varphi \cdot d_i + \sum_{j=1}^{p} \varsigma_j (N_i - 20)^j \cdot d_i + z_i' \gamma + u_i$$

Where the main difference with the specification defined in section 3.2 are the interaction terms $\varsigma_j (N_i - 20)^j \cdot d_i$, which allows for different slopes on both sides of the discontinuity. Some of the results are shown in **Table 16**. We see, for example that results for fertile females, suggest that considering different slopes do not introduces major alterations of our estimates in comparison with the original ones. Similar results hold for other groups.

5.2.4 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 is well

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

[25] We also consider the Imbens and Kalyanaraman (2011) 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.

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 McCrary's (2008) for the density of the assignment variable for the new threshold. Results indicate that a discontinuity on this variables is not appreciated.

Tables 17, 18 and **19** present the results of our falsification tests for fertile females' wages, non fertile females' wages and males' wages, respectively. We see that the estimates are not statistically significant for females (fertile and non fertile) and males workers. These results show that our regression discontinuity design performs well as changing the threshold does not yield statistically significant estimates.

6 Conclusion

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 type of policies on maternal labor supply. There are 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 in the Chilean Labour Code by its Article 203, 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 on treated firms through a substitution of females for 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 transfer the full cost to their workers then we should observe lower wages on those affected (in non-competitive labour markets) or in equilibrium (in competitive labour markets) and no manipulation of the threshold.

Our findings suggest that on average nearly a 100% of the childcare cost is transferred to female workers (fertile and non fertile) and male workers in the form of lower wages. We also observe that there is barely not a 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.

References

Baker, M., J. Gruber and K. Milligan (2005). "Universal Childcare, Maternal Labor Supply and Family Well-Being", *NBER Working Paper* 11832.

Berlinski, S. and S. Galiani (2007). "The Effect of a Large Expansion of Pre-Primary School Facilities on Preschool Attendance and Maternal Employment", *Labour Economics*, Vol. 14, Issue 3, June 2007, 665-680.

Berlinski, S., S. Galiani and P. Gertler (2009). "The Effect of Pre-primary Education on Primary School Performance", *Journal of Public Economics*, Vol. 93, Issue 1-2, February 2009, 219-234.

Berlinski, S., S. Galiani and M. Manacorda (2008). "Giving Children a Better Start: Preschool Attendance and School-age Profiles", *Journal of Public Economics*, Vol. 92, Issue 5-6, June 2008, 1416-1440.

Bernal, R. (2008). "The Effect of Maternal Employment and Child Care on Children's Cognitive Development", *International Economic Review*, Vol. 49, No. 4, November 2008.

Betancor, A. (2011). "The Impact of Accessing Childcare Center on Chilean Mothers' Probability of Employment", *Manuscript*, Comunidad Mujer Research Department.

Blau, D., and E. Tekin (2003). "The Determinants and Consequences of Child Care Subsidies for Single Mothers", *NBER Working Paper* 9665.

Cascio, E. (2006). "Public Preschool and Maternal Labor Supply: Evidence from the Introduction of Kindergartens into American Schools", *NBER Working Paper* 12179.

Carneiro, P., K. Löken and K. G. Salvanes (2009). "A Flying Start? Maternity Leave and Long-Term Outcomes for Mother and Child", *Manuscript*, Norwegian School of Economics.

Cheng, M., J. Fan and J. S. Marron (1997). "On Automatic Boundary Corrections", *The Annals of Statistics*, Vol. 25, No. 4, 1691-1708.

Encina, J. and C. Martínez (2009). "Efecto de una Mayor Cobertura de Salas Cuna en la Participación Laboral Femenina: Evidencia de Chile", *Serie Documentos de Trabajo, Departamento de Economía*, Universidad de Chile.

Gelbach, J. B. (2002). "Public Schooling for Young Children and Maternal Labor Supply", *American Economic Review*, Vol. 92, No. 1, 307-322.

Guzman, J. (2009). "Child Care Subsidies and the Employment of Single Mothers", *PhD. Thesis*, The University of Chicago.

Fan, J. (1992). “Design Adaptative Nonparametric Regression”, *Journal of the American Statistical Association*, 87, 998-1004.

