Paid Leave Extensions and the Behavior of Workers and Firms

Cecilia Machado* and Valdemar Pinho Neto†

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Abstract

The paper studies the causal effects of a sizable paid maternity leave extension (from four to six months) on the behavior of workers and firms. Our empirical strategy exploits the precise leave-taking dates and the staggered implementation of the policy across firms, using monthly information from matched employer-employee data covering the universe of the Brazilian formal labor market. Our results show that only 40% of eligible women take extended maternity leave and employment effects are modest and temporarily confined during the months around the leave. We observe both women's and firms' strategic responses to leave extensions: some women voluntarily quit their jobs after the extended leave period is over, while others are fired when returning to their jobs after a leave. We offer a comprehensive view on the interplay among labor markets, firms' and workers' characteristics driving the take-up rates of paid leave extensions and its impacts. Besides the regressive distributional effects of the policy and evidence of learning from peers for less-educated workers, the findings also indicate that take-up and labor market effects of leave extensions depend on multiple factors, such as: job security, worker's ability, firm's premium, labor market frictions, and workers' substitutability/complementarity within the firms.

Keywords: paid maternity leave, maternal employment, gender equality.

JEL Classification: J13, J18, H42

*Getulio Vargas Foundation (FGV EPGE) and IZA. E-mail: machadoc@gmail.com

†*Corresponding author* Getulio Vargas Foundation (FGV EPGE). E-mail: valdemar.pinho@fgv.br.

1 Introduction

The participation of women in labor markets around the world has considerably increased over the last decades, which led many countries to adapt their labor legislation to assist pregnant women and mothers of young children [Addati et al., 2014]. Because women usually bear the greatest responsibilities for newborns and child rearing, there is already extensive evidence on the role of young children on women's career interruption and its consequent effects on gender inequality [Waldfogel, 1998, 1997, Budig and England, 2001, Bertrand et al., 2010, Kleven et al., 2019b, Molina and Montuenga, 2009]. In this context, maternity leave policies have been widely adopted to alleviate the adverse consequences of motherhood on female labor market outcomes. Advocates of such policies argue that time spent at home with newborns, besides improving child development[1], could help mothers balance work with family demands. However, opponents argue that long periods outside the labor market can also reduce skills as well as employment and earnings, as employers might discriminate against new mothers.

While many empirical studies have already examined the effects of maternity leave policies, extant literature with credible research designs has been conducted almost exclusively in developed countries in North America and Europe[2], where female employment is high and leave entitlements are salient [Rossin-Slater, 2019]. Nevertheless, the impacts of these policies can differ substantially across countries depending on local labor market conditions, as well as socio-cultural norms towards gender roles. Also, the effectiveness of such policies may depend on the specific rules and settings (eg., paid vs. unpaid leave, length of leave, eligibility requirements, job protection) of each context. All these aspects are especially relevant for our research as we note that: (1) female labor market participation in developing countries has improved only more recently and gender inequalities are still prominent; (2) these countries often exhibit notable gender bias against women; and (3) their labor market regulations and maternity-leave rules present peculiarities distinguishing them from the developed world. Studying the effects of leave policies in these distinct contexts can yield new insights into the consequences of these policies for workers, firms, and labor markets.

The present study contributes to the literature by investigating the effects of maternity leave extensions in Brazil, a large developing country marked by sizable gender inequality [Agénor and Canuto, 2015, Van Klaveren et al., 2009, Pinheiro and Medeiros, 2016, Fernandes and Menezes-Filho, 2016] as well as a recent and strong increase in female labor force participation. Furthermore, as discussed in Jayachandran [2020], cultural barriers and social norms play a relevant role in women's participation and success in the labor market in developing countries, and particularly so in Brazil [Codazzi et al., 2018]. In this regard, data from the World Values Survey (see Figure 1) reveals

[1]While an extensive literature has shown evidence of the little impact of leave extensions on children's well-being in developed countries, such as, Canada, Denmark, Austria, Germany and Norway (see Baker and Milligan [2008b]; Baker and Milligan [2010]; Baker and Milligan [2015]; Rasmussen [2010]; Danzer and Lavy [2017]; Dustmann and Schönberg [2012]; Dahl et al. [2016]), the evidence suggests positive effects of leave introduction (rather than extensions) in Norway and US [Carneiro et al., 2015, Rossin, 2011].

[2]See, for example, the following studies: Olivetti and Petrongolo [2017], Rossin-Slater [2019], Baum and Ruhm [2016], Han et al. [2009], Blau and Kahn [2013], Baker and Milligan [2008a], Gregg et al. [2007], Lalive and Zweimüller [2009], Kluve and Tamm [2013], Bergemann and Riphahn [2015], Lequien [2012].

a remarkable degree of opposition to women's participation in the Brazillian workforce, especially compared to developed countries. For instance, we see that people in Brazil are more likely to think that women's participation in the labor market (and earning money) can weaken family bonds and that men make better business executives than women do. Yet not directly related to the workplace, people in Brazil also strongly agree that abortion can never be justified.[3]

Besides offering a distinctive research context regarding socio-economic background and social norms, Brazil also provides a very unique setting in terms of labor market frictions, regulations[4] [Dix-Carneiro et al., 2021] and maternity leave schemes compared to the standard formats in developed countries. In Brazil, the default maternity leave policy entitles eligible workers a 100% wage replacement for a mandatory 120 days of leave, which is paid by the employers and fully reimbursed by the government[5]. There are no special eligibility criteria (e.g., no minimum period of work, or minimum contribution, etc.) for this mandatory leave, except that women must be formally/legally employed. Job protection is guaranteed throughout pregnancy and up to the fifth month after the leave-taking begins. Furthermore, leave extensions from 120 to 180 days were made possible in 2010 through a program – the *Empresa Cidadã* Program (hereafter referred to as EC Program) – that allows tax compensation to firms offering additional 60 days of paid leave.[6] Given that EC adoption was not mandatory, our empirical strategy focuses on firms that eventually allow extended leaves, and then we compare women taking leaves while working for those firms. Using precise event dates (for both leave-taking and EC adoption), we compare two groups: the *eligible* mothers, who start their mandatory leaves after their firms can offer extended leaves through EC Program, whereas *non-eligible* group includes mothers completing mandatory leaves before EC adoption[7].

We use rich administrative data from *Relação Anual de Informações Sociais-RAIS*, the Brazilian matched employer-employee dataset provided by the Ministry of Economy and covering all the formal labor market. RAIS includes information on the employment contracts (e.g., dates of hiring/separations, wages, tenure, etc), demographics (e.g., gender, race, age, education, etc), occupational/industry, among others. It also contains maternity leave start/end dates for (as the 120-days leave is mandatory) all women giving birth while in the formal labor market. It is worth to mention that the voluntary leave extension (of 60 days) is also available to all eligible mothers in EC adopters. Using personal identifiers and start/end dates of each employment spell, we produce monthly employment information for all workers taking maternity leave in Brazil. Moreover, using

[3]In sum, compared to developed countries, Brazilians tend to agree more with the following statements: (a) If a woman earns more money than her husband, it's almost certain to cause problems; (b) When a mother works for pay, the children suffer; (c) Men make better business executives than women do; and (d) Abortion can never be justified.

[4]The main aspects of Brazilian labor market regulations are: (i) presence of a national minimum wage; (ii) unemployment insurance only available to formal workers; (iii) substantial firing costs; and (iv) sizable payroll taxes.

[5]Although the legislation states that the 120-days leave is a right (not an obligation), the Brazilian legal system does not allow women to give up their maternity leaves, and firms failing to obey are subject to significant penalties.

[6]While companies choose whether or not to participate in EC Program, the decision to accept or not accept an extended leave within EC adopters depends entirely on the employee's choice.

[7]We note that firms that sign up to EC Program are larger, pay more on average, and employ a higher educated workforce, which may affect the external validity of our results. But within those firms, eligible and non-eligible women are very similar in various observable dimensions. We also find no evidence of the strategic timing of births relative to EC adoption. These facts validate our empirical approach, which is reinforced by other robustness checks.

unique employer taxpayer identifiers, we match RAIS to the list of firms participating in the EC Program (and dates of adoption), from the Brazilian Internal Revenue Service.

Our paper relates to various strands of literature, which we will highlight as we discuss our findings. Firstly, our results show full compliance with the mandatory four months paid leave, but just a 40% take-up of leave extension. In the US and Canada, where leaves are unpaid or just partially paid, take-up rates are also far below full [Baker and Milligan, 2008b,a, Han et al., 2009]. In contrast, in Norway, where the leave offers 100% income replacement, leave take-up is nearly universal [Carneiro et al., 2015, Dahl et al., 2016]. Despite full wage replacement in Brazil, our results are closer to the take-up rates of unpaid/partially paid policies, suggesting that country-specific factors (eg., social norms, low degree of job security, etc.) can inhibit take-up of paid leave extensions. Second, paid leave extensions had a very limited impact on women's employment. In sum, the positive effect was confined to the period of extension, fading away after it ends and, after one year, about 20% of women taking maternity leave are out of the labor market (irrespective of an extension)[8]. Previous research for developed countries suggests that prolonging the leave, when it lasts less than one year, can improve women's employment prospects many years later (Baker and Milligan [2008a] and Kluve and Tamm [2013]). Our findings are rather similar to those obtained by Dahl et al. [2016], which finds no lasting effects of extensions in paid maternity leave (from four to eight months) on the participation of mothers in the Norwegian labor market.

Notwithstanding the negligible effects on employment, the monthly data allows us to dig deeper into workers' and employers' responses throughout the months just after the leave. The temporary effect on employment is a net combination of multiple scenarios, in which final output may crucially depend on both workers' and employers' decisions about whether or not to terminate a job contract as well as the timing it may occur[9]. Exploring specific data on the reasons/causes for separations, we find evidence of women's strategic behavior (moral hazard) in leave-taking, as voluntary quits decrease during the period of the extension but increase immediately after it ends. On the firm's side, we note that leave extensions solely change the timing at which employees get fired, suggesting at least in part some employers' discrimination against new mothers[10]. To the best of our knowledge, this is the first paper to address the individual's strategic behavior in maternity-leave policies, which is made possible thanks to our rich monthly data combined with information on the causes of job terminations. Complementing this analysis, we note that the impacts of leave extension on employment are mostly due to women staying at the same firms, rather than moving right after the period of leave. This result differs from what Ginja et al. [2020] has shown for a 3-month parental leave expansion in Sweden, where the reform increased the probability that women separate from their pre-birth employers and then switch to a new firm.

[8] It is worth noticing that, as our analysis focuses on a selected subset of companies (and mothers working at them), this rate of women leaving the labor market 1 year after giving birth is greater overall, standing around 40%.

[9] For instance, the positive and temporary effects on employment are the net combination of three potential scenarios: (1) positive effects for women who would terminate their employment contracts in the absence of the extension, (2) negative effects for women fired after the leave extension ends, and (3) positive and temporary effects for women who strategically request the leave extension and quit afterwards.

[10] However, this also might reflect a collusive behavior between firms and workers, because in Brazil they can split the rents from severance pay and unemployment insurance due when a worker gets fired [Van Doornik et al., 2018].