Fan, J. and I. Gijbels (1996). "Local Polynomial Modelling and its Applications", *Chapman Hall.*

Hahn, J., P. Todd and W. van der Klaauw (2001). “Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design”, *Econometrica*, Vol. 69, No. 1 (Jan., 2001), 201-209.

Herbst, C. M. and E. Tekin (2010). “Child Care Subsidies and Child Development”, *Economics of Education Review*, Vol. 29, 618-638.

Imbens, G. W. and T. Lemieux (2008). “Regression Discontinuity Designs: A Guide to Practice”, *Journal of Econometrics*, 142 (2008) 615-635.

Imbens, G. and K. Kalyanaraman (2011). “Optimal Bandwidth Choice for the Regression Discontinuity Estimator”, *Review of Economic Studies*. Vol 79, Issue 3.

INE (2011). “Empleo Trimestral”, *Boletín de Indicadores Mensuales*, Edición No. 150.

Jaumotte, F. (2004). ”Labor Force Participation of Women: Empirical Evidence on the Role of Policy and other Determinants in OECD Countries,” *OECD Economic Studies*, No. 37.

Lee, D. S. (2008). “Randomized Experiments from Non-random Selection in U.S. House Elections”, *Journal of Econometrics*, 142(2), 675-697.

Lee, D. S. and T. Lemieux (2010). ”Regression Discontinuity Designs in Economics”, *Journal of Economic Literature*, 48 (June 2010), 281-355.

Lemieux, T. and K. Milligan (2008). “Incentive effects of social assistance: A regression discontinuity Approach”. *Journal of Econometrics* 142 (2), February, 615-635.

Ludwig, J. and D. L. Miller (2007). "Does Head Start Improve Children’s Life Chances? Evidence from a Regression Discontinuity Design". *Quarterly Journal of Economics,* 122(1): 159-208.

Manning, A. (2003). “Monopsony in Motion, Imperfect Competition in Labor Markets”, *Princeton University Press*, Princeton, NJ.

McCrary, J. (2008). “Manipulation of the running variable in the Regression Discontinuity Design: A density test”. *Journal of Econometrics* 142(2), February 698-714.

OECD (2010). “Employment Outlook, Moving Beyond The Job Crisis”. *OECD Series.*

UNDP (2008). “Chile Crece Contigo: El Efecto de la Implementación de Salas Cuna Públicas en la Participación Laboral Femenina, la Incidencia en la Pobreza y la Distribución de Ingresos en Chile”, *Programa Equidad*, Octubre 2008.

Schlosser, A. (2011). “Public Preschool and the Labor Supply of Arab Mothers: Evidence from a Natural Experiment”, *Manuscript*, Eitan Berglas School of Economics, Tel Aviv University.

Silverman, B. (1986). "Density Estimation for Statistics and Data Analysis". *Chapman Hall.*

Urzúa, S. and G. Veramendi (2011). “The Impact of Out-of-Home Childcare Centers on Early Childhood Development”, *IDB Working Paper Series*, No. IDP-WP-240.

Appendix

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) presents 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.

McCrary's (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 the RD is the inability to alter the treatment assignment rule by individuals. An 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 the treatment assignment rule is known by individuals 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 in 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.

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 female workers and $443,476 CLP for males.[26] The average firm with 19 female workers has 17 female workers, 2 non fertile female workers and 25 male workers. Considering a simple average of the parametric effects of Article N°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. The following Table resumes these calculations:

Table: Cost Transfer Calculations

Type of Worker	Average Wage (CLP)	Number in a Firm With 20 Females[27]	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 the 20th female worker hired is a fertile one and hence the original number of fertile female workers is 17. 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 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 $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

[26] Currently (early may 2012), 1 US$ is nearly $500 CLP.
[27] We consider the average numbers of a firm with 19 female workers and that the next female hired is a fertile one.
[28] Dependent working fertile females from the private sector are considered.
[29] This results is obtained from: 13.9% (probability of having a child aged between 6 and 24 months) × 18 (fertile female workers).
[30] This results is obtained from: 2.5 (number of female workers that will requiere childcare) × $191,000 CLP (average childcare cost).

viceversa 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 viceversa. 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 the following Table:

Table: 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 her workers approximately 100% of the total childcare costs.

[31] This is the cost of Santiago's public transport system, Transantiago.

[32] Assuming that females must travel twice a day, we have that $22,000=$500 (public transport 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 Labour 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.

Tables

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

Note: Percentages are presented in parentheses.

Table 2: Distribution of Fertile 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.

Table 3: Descriptive Statistics for Fertile Female Workers Around the Threshold

Variable	15-19 Female Workers	20-24 Female Workers
Log Wage	12.62	12.63
	(0.59)	(0.60)
Age	33.24	33.34
	(8.21)	(8.20)
Commerce	0.36	0.32
	(0.48)	(0.47)
Financial and Business Services	0.21	0.21
	(0.41)	(0.41)
Communal, Personal and Social Services	0.42	0.46
	(0.49)	(0.50)
Number of Observations	29,779	20,577

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

Table 4: Descriptive Statistics for Non Fertile Female Workers Around the Threshold

Variable	15-19 Female Workers	20-24 Female Workers
Log Wage	12.57	12.60
	(0.54)	(0.59)
Age	54.77	54.69
	(3.87)	(3.83)
Commerce	0.33	0.24
	(0.47)	(0.42)
Financial and Business Services	0.19	0.17
	(0.39)	(0.37)
Communal, Personal and Social Services	0.48	0.60
	(0.50)	(0.49)
Number of Observations	4,363	3,230

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

Table 5: Descriptive Statistics for Male Workers Around the Threshold

Variable	15-19 Female Workers	20-24 Female Workers
Log Wage	12.81	12.81
	(0.60)	(0.61)
Age	37.55	37.37
	(11.34)	(11.38)
Commerce	0.42	0.43
	(0.49)	(0.50)
Financial and Business Services	0.35	0.30
	(0.48)	(0.46)
Communal, Personal and Social Services	0.22	0.27
	(0.42)	(0.44)
Number of Observations	44,463	32,620

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

Table 6: Impact of Article 203 on Fertile Females' Log Wages

Specification	Estimate
Parametric	
Linear	-0.039^{***}
Quadratic	-0.034^{***}
Cubic	-0.038^{***}
Quartic	-0.042^{***}
Nonparametric	-0.040^{***}

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 $h^* = 14$.

Table 7: Impact of Article 203 on Non Fertile Females' Log Wages

Specification	Estimate
Parametric	
Linear	-0.027^{*}
Quadratic	-0.023^{*}
Cubic	-0.035^{*}
Quartic	-0.039^{*}
Nonparametric	-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 $h^{*} = 14$.

Table 8: Impact of Article 203 on Males' Log Wages

Specification	Estimate
Parametric	
Linear	-0.039^{***}
Quadratic	-0.028^{***}
Cubic	-0.029^{***}
Quartic	-0.026^{***}
Nonparametric	-0.040^{***}

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 $h^{*} = 14$.

Table 9: Impact of Article 203 on Fertile Females' Log Wages (Alternative Kernels)

Kernel	Effect
Epanechnikov	-0.039^{***}
Biweight	-0.040^{***}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. The optimal bandwidth for the Epanechnikov and for the Biweight kernel is $h^{*} = 14$ (using the Ludwig and Miller (2007) approach).

Table 10: Impact of Article 203 on Non Fertile Females' Log Wages (Alternative Kernels)

Kernel	Effect
Epanechnikov	-0.039^{***}
Biweight	-0.036^{***}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. The optimal bandwidth for the Epanechnikov and for the Biweight kernel is $h^{*} = 14$ (using the Ludwig and Miller (2007) approach).

Table 11: Impact of Article 203 on Males' Log Wages (Alternative Kernels)

Kernel	Effect
Epanechnikov	-0.031^{***}
Biweight	-0.038^{***}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. The optimal bandwidth for the Epanechnikov and for the Biweight kernel is $h^* = 14$ (using the Ludwig and Miller (2007) approach).

Table 12: Impact of Article 203 on Different Outcomes (Alternative Bandwidths)

Outcome	Difference with Optimal Bandwidth			
	+2	+1	-1	-2
Fertile Females (Wages)	-0.042^{***}	-0.040^{***}	-0.040^{***}	-0.040^{***}
Non Fertile Females (Wages)	-0.040^{***}	-0.039^{***}	-0.036^{***}	-0.035^{***}
Males (Wages)	-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.