We then turn to examine the mechanisms underlying our main findings: low take-up rates and temporary small effects on labor market outcomes. We center primarily on five possible explanations: (1) imperfect compliance based on women's socio-economic background; (2) knowledge and learning from peers' experience about leave-taking; (3) the role of job protection; (4) firm's premium and worker's ability and (5) labor market frictions and workers' substitutability in the firms. Each of these channels connects to a particular strand of literature, as discussed below.

We start by showing that take-up varies by social background: the probability of taking extended leave is significantly larger (smaller) for women who hold a college degree and earn higher wages (who are black or brown). Although this result emerges as an endogenous choice of mothers, it accentuates the regressive redistribution properties of the policy, because women working for EC adopters already have higher incomes and education levels. Also, the presence of a large informal sector in Brazil [Ulyssea et al., 2014, Meghir et al., 2015] leads to disparities in access to the leave policy – as it does not cover women in the informal sector – and regressive redistribution properties are further reinforced when the length of leave is extended. Dahl et al. [2016] has already suggested that generous extensions to paid leave in Norway were costly and had negative redistribution properties, with a significant increase in taxes at a cost to economic efficiency. Surprisingly, previous literature has paid little attention to the distributional effects associated with this type of intervention. Our findings are particularly valuable in the context of developing countries, where resources are scarcer and the trade-offs are amplified by unfavorable socio-economic conditions.

As education is an important driver of extended leave take-up, one may wonder whether women who do not take-up such extension could be caused by a lack of knowledge about their company's maternity leave policies. While we find no evidence of learning from peers for women with college degrees, we do observe that sharing information can play an important role in take-up rates for less-educated women: the ones without college are significantly more likely to take extended leaves if there are cases of coworkers taking leaves previously at the same firm after EC adoption. Amongst a vast literature on the role of peers in various aspects of individual behavior, more directly related to our paper, prior work by Dahl et al. [2014] also suggests that peers are particularly important sources of influence for paternity leave policies. The authors advocate that the most likely mechanism is information transmission, including increased knowledge of how an employer will react after a leave-taking[11]. In our context, in which peer effects are observed solely among less-educated workers, social norms (which vary by education) could be another potentially relevant mechanism, considering that less educated mothers are usually less willing to work for pay (*vis-a-vis* home chores)[12]. This potential mechanism, although hard to provide definitive evidence, has gained more attention recently, given the inherent influence of gender norms and culture in both households and the workplace [Bertrand, 2011, Avdic and Karimi, 2018, Olivetti et al., 2020, Kleven et al., 2019a].

[11]For instance, if workers can take leave without facing negative career consequences, their peers may be more likely to choose to do so later as well.

[12]In Figure 2, based on World Values Survey, we show that Brazilian mothers without a College degree are more likely (relatively to those holding College degrees) to agree with statements like: (a) When a mother works for pay, the children suffer; or (b) Being a housewife is just as fulfilling as working for pay.

We then examine how employees' job security (*proxied* by tenure[13] in the firm) can affect take-up of extended leave and its impacts on labor market outcomes. Despite the International Labour Organization standards promoting the right to return to one's pre-leave employer, according to Rossin-Slater [2019], out of 146 countries with available information, 82 do not guarantee job stability during maternity leave. As mentioned before, in Brazil workers in the formal labor market have assured job protection for up to five months after giving birth. Because this scheme is universal, we lack a source of exogenous variation to explore the causal impacts of job protection. Nevertheless, the degree of job protection may also affect workers' willingness to take up leave and its consequent impacts ([Stearns, 2018], [Baker and Milligan, 2008a], [Ginja et al., 2019]), so we explore the heterogeneous effect (by tenure) of the leave extension in Brazil. Although take-up does not seem to be influenced by the level of job security, we observe that the positive (and still temporary) effect of leave extension on employment is significantly higher for women with lower job protection (less tenure in the firm). Exploring the reasons/causes of job separations, our findings are compatible with a setting in which less-protected workers are more likely to quit voluntarily after their period of leave, and those returning to work are also more likely to be fired.

We also address the importance of workers' ability and firm premium for extended leave and its effects. These are important elements to be taken into account as, for instance, a worker with higher (lower) ability may have a higher (lower) probability of getting a new job offer, and usually earn higher (lower) wages. The literature has emphasized the role of firm-specific factors (firm premium) in explaining formal labor market outcomes and inequality. In this regard, Alvarez et al. [2018] document a large decrease in earnings inequality in Brazil, in which specific firm factors account for 40% of the total decrease and worker effects for 29%[14]. Following a standard approach in the literature (see Abowd et al. [1999]), we estimate an AKM model that allows us to separately identify the firms and workers' fixed effects[15]. In a recent paper, Bana et al. [2018], employing a similar framework in the US, found a higher take-up of leave-taking benefits for firms with higher earning premiums. Our results suggest that this is also the case for Brazil and we additionally find greater take-up rates for higher ability workers. We also note that the positive effect on employment is more lasting for low-ability workers employed at high-premium firms and, although this may suggest some adverse selection phenomenon, the overall effect is still null in the medium-term.

Finally, our results also show that labor market frictions across sectors and sector-specific human capital can play an important role in leave extension take-up, along the lines of the findings by Dix-Carneiro [2014] and Alves et al. [2016] showing the influence of these factors for job reallocation

[13]The main idea of utilizing tenure is because: (1) experience in the same firm can represent some level of firm-specific human capital investment that can make costly for a firm to fire an employee and (2) Brazilian regulations force employers to provide pecuniary compensations to workers who are dismissed without a "fair reason", and the amount due is increasing with tenure in the firm.

[14]Similar results have been found in developed countries: Germany (Card et al. [2013]), Italy (Iranzo et al. [2008]), Portugal ([Card et al., 2016]), Sweden ([Bonhomme et al., 2019]), and United States ([Engbom and Moser, 2017]).

[15]In sum, our empirical strategy involves two steps. First, we estimate employer earnings premiums and workers' ability by running the wage regression including both worker and firm fixed effects, to account for nonrandom sorting of workers across firms, and also controlling for a broad set of individuals and firms time-varying controls. Second, we use the worker and firm fixed effects as measures of worker's ability and firm's premium, respectively.

in the Brazilian labor market. As in Brenøe et al. [2020] and Jäger [2019], we further document the importance of workers' substitutability within the firm for leave extension take-up, especially for smaller firms and workers performing non-routine tasks. Taking together, these findings suggest that workers internalize, at least partially, the firm's costs due to temporary leaves and act according to the market and firm context when choosing whether or not to take an extended leave.

The remainder of the paper is divided as follows. The next section provides a background on maternity leave policies in Brazil as well as women's participation in the Brazilian labor market. In sections three and four, we present our data and the empirical strategy, respectively. Section five describes the main results, and section six explores mechanisms underlying our results. Finally, section seven concludes.

2 Institutional Context

In this section, we provide the background on maternity leave policies in Brazil and the necessary background on the female participation in the Brazilian labor market, which can be skipped by those familiar with these statistics.

2.1 Maternity Leave Policies in Brazil

The current maternity leave policies in Brazil can be classified into two cases (Mandatory and Voluntary Leave) as discussed below..

2.1.1 Mandatory Leave

Maternity leave in Brazil is a constitutional right established in 1988.[16] It guarantees *paid* and *mandatory* maternity leave for *120 days*, without any prejudice to employment, job position or salary. There are *no eligibility requirements* for the benefit, such as minimum hours of work or experience in the previous months, aside from formal employment at the time of pregnancy (as those women are paying payroll taxes that entitle them to the benefit).[17] The policy guarantees *job protection* from the moment the women become pregnant up to five months after giving birth, as they cannot be fired during this period. Separations occurring during this job-protected period are subject to a full indemnity by firms to workers.[18] During pregnancy, women are allowed time off for

[16]Before 1988, working mothers were entitled a 12 week leave period. Previous research in Brazil (Carvalho et al. [2006]) estimates the effects of this mandatory expansion in the maternity leave period that occurred in 1988, which changed the period of leave from 12 weeks to 120 days. By using a differences-in-differences strategy for the period 1986-1991, they find that the extension in the leave-taking period did not significantly affect neither women's employment nor wages.

[17]Maternity leave extends to workers who adopt a kid or get judicial custody for adoption purposes, regardless of the child's age. Women who have experienced a miscarriage or have obtained the legal right to abortion (eg., in cases of rape, anencephalic fetus, and risk to woman's life) are also entitled to the mandatory maternity leave, but only for 14 days. The full 120 day leave is also guaranteed in cases of premature babies, who are born after the 23rd week of gestation (before that it is considered an abortion).

[18]Job stability is acquired as soon as the women becomes pregnant, even if she has not yet communicated this to the employer. Furthermore, the period of stability is guaranteed even in temporary employment contracts or during job experience periods.

up to six medical appointments and have the right to be temporarily transferred to an alternative job position if the current position offers any risk to health.

While on leave, mothers receive their full wages (100% replacement), which are paid monthly by firms, but entirely reimbursed by government. Leave-taking generally starts at some point between the last month of pregnancy (28 days before the birth) and the birth of the child[19], and can be extended by 2 (two) extra weeks for medical reasons.

2.1.2 Voluntary Extension

Maternity leave extensions are encouraged after January 1st, 2010, under a government sponsored program called *Empresa Cidadã*, which provided incentives to maternity leave extension through a tax compensation policy.[20] Firms under the program must offer a *paid* (100% replacement) maternity leave extension of *60 days* to its workers, but would be able to deduct, as an operating expense, the full wage bill cost of the extension from the income tax of the preceding tax year. Stolar [2018] estimates that 85% of the wage bill cost was carried over to the government, while 15% was borne by the firm. Additional costs to firm include the benefits package, such as health insurance, pensions and childcare assistance. As only firms that were taxed based on actual profit were eligible for the benefits, the program ended up covering few but sizable firms.[21]

Signing up to *Empresa Cidadã* was a voluntary decision of firms. Once under the program, firms offer all workers the right to maternity leave extension. Workers, in turn, can choose whether or not to file for an extension. In those cases, the extension should be requested at most 30 days after birth, and would start as soon as the regular maternity leave of 120 days ends.[22] Thus, maternity leave extension was a voluntary decision of firms, and also a voluntary decision of workers taking leaves in firms that are EC adopters.

2.2 Women in the Brazilian Labor Market

Over the past two decades, Brazil has made significant progress in reducing gender inequality, especially in the labor market (Elborgh-Woytek et al. [2013]). According to Agénor and Canuto [2015], the female to male labor force participation rate increased from 52.2 in 1990 to 66.7 in 2000, and 73.3 in 2010. However, gender gaps in access to formal employment still persist. According to data from the National Household Sample Survey (PNAD), in 2015 Brazil had almost 32 million

[19] Leaves starting as early as 28 days of expected delivery only occur under medical recommendation. However, as a rule, the total leave period lasts 120 days, regardless of when it starts.

[20] The program was established on September 9th of 2008, but only became effective on January 1st, 2010. This happened because the Brazilian Fiscal Responsibility Law requires that all impacts of any tax exemption must be included in the Budget Law one year before. However, there was not enough time to include the *Empresa Cidadã* impacts in the budget of 2008. Thus, it was included in the budget of 2009, and came into force in 2010, with its regulation by Decree No. 7,052 of December 23, 2009.

[21] Even though the tax reimbursement applies only to companies that are taxed based on actual profits, firms taxed by presumed profit or participants of *Simples Nacional* Program could also join to the program, even if they don't benefit from the tax compensation policy. In practice, these cases are not common.

[22] During the extension period, employees must not participate in any paid activities, and the child cannot be put in daycare or similar organization.

of women aged between 25-44 years old, of which approximately 62 percent had worked during the reference week of the survey. The fraction of men in the same age group employed in 2015 was over 85 percent. Among employed women, 40.8 percent were working full-time, and 68.9 percent were in the formal labor market (see Table A.1).

On the other hand, almost 92% of the women in the survey reported having worked in household tasks, while this fraction for men was just around 54%. Not surprisingly, women also earn on average lower wages in comparison to men and, considering income from all sources, men earn approximately 60% more than women (Table A.1, 1-(2044/1274)). These gender inequalities are not explained by differences in human capital, since women and men are quite similar in that respect, with women being even marginally more educated.

As in many other countries, mothers in Brazil carry much more responsibility for their children when compared to fathers. The employment gap between married men and women increases considerably after the birth of a child (see Table A.2). Mothers of young children (less then one year old) have very low participation rates: 41 percent are working and 28 percent work full-time. For men, participations rates are 92% and 82%, respectively. While the association between participation rates and fertility is contaminated by other cofounders, research suggests that part of the relationship is indeed causal [Kleven et al., 2019b].

3 Data and Background

3.1 Data Description

In this paper, labor market data comes from RAIS (*Relação Anual de Informações Sociais*) and it is combined with information on EC adoption. While RAIS only covers formal labor market contracts – and informality is substantial in Brazil – maternity leave entitlements apply only to workers in the formal sector. Thus, the maternity leave policy covers 42 percent of women in the country (Table A.1, 0.620×0.689). The low incidence of maternity leave entitlements is both due to low attachment of women to the labor market and the prevalence of informal labor contracts.

Receita Federal Data

A list of all companies adopting the *Empresa Cidadã* program, as well as their corresponding adoption dates, was provided by the Brazil's Federal Revenue Department (*Receita Federal*). From the beginning of the program (in 2010) until 2016, 19,519 firms have decided to participate in the EC Program, with more than half of them (10,898) entering in 2010. In the second year, 2011, the program included other 4,714 firms. Therefore, nearly 80 percent of the total number of companies registered for the program in the first two years (see Table B.1).

RAIS Data

We also use RAIS (*Relação Anual de Informações Sociais*), which is the Brazilian matched employer-employee dataset provided by the Brazilian Ministry of Economy. Apart from firm and worker unique identifiers, useful to track workers and firms over time,[23] RAIS also contains several relevant demographic information for workers (such as gender, age, race, education), occupation and other characteristics of the employment contract (such as date of separation/admission, wages and hours worked per week). Important to our analysis, maternity leave start and end dates are also available as well as the causes of separations (if any).[24]

Although RAIS is an annual cumulative data, we can generate precise monthly information on maternity leaves and employment status using start/end dates of the maternity leaves, admissions, and separations for each employer-employee pair. Individual identifiers (*Social Identification Number-PIS*) allow us to track individuals over time and build a rich monthly panel dataset, containing basic demographic, occupational and income characteristics for women who take maternity leave while working in the formal labor market.

Data Linkage

Appendix B of this paper details all the steps performed to match RAIS and *Receita* databases, in order to have information on all workers taking maternity leave in companies which adopted the EC program. In a nutshell, we match firms that decided to participate in the program at some point from 2010 to 2014, and workers of these firms who took maternity leave at some point between 2009 and 2015. As maternity leave is mandatory, we can identify all births of women formally employed in RAIS data. In addition, we restrict our sample to workers taking maternity leave within a margin of 360 days from the time in which the firms decided to become an EC firm. In the end, a total of 65,989 female workers remain in our main dataset, who took maternity leaves in 17,978 establishments of 4,150 firms (see Table B.8).

3.2 Analysis Sample

Our analysis sample corresponds to women taking mandatory maternity leave in EC firms around dates of EC adoption, whether or not these women file for a leave extension. Therefore it is important to discuss two margins of sample selection in the analysis: the voluntary adoption of EC program by firms and the resulting sample of EC firms that have some women taking a leave close to adoption dates.

We start by presenting the characteristics of adopters and examine to which extent the workforce in these firms differ from the rest of the Brazilian formal labor market. Using data from RAIS-2009 (i.e., one year before EC Program starts), we compare firms that adopted EC between 2010 and 2014 with non-adopters. In Table 1, we note that adopters are different in many aspects. Comparing columns 1-2 with columns 3-4, we observe that EC firms are on average much larger than other firms in the market[25]. Additionally, workers in EC firms on average earn higher wages and are more

[23]RAIS provides unique identifiers for both firm (National Registry of Legal Entities-CNPJ) and the employee (Social Identification Number-PIS).

[24]In recent years, control mechanisms were instituted to enforce the firms to comply with the legislation, which makes RAIS mandatory. Moreover, declaration through the internet also facilitated compliance and improved data quality. According to the Ministry of Labor, RAIS is annually declared by 98% to 99% of officially existing firms.

[25]While we observe around 50 million workers market distributed across 3,1 million establishments in the whole,

educated. Because our empirical approach is focused on these firms, the external validity of the findings is also confined to firms with those characteristics.

Conditioning on firms that adopted EC Program at some point in the period 2010-2014, we also focus on women who took mandatory maternity leave during the period 2009-2015. Table 1 also shows how the characteristics of the workforce in these firms change as we apply restrictions to generate the analysis sample (see Section 3.1 and Appendix B). In particular, we clean the data to consider correctly sized mandatory leaves within the window of EC adoption dates. We observe that the workers' characteristics do not notably change after we condition on EC adoption, as seen in the comparison of columns 5-8 to columns 3-4. This means that our data cleaning procedure generates a sample that is representative of EC adopting firms.

4 Empirical Strategy

In our data, we can calculate the distance (in days) between the date at which a firm adopts EC Program and the date at which each maternity leave starts, suggesting a regression discontinuity design as a natural methodological approach. Since leave extension requests had to be claimed at most 30 days after birth, women giving birth up to 1 month before EC adoption would be eligible for an extension, while those giving birth before that would not. Empirically, however, our data reveals that firms were lenient to offer an extension to women reaching the end of the mandatory leave period by the time of adoption (see Figure C3). Therefore, there are no jumps in the probability of taking an extended leave near the adoption dates. Appendix C brings a full description of the gradual take up of extended leaves by mothers working in EC adopting firms.

While workers who start maternity leave up to six months before EC adoption could have claimed a leave extension, this is clearly not the case for women whose leaves end just before EC adoption. Women who take mandatory maternity leave six or more months before EC adoption take the standard 120 days of leave, and after that either quit or return to work. However, women starting their mandatory leaves after EC adoption automatically become eligible for an extension.

This evidence suggests that we can split the analysis sample into three groups of women, according to their starting dates of the mandatory leave. First, some women start their leaves six or more months before EC adoption, second, there are those whose leave starting dates are within six months from EC adoption, and finally, women who take the leave only after EC adoption. Table 2 presents descriptive statistics for each of these groups, and each column indicates the grouping of leave starting days relative to EC adoption. Negative numbers indicate the maternity leaves taken (up to -360 days) before adoption and positive values indicate the maternity leaves starting (up to 360 days) after firms adopt EC Program. Maternity leaves that fall into the interval [-360;-180] last on average 123 days, meaning that these mothers usually take only the mandatory leave of four months. On the other hand, almost half of the women in the interval [0;180] take extended maternity leave of six months (see column 4).

there are around 3 million workers in just around 44 thousand EC establishments.

The table also shows evidence that women taking leaves before and after EC adoption are similar in all observable characteristics that can be measured in our data, except for the likelihood of having a leave extension. This suggests that we are able to create two groups of workers who are similar in various dimensions (for instance, they sort into the same firm), except for their eligibility for the leave extension.

Since there is a gradual take-up of the extension up to 180 days before EC adoption, our empirical approach will compare women taking leaves between 360 and 180 days *before* EC adoption (*not eligible* for the extension) and women taking leaves up to 180 days *after* EC adoption (eligible for the extension). In the following sections, we formalize our econometric approach and give support for the validity of our research design. The final sample consists of 17,861 (15,078) women in the eligible (non-eligible) group, who were working in 2,392 (1,608) firms and 8,165 (6,684) establishments. We track and compare these workers monthly in the formal labor market from five years before until five years after the mandatory maternity leave starts.

4.1 Research Design

Let t_i^{ml} be the calendar time (in days) in which worker i takes maternity leave and $t_{e(i)}^{ec}$ the calendar time (in days) when firm e (where i works at the time of maternity leave) joined EC Program. Also, define a running variable as $R_i \equiv t_i^{ml} - t_{e(i)}^{ec}$, which is the distance between the day in which women i takes maternity leave and the day in which her company joined EC Program. Based on this running variable, we then create the variable E_i indicating leave extension eligibility status. The variable E_i indicates $t_i^{ml} - t_{e(i)}^{ec} \in [-180 - x, -180]$ relative to $t_i^{ml} - t_{e(i)}^{ec} \in [0, x]$, for $x \in \{60, 120, 180\}$. Our baseline results will focus on $x = 180$ to maximize sample size, but we examine also smaller grouping of treatment and control units in the robustness analysis. We then estimate the following econometric model to compare eligible and non-eligible women over (relative) time:

$$y_{imjr} = \gamma_m + \lambda_j + X'_{i(l)}\beta + \alpha_r \times E_i + \epsilon_{imjr} \tag{1}$$

where y_{imjr} is the employment/separation/hiring indicator for woman i taking the leave in month m while working for firm j, and observed r months apart from the leave starting month l, i.e., $r = t - l$. Also, separation (hiring) is defined as being employed (unemployed) in r but unemployed (employed) in $r + 1$. We compare the two groups (*eligible* and *non-eligible*) month-by-month over five years before and after the maternity leave, so that we run the above regression considering $r \in \{-60, ..., 60\}$. The vector $X_{i(l)}$ contains a set of individual controls (age, race, occupation, education, wage and hour worked per week) at the time of the leave l, λ_j are fixed effects of firms where the leave is observed and the term γ_m represents a set of fixed effects for months. The errors are clustered at the firm level.

Therefore, we are primarily interested in the patterns of α_r across different horizons in r. These coefficients measure outcome differences between women with different eligibility status for maternity leave extensions.

4.2 Threats to Identification

The first threat to our empirical strategy would occur if eligible and non-eligible women were considerably different in terms of characteristics that could influence take-up or employment directly. We exhibit a set of tests to confirm that workers taking maternity leave at some point between 180 and 360 days before a firm join EC Program are a reasonable group of control for workers taking maternity leave up to 180 days after EC adoption. To do so, we proceed with balancing tests to see if workers in these two groups differ significantly across a broad set of baseline observable characteristics. Table 3 presents the results from multiple simple regressions in which the dependent variable is a particular characteristic of the workers, and the independent variable is the indicator of eligibility, E_i.

We find no evidence of differences between the two groups for several variables (such as education, wage, hour worked per week, occupation, etc), which confirms that women in treatment and control groups are notably similar. Indeed, *Age* is the only variable for which we find a small but statistically significant difference between the two groups. However, this is an inherent peculiarity of our sample analysis, as the control group, by its definition, takes the leave in an earlier calendar date. In our study, we will consider all observable characteristics as controls in the main regressions, but expect little changes in results with their inclusion.