Table 13: Impact of Article 203 on Fertile Female Workers' Wages (Smaller Bandwidths)

Bandwidth	Estimate
6	-0.033^{***}
7	-0.041^{***}
8	-0.043^{***}
9	-0.043^{***}
10	-0.043^{***}
11	-0.042^{***}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. We consider the triangular kernel in these estimations.

Table 14: Impact of Article 203 on Non Fertile Female Workers' Wages (Smaller Bandwidths)

Bandwidth	Estimate
6	-0.057^{**}
7	-0.046^{*}
8	-0.043^{*}
9	-0.039^{*}
10	-0.037^{*}
11	-0.032^{*}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. We consider the triangular kernel in these estimations

Table 15: Impact of Article 203 on Male Workers' Wages (Smaller Bandwidths)

Bandwidth	Estimate
6	-0.075^{***}
7	-0.089^{***}
8	-0.085^{***}
9	-0.072^{***}
10	-0.065^{***}
11	-0.054^{***}

Note: ***, ** and * represent statistical significance at 1%, 5%, 10%, respectively. We consider the triangular kernel in these estimations.

Table 16: Impact of Article 203 on Different Outcomes (Different Slopes on Both Sides of the Discontinuity Allowed)

Polynomial	Fertile Females (Wages)
Linear	-0.037^{***}
Quadratic	-0.039^{***}
Cubic	-0.041^{***}

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

Table 17: Falsification Test: Effects of Considering Different Thresholds on Fertile Females' Wages

Polynomial	Threshold		
	17	23	30
Linear	-0.002	-0.012	-0.019
Quadratic	-0.012	0.010	0.015
Cubic	-0.003	0.026	-0.005

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

Table 18: Falsification Test: Effects of Considering Different Thresholds on Non Fertile Females' Wages

Polynomial	Threshold		
	17	23	30
Linear	-0.003	0.002	-0.01
Quadratic	-0.009	0.022	0.016
Cubic	-0.009	0.031	0.018

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

Table 19: Falsification Test: Effects of Considering Different Thresholds on Males' Wages

Polynomial	Threshold		
	17	23	30
Linear	0.024	-0.039	-0.029
Quadratic	0.007	0.002	0.055
Cubic	0.026	0.012	0.064

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

Figures

Figure 1: Incentives generated by Childcare regulation in Chile

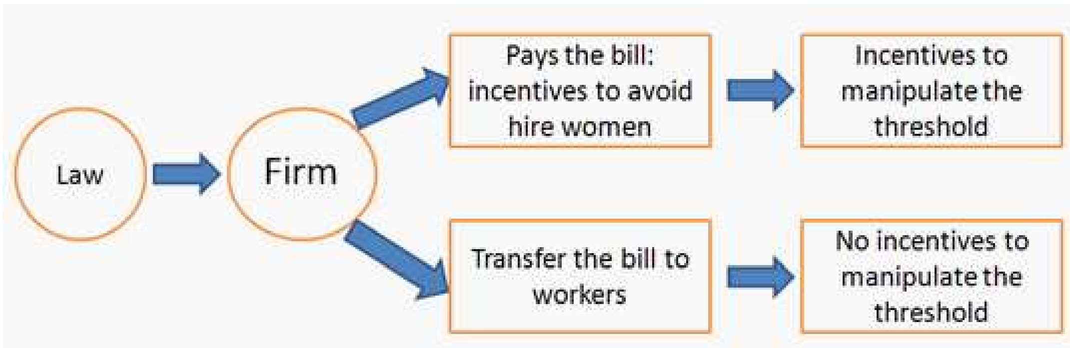

Figure 2: Log Wages (Mean) of Fertile Female Workers by Number of Female Workers

Figure 3: Log Wages (Mean) of Non Fertile Female Workers by Number of Female Workers