A second threat to identification is the strategic timing of births relative to EC adoption. Indeed, the EC program was enacted before it came into force in 2010, and women could have postponed their fertility intentions in anticipation of the program. However, leave extensions also dependent on the voluntary sign up of firms, leading the strategic timing of birth by women an unlikely event. More important seems to be the endogenous adoption of firms according to the perceived number of women who could benefit from the extension. While possible, Figure C1 shows a roughly uniform distribution of birth relative to EC adoption, a finding that is also evident in Table 2 through a similar number of observations between the different eligibility groups, and the little higher number of observations on the right side is expected due the increasing formalization of the labor market.

5 Results

In this section, we start by investigating the take-up rate of the EC Program by eligible women, and then we show its effects on a variety of labor market outcomes. Further, we check the robustness of our findings to several choices of sample data and econometric specifications.

5.1 Take-up

Table 4 shows that around 40% of the eligible workers take extended maternity leave when they qualify to it. This estimate is robust across a wide range of model specifications, such as the inclusion of control variables and establishment fixed effects. Our preferred specification is in column (4), which controls for individual characteristics and month of the maternity leave, but not for establishment fixed effects. The inclusion of establishment fixed effects reduces sample size by more than 20%, as it requires that two women take leaves before and after EC adoption within the same establishment. Still, results barely change in this within specification. The amount of time on leave increases on average by 23 days, which corresponds to approximately 40 percent of women taking up the 60 days of extension.

Take-up rates in leave-taking can vary substantially due to several key aspects of the leave policy and the context in which it is applied. In particular, there is substantial heterogeneity across countries regarding whether the leave is paid or unpaid and the degree of job security. In the US and Canada, where leaves are unpaid or just partially paid, take-up rates are far below full [Baker and Milligan, 2008b,a, Han et al., 2009]. In contrast, in Norway, where the leave offers 100% income replacement, leave take-up is nearly universal [Carneiro et al., 2015, Dahl et al., 2016]. Our findings are close to the take-up rates of unpaid/partially paid policies, highlighting that the low degree of job security – as workers can be fired after returning from their extended leaves – inhibits take-up in Brazil, even when there is 100% income replacement during the leave.

This setting also sheds light on whether switching from mandatory to voluntary leave take-up decision matters. Our results indicate that it does, in contrast to evidence in developed countries, where take-up is high when the leave is voluntary and paid. Importantly, our findings are not subject to sample selection in initial leave-taking, as all working mothers must take the 120 days of mandatory leave. Consequently, the leave extension eligibility applies to the entire universe of working mothers.

5.2 Effects on Employment

Although it is more obvious that extended paid leave induces take-up, its effects on employment are more ambiguous and may depend on a number of factors, such as the length of the leave, whether the leave is paid or unpaid, if there is job protection and so on. Considering a short and unpaid leave policy with job protection, as the case of the Family and Medical Leave Act in the US, the usual argument is that employed women with newborns fall into three categories: those women who continue working without taking the leave, those who take a leave and return to the job, and those who do not take the leave and quit [Rossin-Slater, 2019]. In this case, the net effect of the leave on employment could be positive if there are women who would have quit their jobs in the absence of the leave policy.

In contrast, Brazil has a universal and mandatory paid maternity-leave policy during the four months after birth, with job protection only until the fifth month. In this context, the three cases above would change to just two alternatives: taking leave and returning to work when it ends or taking the leave and being separated (either by being fired or voluntarily leaving) from the job after it ends. Most importantly, now a new possibility opens up in the case of Brazil, when the mothers also have access to a paid and voluntary leave extension: women who take the paid extended leave and are separated from their jobs when the extension ends. The Brazilian setting is additionally interesting because there is no juridical job protection after their leave extension ends, so that separations can be either by employer or employee initiatives. For instance, if mothers are dismissed because they took an extended leave, employment effects could be detrimental to them.

We start by investigating the net effect of the leave extension policy on employment in Figure 3. Each point comes from the estimation of the econometric model in Equation 1, in which the dependent variable is an indicator for formally employed over five years (i.e., r varying from -60 to 60 months) around the (mandatory) leave starting date (i.e., $r = 0$). The results indicate that the impacts of the extension are confined to the months immediately after the conventional maternity leave of four months (around months 5 to 9). Noteworthy is the absence of pre-trends in employment for $r < 0$, reassuring to our empirical strategy.

Table 5 (column 1), display point estimates of those regressions. It shows a small and significant difference in the probability of being employed, but the effect reaches its maximum (3.8 percentage points) in the seventh month and becomes null from the tenth month onward. In column 2, we examine the sensitivity of results to the exclusion of control variables (education, race, age, occupation, wage, and hours worked per week) at the moment of the maternity leave. Since the sample is balanced, results barely change. Column 3 considers IV results that take into account imperfect compliance in leave-taking: we estimate a variant of Equation 1 in which employment depends on an indicator of leave extension (equal 1 if lasting more than 120 days), and eligibility is used as an instrument to the leave extension indicator. Coefficients get re-scaled by the take-up rate of 40%, and the timing of effects remains in line with results from columns 1 and 2.

To put these magnitudes into perspective, columns 4 and 5 show the average probability of being formally employed over five years before and after the maternity leave. The numbers reveal that the employment patterns of eligible and non-eligible workers are remarkably similar and differ only with respect to the timing in which separations occur. In any case, one year after childbirth, 20% of mothers are out of the formal labor market, whether eligible for extensions or not. Surprisingly, employment rates do not recover up to five years after childbirth.

5.3 Separations and its Causes

Separation rates can be seen as the mirror image of employment rates, as employment goes down when separation goes up, for a given hiring rate[26]. We note that separations occur more frequently in the months where leaves are over, and the job is no longer protected. For non-eligible women, separations rates peak six months after childbirth, while for eligible women, this happens at the 7th month, as can be seen in Table 6.

Taken together, our findings so far indicate the net effect on separations are temporary and confined to the months of the leave extension. It is the result of three possible scenarios for employment: a positive effect for women who would quit in the absence of the leave extension; a negative effect for women who are fired after taking the extended leave; and a temporary positive effect during the leave extension for women who take the extended leave and quit right after it ends (because the leave is paid).

[26] Our results indicate that EC adoption has a null effect on hiring, so we do not show results for this outcome in our main analysis. The effects on hiring can still be found in Appendix D of this paper.

Since our data contains information on the causes of separation, it allows us to study whether they occur by employer's or employee's initiative. In the first case, employers could take leave extension as a negative signal and decide to fire the women when the extension ends. If this is the case, separations by employer initiative should become relevant as soon as the leave extension ends. Alternatively, women who would quit after the mandatory leave ends have incentives to request a leave extension since the policy offers 100% income replacement. Under this second case, voluntary quits should increase after the extension ends.

Panel A of Table 7 decomposes separations into three mutually exclusive causes: by employer initiative (fired), by employee initiative (voluntary quit) and other.[27] Column 1 displays the same results as column 1 of Table 6: separations occur right after the extension ends (month 7) and until month 11. By month 12, separation (and employment) rates are similar for both eligible and non-eligible groups of women. In column 2 we see the leave extension policy only changes the timing at which employees get fired: the likelihood of being fired is reduced during the leave extension, but increases after the extension ends, especially around months 9 and 10. Likewise, voluntary quits become less likely during the extension period, but spike immediately after the extensions end in month 7 (column 3). Figure 4 display these regression results graphically, in which we can have a better sense of the effects and magnitudes.

While separations by employer initiative after leave-taking could be considered as evidence of employer prejudice against new mothers, it might also reflect the collusive behavior of firms and workers. This may occur because firms and workers can split the rents from severance pay and unemployment insurance that are due when a worker gets fired [Van Doornik et al., 2018]. However, the evidence of voluntary separations that take place exactly when the paid extension ends suggests a strategic behavior of women who would quit their jobs anyway. As the extra two months of leave can benefit women with two additional months of salary, without any costs, they are induced to request a leave extension.

This result indicates that workers who take the extended leave are either those who would quit anyway or those who would have stayed working anyway, irrespective of the leave extension itself. In the end, we observe no positive employment effects for women who would have quit in the absence of the extension.

5.4 Other Labor Market Outcomes

Our previous measure of employment has considered any job in the formal labor market, be it in the firm where women took the initial mandatory leave or in other firms of the economy. Table 7, Panel B, shows that switching jobs around the period of leave is an unlikely event, and that most variation in employment is driven by employment at the same firm (columns 1-3). Moreover, looking at the effects on wage (wee column 4), we see that there is a positive impact observed mainly in the sixth and seventh months after the leave starts. However, as we found for employment, there are

[27] Other causes of separation have low incidence in our sample, and include reasons such as retirement, death and transfers.

no long-lasting effects on wages[28] as well.

5.5 Robustness Check

There are basically two margins for discretionary decisions in our empirical framework, which, at least in theory, could drive our findings. First, choosing the size of the window (distance between the date of leave and date of EC adoption) when defining eligible and control groups could be critical for the results. Besides, the main results obtained from our baseline econometric model can differ according to its specification (e.g., by including establishment fixed effects, excluding control variables, etc.).

To assess the robustness of our findings, we first show that our conclusions are not driven by a particular choice of the window when creating the treatment and control groups. To check this, we re-estimate the results by considering a window of 60 and 120 days (instead of 180 days). We observe that the effects do not change substantially if we compare women who take maternity leave until two (four) months after adoption with women who take maternity leave from the eighth (ten) to six months before that, i.e., using $x \in \{60, 120\}$ in the estimation. The impacts on labor market outcomes in which we explore changes in the size of the estimation window can be observed in Tables D.1 and D.2.

To comprehend to what extent the specification of our econometric model drives our main findings, we present the results also based on multiple versions of the baseline model. We exhibit alternative specifications (fixing a window of 180 days) in which we examine the sensitivity of the results to the inclusion/exclusion of establishment fixed effects, control variables, and month fixed effect. In sum, irrespective of the econometric specification, we would find virtually the same effects on labor market outcomes as we encounter in our main set of results presented in the paper (see Tables D.3, D.4 and D.5).

Finally, we also exhibit the take-up rate varying both the size of the windows for the estimation and the specification of the econometric model. In any case, the probability of having an extended maternity leave stands around 40% (see Tables D.6 and D.7), showing that our findings are strongly robust.

6 Discussion of Mechanisms

So far, the main results reveal a low take-up rate for a paid and voluntary extension starting after a mandatory leave. Aside from some evidence of moral hazard in women's behavior, we note only a negligible and short-run effect on employment and separations. To help us understand the mechanisms behind our findings, we now focus on essentially five potential interpretations: 1) the heterogeneous take-up by women's characteristics (relative to the average woman in our data); 2) the role of knowledge and learning information from peers experiencing leave-taking after EC

[28]For this analysis, when a employee is not found in formal labor market, we input the missing with wage equal zero.

adoption; 3) the importance of job security on take-up rates and mothers' outcomes; 4) the role of firm's premium and worker's ability and 5) labor market frictions and worker's substitutability. In the next subsections, we discuss each of these potential mechanisms separately.

6.1 Imperfect Compliance and Complier Characteristics

Imperfect take up in leave extension means that the IV results apply to the subpopulation of complier when effects are heterogeneous. Moreover, since there are no always takers by design (as non-eligible women cannot take an extended leave), this local average treatment effect is also the average effect for the treated population. We turn to investigate the compliers by looking at whether they are more or less likely to hold a certain demographic characteristic, as the relative likelihood a complier holds a given characteristic is given by the ratio of the take-up rates among this group to the overall take-up rate.

We consider three groups of education and wage, and two groups of race and managerial occupations in Table 8. The result shows that the probability of having extended maternity leave is higher for women who are more educated. For instance, women with College present a take-up 17 percentage points higher compared to women without High School. Looking at the interaction between the treatment and indicators for three terciles[29] of income, we see that the take-up rate for the poorest workers stood around 31%. Moreover, we find evidence of black/brown women being less likely to take up extensions in the period of leave. On another hand, we do not observe heterogeneous effects by the position of the worker in the firm, since Managers and Non-Managers present a similar probability of taking extended leave.

Our finding indicates that the paid leave extension favors women in higher socioeconomic status, as found by Dahl et al. [2016] in Norway. In contrast to that study, where leave extension take-up is universal, we show that this result emerges as an endogenous choice of working mothers. Since leave entitlements require formal labor market employment, our setting is one in which high informality and low levels of female labor force participation increases disparities in leave usage and exacerbates the negative redistribution properties of the leave extension policy. Although the results point out for the social background as an important factor explaining the woman's request for an extension, information can be a reason for the higher take-up among these mothers.

6.2 Information and Peers

Given our results, the lack of information about the possibility of prolonging the period of leave can play an important role in the unequal use of benefits. Indeed, as we previously pointed in our descriptive statistics, the firms in our final sample are mostly large firms, which may affect awareness about the program. Also, on the mothers' perspective, there is some degree of uncertainty regarding the costs and benefits of the extension. Recent studies have addressed this subject in developed

[29]These terciles are represented by the following intervals: 1) woman earning less than 2 minimum wages; 2) those making 2-5 MW and 3) those earning more than 5 MW.

countries, such as in Germany (see Welteke and Wrohlich [2019]) and Norway (see [Dahl et al., 2014]), and have found that leave decisions are significantly influenced by coworkers' decisions.

To address the informational aspect of the maternity leave extensions, we examine take up far from adoption, as well as the role played by peer effects and learning. We start by looking at the take-up rate far from the cutoff, i.e., we observe women taking maternity-leave up to 48 months after EC adoption in their companies. Based on Figure 5, we can not see a notable increasing take-up over time, which can indicate that time after EC adoption itself is not a key factor explaining the low interest of women in taking the extended leave[30].

Possibly the most effective way in which women can learn about the maternity leave scheme available in their firms would be by observing claims of other mothers taking maternity leave while working for the same firm in the past. To formalize this idea, we consider a variant of our baseline model that allows for learning from previous occurrences. The model is as follows:

$$y_{imjr} = \gamma_m + \lambda_j + X'_{i(l)}\beta + \sum_{g \in G} \alpha_r^g \times E_i \times I_i(g) + \epsilon_{imjr} \tag{2}$$

Now we add an indicator variable, $I_i(g)$, interacting with the eligibility status and, as a consequence, the parameter of interest, α_r^g, is flexible depending on the group g. To create such groups, we list all mothers who are eligible for an extension according to the order (within their firms) in which they gave birth. Based on that list, we then assign workers into groups $g \in G$ to indicate mothers who are, for example, the first person to take a leave after EC adoption and so on. In particular, in this paper, we split our sample of eligible women into four groups[31]: (a) the first women who took leave after EC adoption in that firm; (b) women who were from 2nd up to 5th taking leave after EC adoption; (c) women who were from 6th to 9th women taking the leave in the firm and (d) cases in which more than nine coworkers already took maternity leave before her and after EC adoption.

Table 9 displays the results of the regressions allowing for heterogeneous effects according to the order of leave-taking in the firm and after EC adoption. Panel A exhibits results based on the expanded sample used in the previous Figure 5, while Panel B presents the results for our main sample of study. In any case, we see a lower take-up rate for women who are the first ones to take maternity leave in the firm after EC adoption. However, these heterogeneous effects are not statistically significant. Indeed, the differences become statistically significant only when we add firms' fixed effects, but at the cost of losing several observations.

In the previous results, we saw that women more educated are more likely to take an extended leave. Now we can separately distinguish between the role of education and learning from peers. To do so, we split the sample into two groups: women with and without a college degree. Table 10 indicates that, for more educated women, it does not matter whether or not they are the first to

[30] We have results showing that these small differences also are not statistically significant (available upon request).

[31] When doing this cut, we looked for a roughly equal distribution of women among all the groups. However, the conclusions will be robust to several other cuts.

take maternity leave in the firm after EC adoption, or if there are other cases based on which they could have learned about the leave policy.

On another hand, this does not seem the case for women without College; we see that having someone within the firm who already took maternity leave after EC adoption can increase the probability of extension by almost twice. As can be seen in column (7), the take-up for a woman without a college degree and who are the first employee taking maternity leave after EC adoption is 27.86%. Yet for women who gave birth after ten or more coworkers previously experienced maternity leaves in the same firm, the take-up rate doubles to 54.54%. Furthermore, column (8) of Table 10 confirms that the difference of around 26.68 percentage points in take-up rates is statistically significant.

Thus, while formal education seems to play an important role in take-up rates, when we focus on less-educated workers, the knowledge and learning from coworkers also can be an important determinant of leave extensions for eligible women. In other words, learning from peers is an essential source of information and key for compliance when women are less educated.

6.3 The Role of Job Security

Usually, maternity leave policies consist of a wage replacement and a period of job protection that assure the right to return to one's pre-leave employer. However, out of 146 countries with available information, 82 do not guarantee job protection during maternity leave ([Rossin-Slater, 2019]). The degree of job protection may also affect workers' willingness to take up leave ([Stearns, 2018], [Baker and Milligan, 2008a], [Ginja et al., 2019]).

As discussed before, the Brazilian legislation for the mandatory maternity-leave policy states that all formally employed women have job security up to five months after birth. But there is no specific rule to prevent dismissals happening after the period of job security. Neither employers nor employees can abstain from the mandatory period of maternity leave, so that examining the consequences of job protection is not straightforward. Essentially, at first glance, there is no formal differentiation in the levels of job protection between eligible and not-eligible women in our analysis. Additionally, the fact that extensions (after the mandatory leave) are optional for women working for firms that (also voluntarily) opted for the EC program makes this analysis even more challenging.

Nevertheless, thinking in terms of incentives, different levels of job protection could emerge in practice if we assume that it may depend on the amount of experience women accumulate in the firm. This holds insofar as firm-specific human capital investments can affect the willingness of the employers to maintain the worker in the company. Moreover, in Brazil, the firing cost for firms is an increasing function of tenure, as well as the amount due to unemployment insurance that benefits the fired workers (Van Doornik et al. [2018], Dix-Carneiro et al. [2021]). We address the role of job security in our context by exploring a variable in RAIS that reports the number of months that each person accumulated working in the firms. Thus, we observe the tenure (in months) that a mother had until the year in which she took maternity leave.

Our empirical strategy allows us to investigate the connection between take-up rates (as well as other labor market outcomes) and the tenure in the firm when she takes the leave through a modified version of the baseline model. Specifically, we expand the original model to allow for interactions between the eligibility status (women taking leave after EC adoption) and a cubic polynomial of workers' experience in the same firm. Formally, let x_i be the total amount of months that a mother i had in the firm at the moment in which she took maternity leave. We estimate the model of Equation (1) replacing the term $\alpha_r \times E_i$ by its interaction with experience as below:

$$\alpha_r \times E_i = \alpha_{0r} E_i + \delta_{1r} x_i + \delta_{2r} x_i^2 + \delta_{3r} x_i^3 + \theta_{1r} E_i x_i + \theta_{2r} E_i x_i^2 + \theta_{3r} E_i x_i^3 \tag{3}$$

After estimating the collection of parameters $(\alpha_{0r}, \delta_{1r}, \delta_{2r}, \delta_{3r}, \theta_{1r}, \theta_{2r}, \theta_{3r})$ in the model above, we are able to estimate the marginal impact[32] of being eligible for an extension conditioning on the experience (*job security*) of the worker in the job. As our findings show that the effects of EC adoption are confined at most to the first year following the maternity leave, we focus on what occurs from the fourth month up to the twelfth month after the birth. Also, we show the main results conditioning on having from one years (12 months) up to ten years (120 months) of experience in the firm at the time of the birth.

We start by showing no substantial influence of experience on take-up rates[33], as can be seen in Figure 6. Based on this picture, we note a very modest increase in take-up rates for women with more experience. However, these observed differences are not statistically significant. Despite the homogeneous take up by tenure, we still can observe heterogeneous impacts of EC adoption on the labor market outcomes. We examine the possibility of tenure (*proxy* for job security) influencing the effects of EC adoption on employment and separations (fired or voluntary) up to twelve months after maternity leave starts.

In Figure 7, we present evidence of heterogeneous effects on employment by experience in months (*job security*). We start by showing the effects of the eligible condition on employment during the sixth month, since this is the month in which a woman must be employed if she applies for an extension. In Panel (a) of the figure, we observe that the effects of EC adoption are much higher for women with less experience (e.g., 12 months of experience), and the impact decreases monotonically with tenure. Moreover, we note that the impact of the program disappears over time and becomes null after twelve months, irrespective of tenure (see Panel d).

To go in-depth with the explanation for this mechanism, we turn to examine the heterogeneous effects on separation and its causes. In Figure 8, we see a panel containing nine figures, where in the first row, we show the marginal effects on separation for the 5th, 7th, and 9th months after maternity leave. Confirming what we have found for employment, we note a higher impact of EC adoption to prevent separations for women with less than one year of tenure. For instance, for women with only twelve months of experience, the effect of the program on separations happening

[32] It is measured by $\alpha_{0r} + \theta_{1r} x_i + \theta_{2r} x_i^2 + \theta_{3r} x_i^3$ and we use Delta method to calculate the standard errors.

[33] Since the parameters of the regressions themselves have no meaningful interpretation, we omit the estimates of the regressions underlying figures in this section. Instead, we present the marginal impacts throughout figures, but the results of the regression estimates are available upon request.

in the 5th month can be around four times bigger, compared to women with more than five years of experience (see Panel a).

Also, as shown in the previous results, the negative effects on separations are followed by positive effects later, after the extended leave period ends (see Panels b and c). Similarly, the positive impacts are stronger for less experienced workers so that the ultimate result after twelve months do not depend on the worker's experience.

Finally, when we disaggregate the measure of separation based on its causes in the fifth month after birth, we find evidence supporting a reduction from both reasons; firing (Pane d) or workers who voluntarily quits (see Panel g). Looking at the seventh month after leave starts, which is when the extended leave period ends, we observe that all the positive effects on separation arise from workers voluntarily quitting their jobs after taking an extended leave, and this is stronger for workers with less experience. This picture inverts when we focus on the 9th months, in which we observe a null effect on separation coming from workers' initiative, and the separations are due firms firing eligible workers with less experience.

The results are consistent with a setting in which women less experienced (with lower costs of dismissals) are more likely to behave under moral hazard and request a maternity leave and quit afterward. On the other hand, when this is not the case, employers can still screen their employees, after a period of extended leave, to be fired based on their levels of experience.