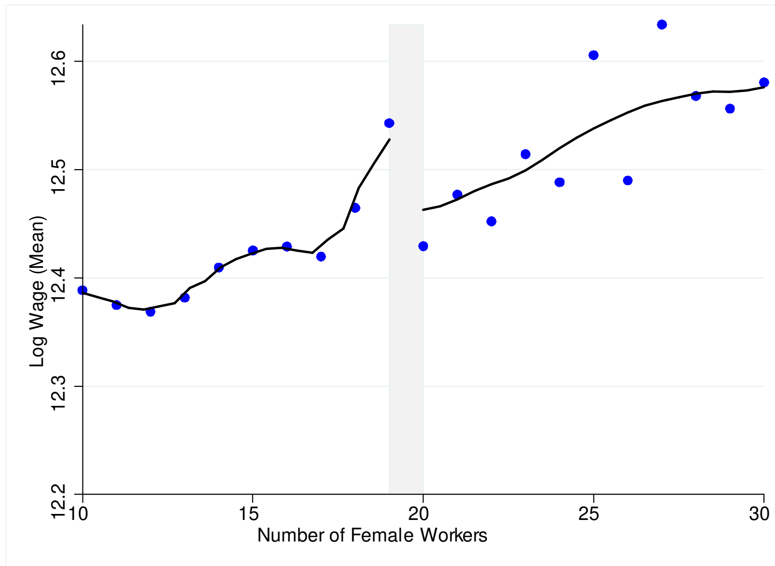

Figure 4: Log Wages (Mean) of Male Workers by Number of Female Workers

Figure 5: Log Wages (Mean) of Male Workers by Number of Male Workers

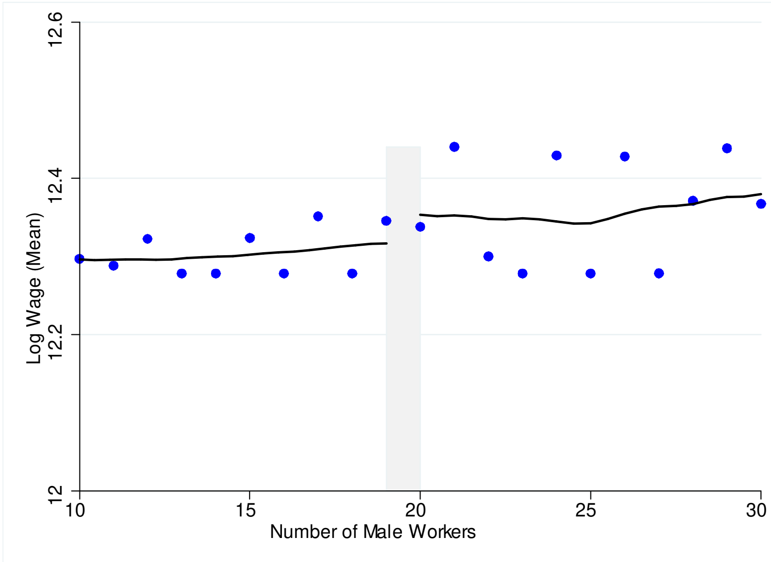

Figure 6: Log Wages (Mean) of Non Fertile Female Workers by Number of Non Fertile Female Workers