6.4 Firm Premium and Worker's Ability

We also investigate to what extent the take-up rates depend on the inherent characteristics of the employees. In particular, we are interested in understanding whether the worker's ability/productivity may influence the chance of taking an extension. Contrasting with other usual individual characteristics (e.g., education, experience, race, occupation, age), now we seek to classify workers based on the component of pay that is not influenced by general personal characteristics, time, or even the specific firm where she is working (*proxy* for individual ability).

On another hand, recent literature also has emphasized the role of firm-specific factors (such as, size, workforce composition, sorting of individuals to firms, firm's premium, etc) in explaining the formal labor market outcomes and earning inequality in developed countries (Germany ([Card et al., 2013]), Italy ([Iranzo et al., 2008]), Portugal ([Card et al., 2016]), Sweden ([Bonhomme et al., 2019]), and United States ([Engbom and Moser, 2017]). Similar evidence is already documented in Alvarez et al. [2018] for Brazil, in which the authors document a large decrease in earnings inequality with the specific firm factors accounting for 40% of the total decrease and worker effects for 29%.

In order to investigate the influences of these two elements (worker ability and firm premium) in our setting, we follow the empirical approach proposed in [Abowd et al., 1999].[34] The AKM model allows us to separately identify the firms and worker fixed effects. This empirical strategy has been widely used to disentangle the components of worker ability and firm premium in wage regressions

[34]Which was also later theoretically rationalized in Card et al. [2018] by presenting well-documented empirical regularities that can be rationalized in the AKM framework.

based on matched employer-employee data. In a nutshell, our empirical strategy involves two steps. First, we estimate employer earnings premiums and workers' ability by including both worker and firm fixed effects to account for nonrandom sorting of workers across firms. Second, we use the worker and firm fixed effects as measures of worker's ability and firm's premium, respectively, after controlling for a broad set of individuals and firms time-varying controls.

A crucial point of this analysis refers to the construction of the data to be used to estimate the AKM model. In this regard, we adopt the following approach[35]: (1) select all firms in our final dataset used for the main analysis; (2) select all women ever employed in those firms during the period 2008-2016; (3) select all women (and their firm's identifiers) who were ever a co-worker of individuals in point 2, irrespective of the firm, and at some point during the period 2008-2016[36]. After constructing this panel data containing all the relevant links employer-employees for the period 2008-2016, we estimate the following equation:

$$\log w_{ijt} = a_i + \Phi_{j(i,t)} + Cont'_{ijt}\Theta + \varepsilon_{ijt} \tag{4}$$

where $\log w_{ijt}$ is the log yearly earnings of worker i employed at firm j in year t. The variable a_i is the individual fixed effect, which captures any time-invariant characteristics of the worker that are rewarded equally at all firms (*proxy* for personal ability). The firm fixed effect, $\Phi_{j(i,t)}$, represents the earnings premium that firm j pays to all workers[37]. To make sure that the worker/firm fixed effects are measuring the worker's ability and firm's premium, we control for a very rich set of individual and firm characteristics included in $Cont_{ijt}$. More precisely, in the estimation, we control for occupation-year, cubic polynomial in tenure in the same firm, race-year, education-year, cubic polynomial in (log) firm's size.

Once we have the estimated measures of ability, a_i, and premium, Φ_j, we then explore heterogeneous take-up based on the level of these measures. To do so, we split the mothers in our main dataset into groups based on their abilities (low v.s high) and the premium (low v.s high) paid for the firms in which they work when take the leave. We define low (high) ability workers as those with ability below (above) the median considering the empirical distribution of abilities in the data. We proceed similarly to classify low-high premium firms. In the end, we create four groups of individuals based on the pair ability-premium (low-low, low-high, high-low, and high-high).

We start by examining the influence of ability/premium on the take-up rate by interacting indicators for each of these four groups with the dummy of eligibility, E_i, in the original model in equation 1. Table 11 shows take-up estimation allowing for heterogeneous effects based on workers'

[35]We could recursively add more and more steps until, in the end, we cover all the Brazilian formal labor market. However, workers and firms that are never linked to each other would not add relevant information to our measures of ability and premium for all final sample

[36]Note that the set of workers and firms in our main dataset is a subset of this data (containing individuals and firms) generated to run the AKM.

[37]Because we are estimating both worker and firm fixed effects, firm's premium is identified only within a "connected set" of employers, i.e., the group of all workers who ever worked for any employer in the group and all employers at which any worker in the group was ever employed.

productivity and firms' premium. We find evidence of statistically significant higher take-up rates for high ability workers (see columns 1-2) and also for women who take leave in firms paying a higher premium (see columns 3-4). It is worth mentioning that part of these results could arise from the likely assortative matching between high-quality workers willing to work for firms that pay a higher premium and *vice-versa*. To account for this event and isolate each of the cases, we then look at a more flexible version in which we add interactions, i.e., the four groups of ability-premium (see columns 5-6). The results of the regression can also be seen in Figure 9, based on which we notice two main findings. First, women working for higher premium firms are more likely to take extended leave, notably for low-quality workers. Second, the take-up increases with workers' productivity only in firms paying a low premium. In a recent paper, Bana et al. [2018], employing a similar framework for the US, find a higher take-up of leave-taking benefits for firms with higher earning premiums, likewise in our findings for Brazil.

Furthermore, we also investigate how the ability and firm's premium interact with eligibility status to explain employment outcomes right after the period of leave ends until twelve months after birth. As shown in Figures 10, we note a greater take-up rate for higher ability workers and we also observe that the (still small and temporary) positive effect on employment is more lasting for low-ability workers employed at high-premium firms.

All in all, our results show that the maternity leave extension protects relatively more low-quality workers, and mainly those working for firms that pay a higher wage premiums, which in part could reveal some adverse selection. Nevertheless, the overal impact in the medium term (after 12 months) is still null.

6.5 Labor Market Frictions and Workers' Substitutability

In the presence of labor market frictions or because workers' competencies can be very heterogeneous, worker's decisions could vary according to sector-specific human capital or worker's substitutability/complementarity within the firms. Dix-Carneiro [2014], for instance, argues that sector-specific experience is imperfectly transferable across sectors, which can lead to barriers to mobility in the Brazilian labor market. As shown in Alves et al. [2016], there are substantial frictions when they compare, for instance, manufacturing and services sectors in Brazil, causing some asymmetries in the cost of switching sectors as well as returning and reallocation within and across sectors which. As a consequence, these frictions can also affect bargaining power, unemployment, and salaries in each sector. In this context, it is reasonable to imagine that such sectorial differences reflect also on the willingness to take-up an extended leave, which we also investigate in this paper.

To do so, we interact the main variable for eligible (to extend the leave) status with dummies for sectors (following the classification proposed by Dix-Carneiro [2014]) in order to estimate heterogenous take-up by sector. In Figure 11 we note a substantial heterogeneity in take-up rates across sectors (see panel a), ranging from 20% in Trade sector up to 60% in Transportation/Utilities/Communication (mainly Communication). In Panel b we display the differences ("Trade" is the baseline) and verify that these differences are statistically significant. Going one step further, we also show a positive correlation (see Panel c) between take-up rates in each sector and the “costs of mobility" estimated in Dix-Carneiro [2014], which indicates that the likelihood of taking an extended leave increases with the human-capital specificities of the sectors.

We then turn to investigate the role of worker's substitutability in the firm and, following previous work by Brenøe et al. [2020] and Jäger [2019], we assume that coworkers in the same (different) occupations are substitutes (complementary). Therefore, we interact the number of substitutes (workers in the same 6-digits occupation) within the firm with the variable indicating eligible status. In particular, we split the number of substitutes into four groups: zero substitutes (*baseline*), 1 or 2 substitutes, from 3 up to 9 substitutes, and 10 or more substitutes in the firm. In Table 12 (column 1) we observe the results over the whole sample analysis, in which we note only a slight increase in take-up rates as the number of substitutes increase.

Furthermore, when we split this analysis according to firms sizes (columns 2-6) we observe a stronger and significant influence of the presence of substitute workers on women's take-up of extended leave for smaller firms. For instance, conditioning on firms with up to 15 workers (column 2), the take-up goes from around 26.6% (when there are no substitute workers) to 75% (when there are 10 or more substitutes). Results from Table 12 also indicate that these differences in take-up rates due to worker's substitutability fade away as the size of the firm increases (see columns 3-6).

Some authors have already investigated the relevance of task-specific human capital, transferability of skills among workers, types of jobs, and the role of portable skill accumulated (Gathmann and Schönberg [2010], Autor et al. [2003], Gonzaga and Guanziroli [2019]), which may also affect the worker's substitutability/complementarity within the firm. Following their ideas, we also look closely at the type of tasks performed by workers. In particular, we distinguish workers who perform routine *versus* non-routine tasks. To do so, we use an occupation-task mapping constructed in Gonzaga and Guanziroli [2019][38], and classify the occupations into two groups: Non-Routine (*Analytic, Interactive or Manual*) and Routine (*Cognitive or Manual*).[39] Columns 7-8 of Table 12 show that the number of substitute workers matters for take up only among workers performing non-routine tasks, which may require specific skills to be replaced by co-workers in the firm.

[38]The authors have the task content of 275 four-digit occupations, which represents 87% of workers' observations. The mapping characterizes the intensity of use of each task in an occupation such that the sum of the task measures within an occupation equals 100%. For more details, refer to the original study (Gonzaga and Guanziroli [2019]).

[39]The tasks performed in each group are: **Non-Routine Analytic** (*Researching, Investigating, Analyzing, Examining, Studying, Evaluating, Planning, Budgeting, Making diagnosis, Judging*),**Non-Routine Interactive** (*Negotiating, Practicing Law, Coordinating, Leading people, Teaching, Training, Spreading knowledge, Instructing, Selling, Marketing*), **Routine Cognitive** (*Calculating, Programming, Transforming, Bookkeeping, Recording, Measuring, Verifying*), **Routine Manual** (*Operating, Distributing, Transporting, Equipping, Assembling*), and **Non-Routine Manual** (*Repairing, Renovating, Serving, Accommodating, Cleaning).* We sum up the three (two) non-routine (routine) occupation-tasks indexes together and then split each of them to measure a non-routine (routine) task when those indexes are above the median of the index in our sample analysis..

7 Conclusion

The past few decades have experienced a notable increase in the number of countries offering maternity leave policies, which is essentially a consequence of a global trend in which women's participation in the labor market has also increased remarkably. In this context, maternity leave policies have been adopted to address critical social goals by helping mothers to balance job and family duties, and then mitigate gender inequalities in the family and labor markets.

While the effects of these policies can vary considerably across countries depending on local labor market conditions, socio-cultural norms as well as specific labor market regulations and maternity leave settings, the vast majority of research has focused on developed nations. In this paper, we contribute to the literature by analyzing the effects of leave extensions in the context of Brazil, a large developing country, which allows us to yield new insights into the consequences of these policies on workers, firms, and labor markets.

In particular, examining the causal effects of a paid maternity leave extension (from four to six months) in Brazil, we find that about 40% of eligible women take extended leaves, and employment effects are modest and temporarily restricted to just after leave extension. We find evidence of women's and firm's strategic responses to paid leave extensions and note regressive distributional implications of the policy. We also examine how this policy (and its impacts) interact with labor markets, firms' and workers' characteristics, such as: sharing information among peers, degree of job security, worker's ability, firm's premium, frictions in the labor market, and the degree of workers' substitutability within the firms.

Taken together, our findings suggest that the extension of paid leave examined in this paper had no measurable effect on labor market outcomes, and presents regressive redistribution properties[40]. In a time of harsh budget realities, our findings have important implications for countries that are considering future expansions or contractions in the duration of paid leaves. Further policies are needed to promote a higher attachment of women to the labor market and some of the alternatives already implemented and studied in the literature include: parental leave policies, work flexibility based on family-friendly occupations, and availability of affordable (public) child care facilities.

[40] Aside from being focused on firms (and workers at them) with particular characteristics, results are also limited to employment in the formal sector. The data does not allow us to say much about women who took maternity leave and go into the informal sector. For instance, we can not distinguish whether higher participation in the informal sector counterbalances lower participation in the formal labor market.

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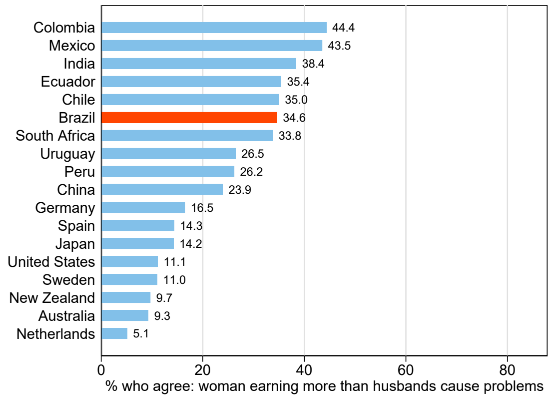
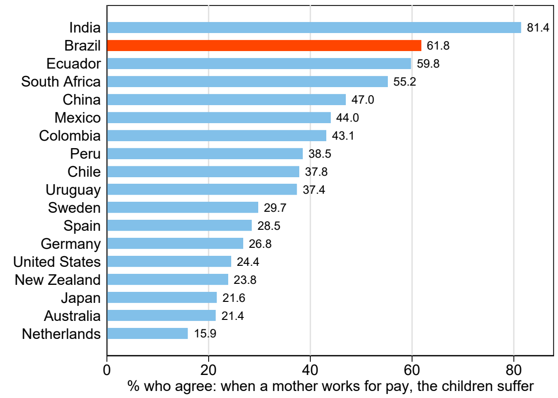
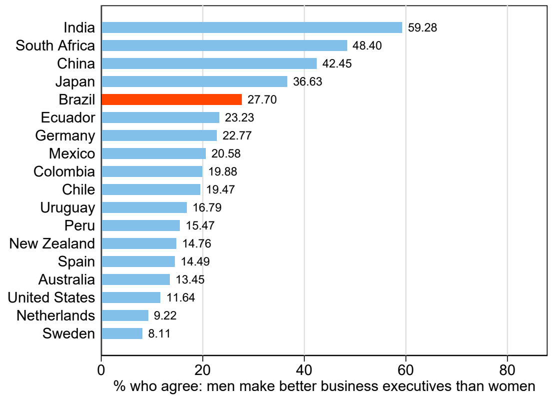


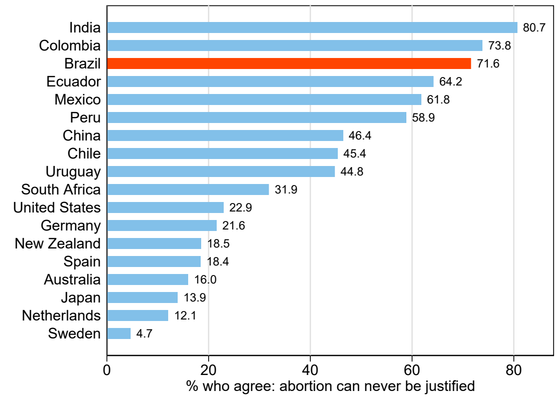
(a) **Earning**



(b) **Children**



(c) **Business**



(d) **Right to own body**

Figure 1: Social/Cultural norms on the role of women in the household, workplace and the society

Notes: This figure shows the percentage of individuals in Brazil, among selected countries in the World Values Survey, who agree with certain statements regarding the cultural role of women in society. The choice of countries aims to compare representative (developed and developing) countries from each continent around the world.

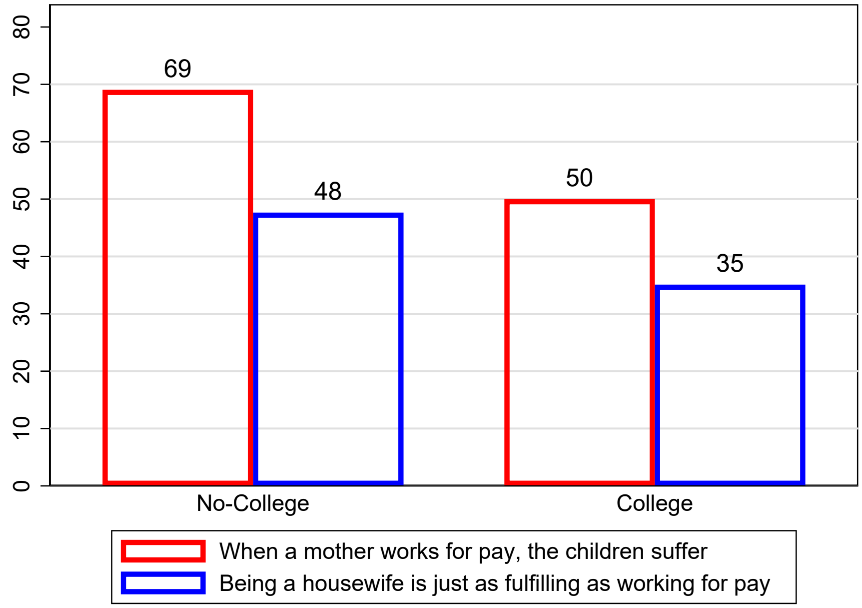


Figure 2: Gender norms by education (College versus Non-College) among mothers in Brazil: share who agree with each sentence.

Notes: This figure shows the percentage of mothers (College versus Non-College) in Brazil, based on the World Values Survey, who agree with certain statements regarding woman's participation in household chores and in the labor market.

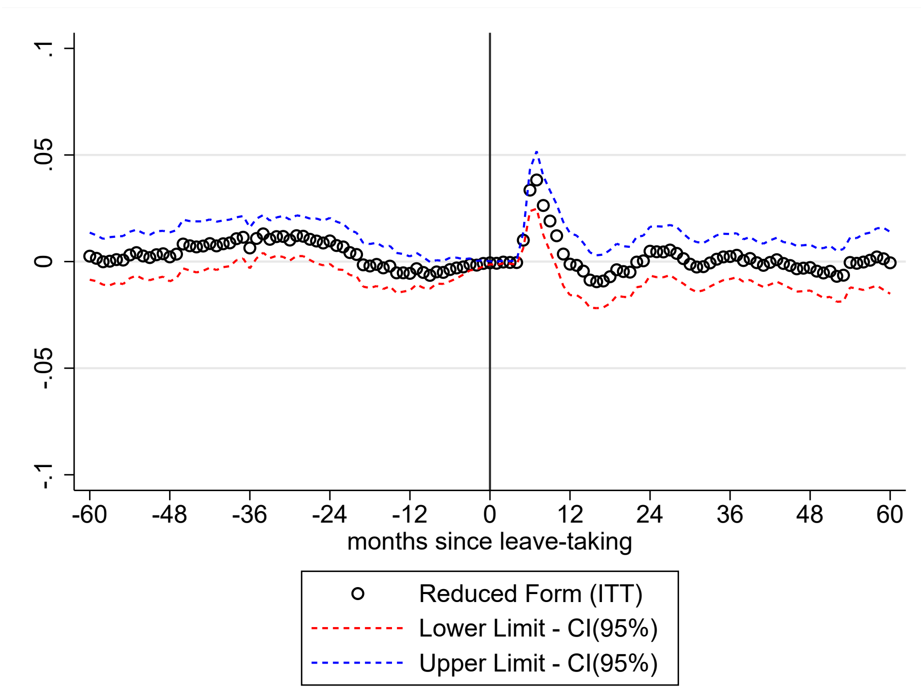
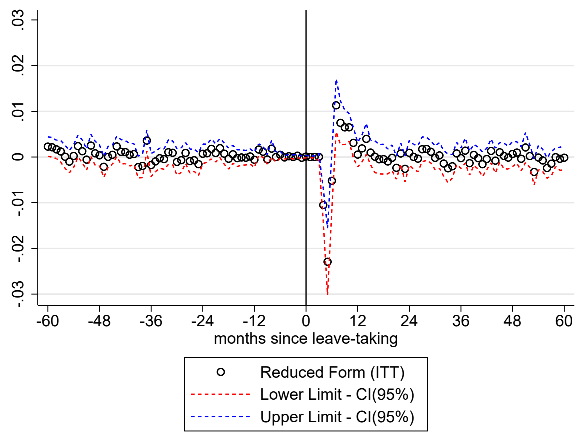
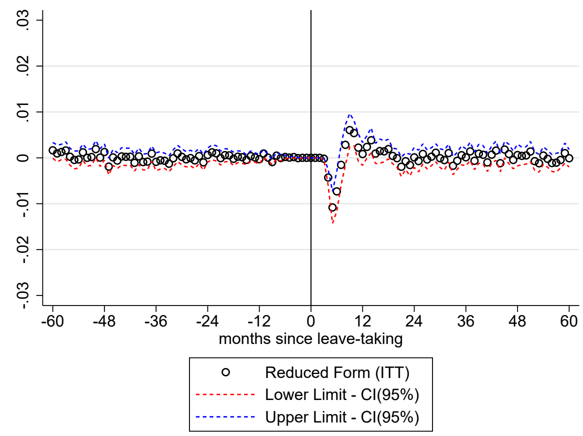


Figure 3: Effects of extended maternity leave on employment until five years after the leave

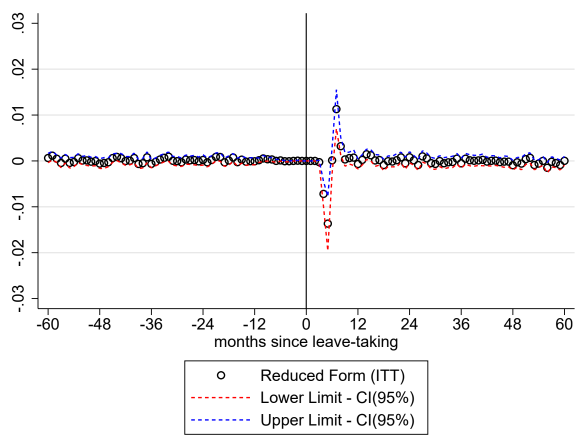
Notes: This figure shows the effects of maternity leave extension (from 120 to 180 days) on the probability of being employed $r \in \{-60, ..., +60\}$ months before/after the maternity leave. Each dot plotted in the figure is estimated based on a regression as in Equation 1 presented in subsection 4.1, in which we show the patterns of of employment across different horizons in r.