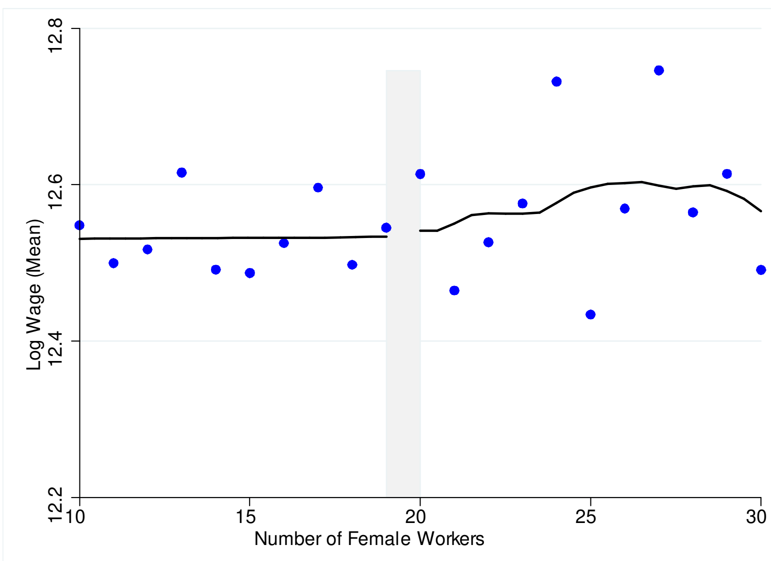

Figure 7: Covariates of Fertile Female Workers by Number of Female Workers

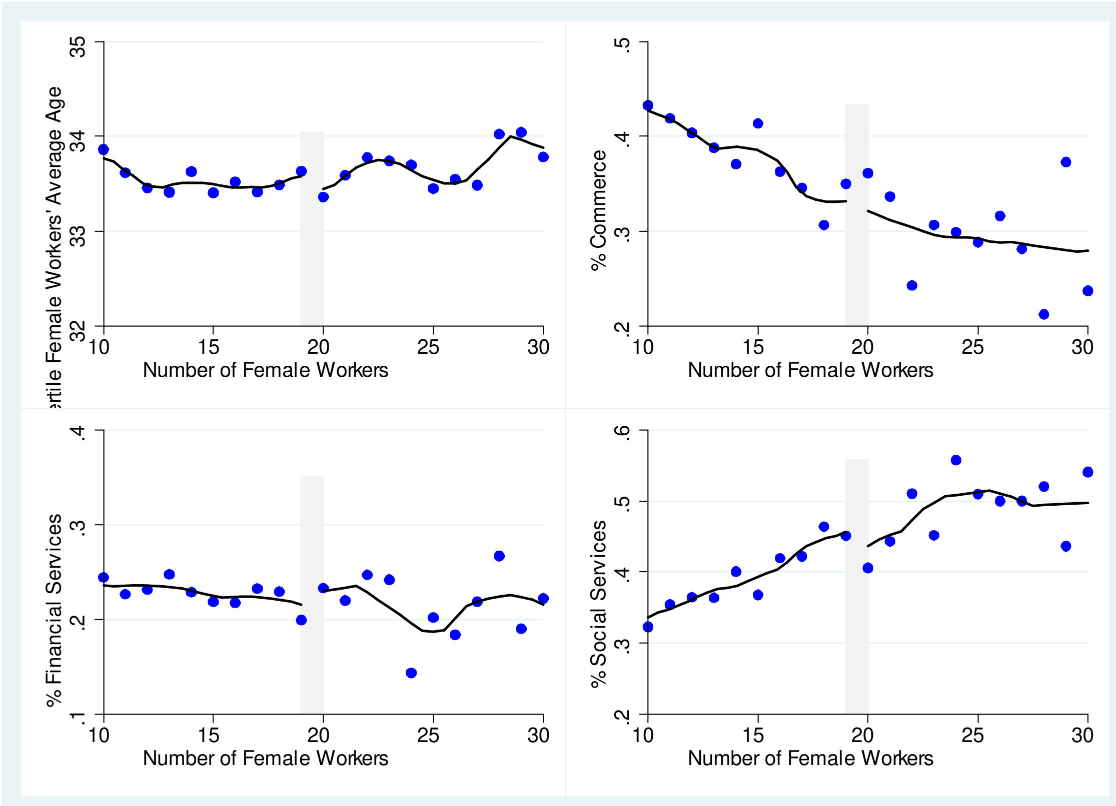

Figure 8: Covariates of Non Fertile Female Workers by Number of Female Workers

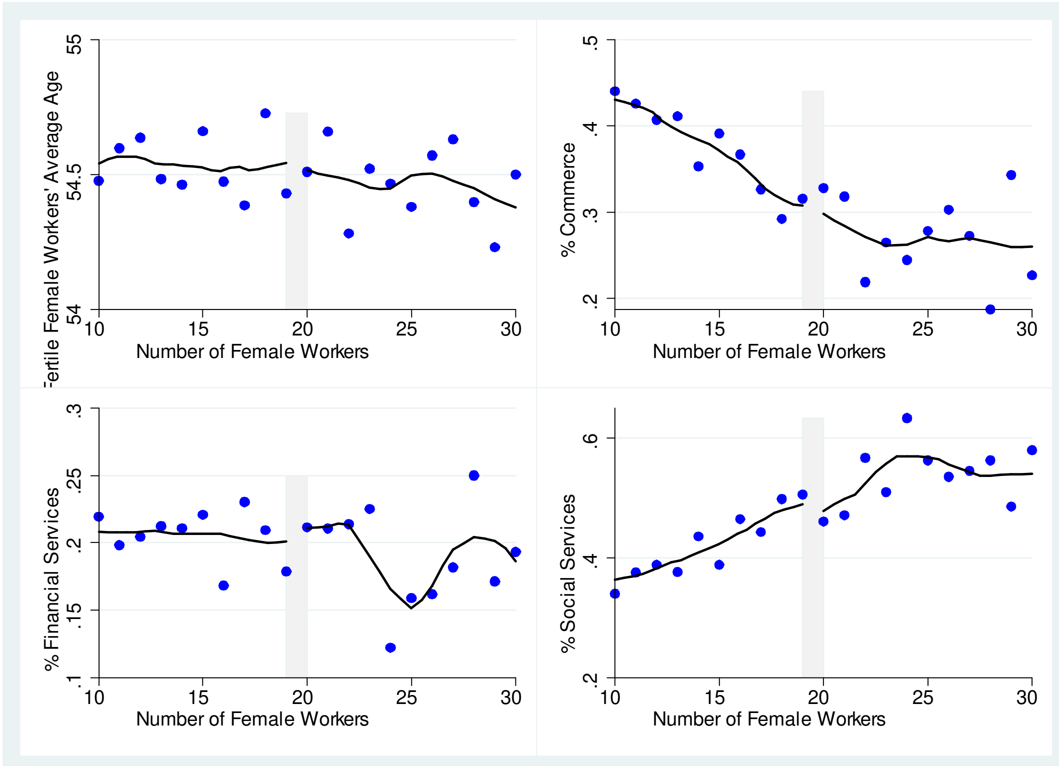

Figure 9: Covariates of Male Workers by Number of Female Workers

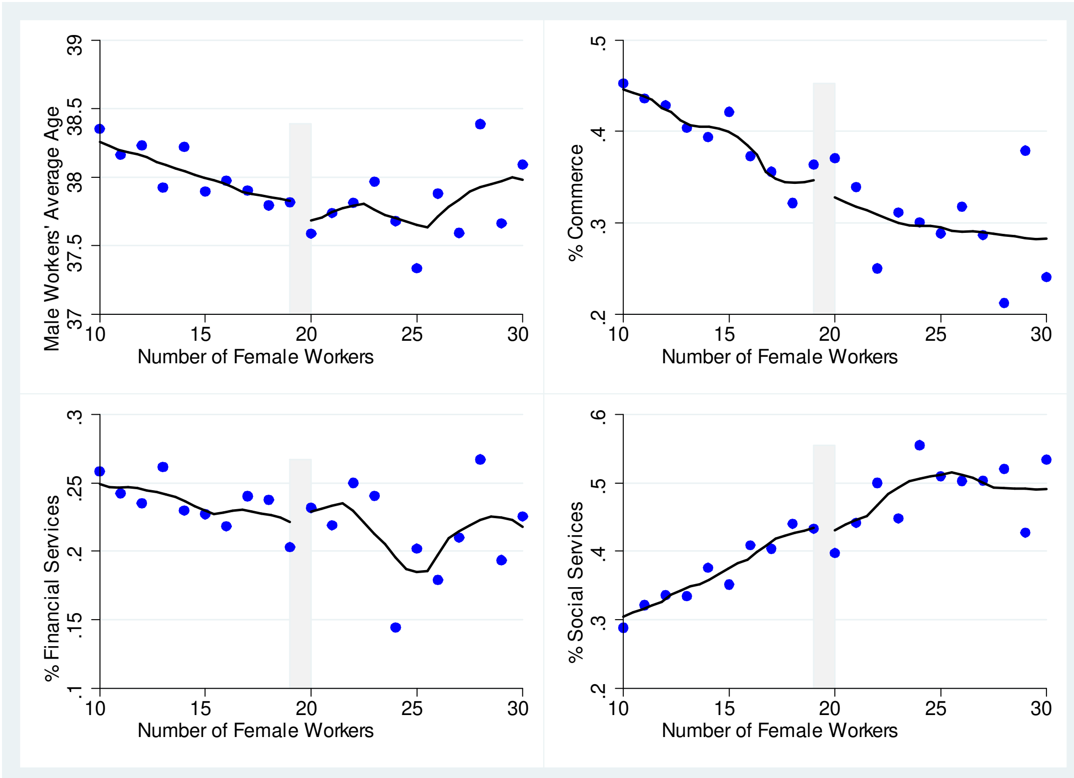

Figure 10: Density of the Firms by Number of Female Workers