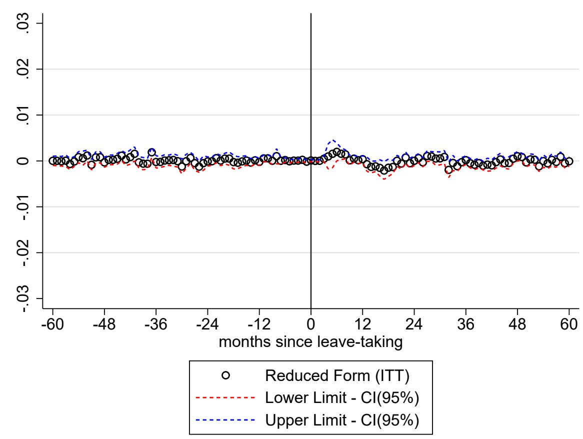
(a) **Separation**



(b) **Fired**



(c) **Voluntary**



(d) **Others**

Figure 4: Effects on Separation by Type

Notes: This figure shows the effects of maternity leave extension (from 120 to 180 days) on the probability of separation $r \in \{-60, ..., +60\}$ months before/after the maternity leave. Each dot plotted in the figure is estimated based on a regression as in Equation 1 presented in subsection 4.1, in which we show the patterns of separation across different horizons in r (in Panel a). We then split the variable "separation" into two main groups of interest (Fired versus Voluntary quits) and a residual group (Others), as can be seen in Panel b, c and d.

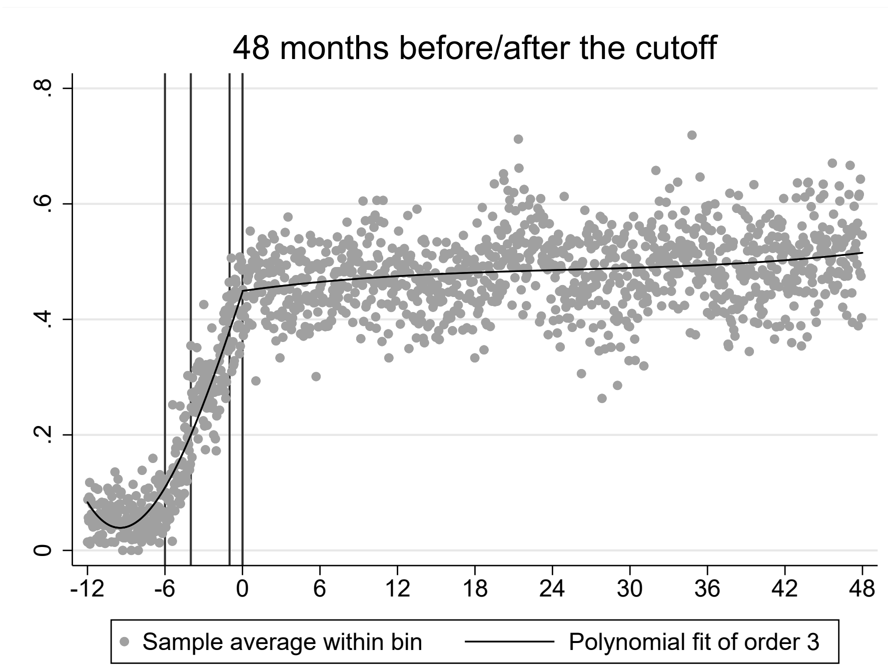


Figure 5: Take-up rates up to 48 months after EC adoption

Notes: This figure shows the take-up rate from 12 months before and until 48 months after EC adoption. Results are generated by local (3rd order) polynomial smooth plots, in which the dependent variable is an indicator equals to one if a woman takes extended leave. The running variable in the x-axis is the months (each 30-day period) since maternity leave.

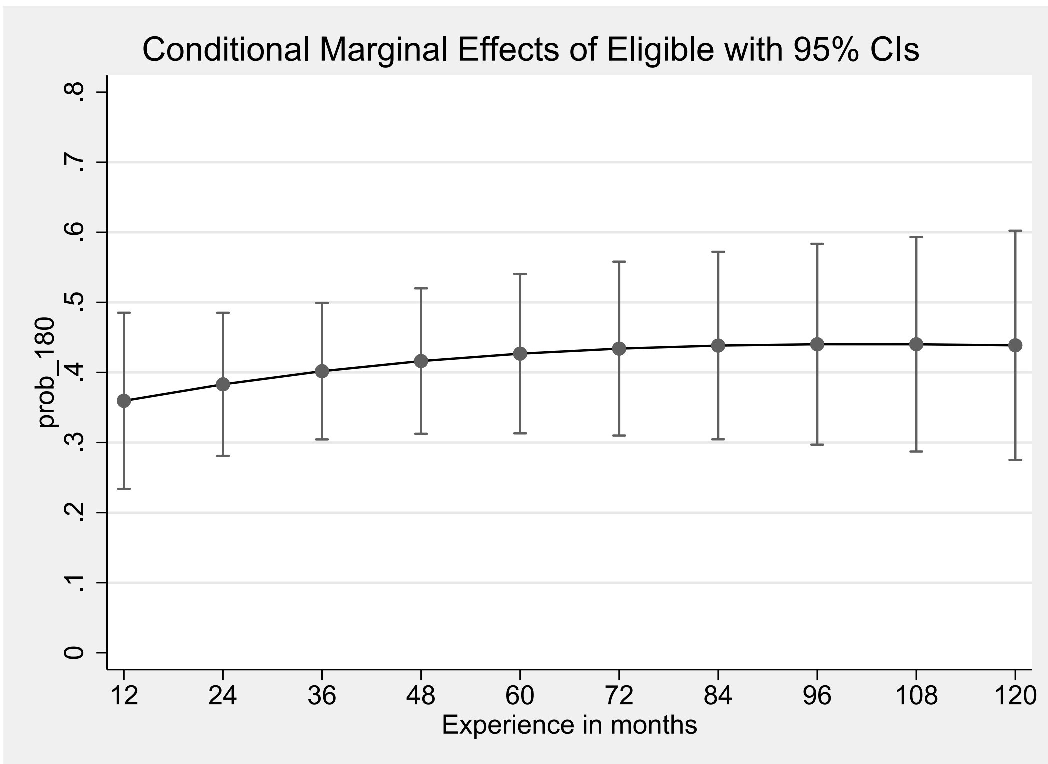
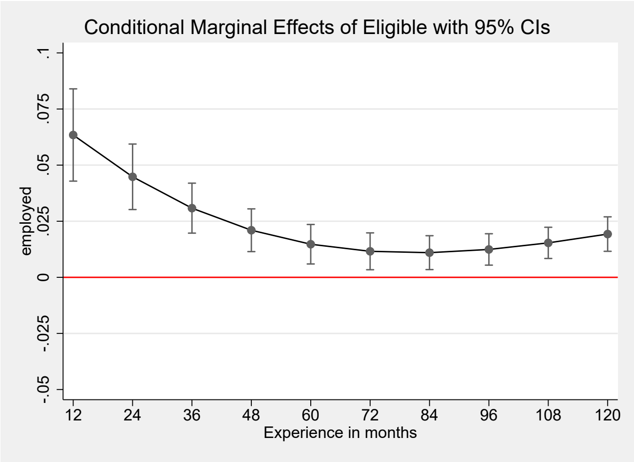
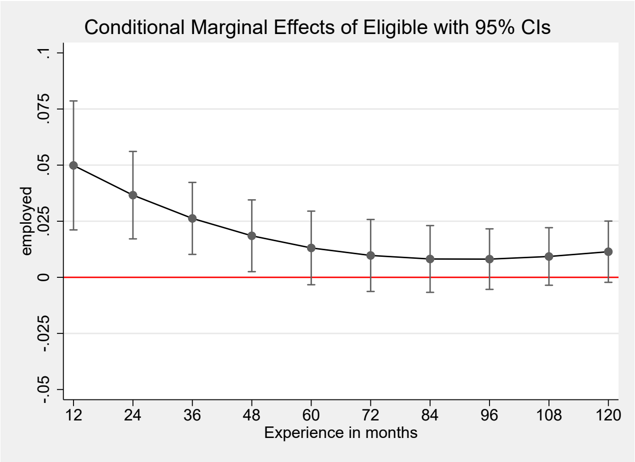


Figure 6: Take-up rate by level of job protection (tenure in months)

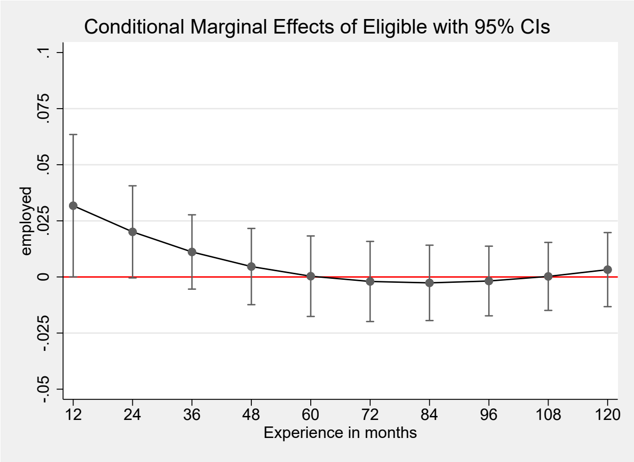
Notes: This figure shows the take-up rate by level of job protection, according to levels of experience in the firm (varying from 12 to 120 months). Results are estimated based on the interaction between the treatment variable and a cubic polynomial on tenure, as discussed in subsection 6.3 and as in Equation 3.



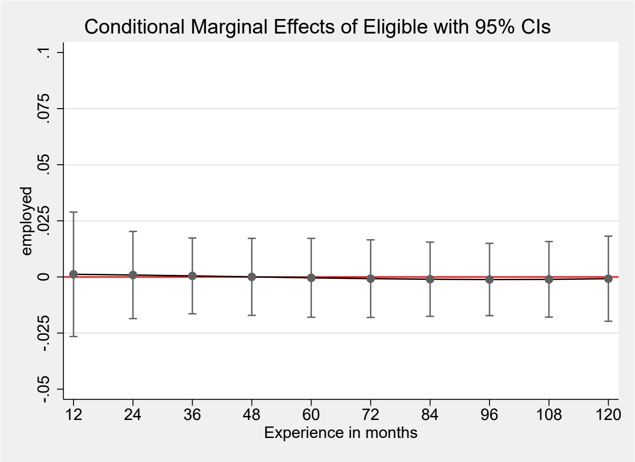
(a) **6th month**



(b) **8th month**



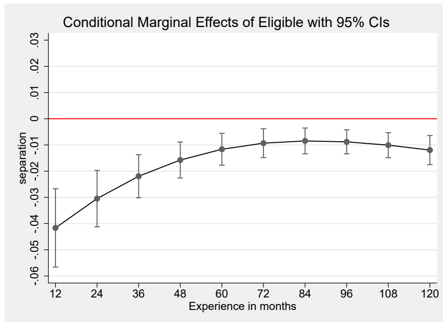
(c) **10th month**



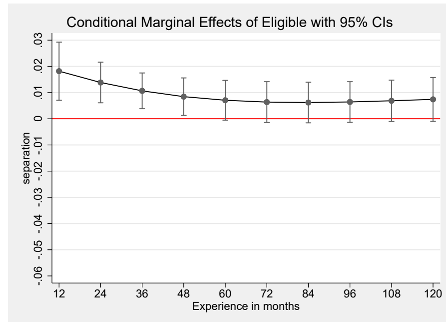
(d) **12th month**

Figure 7: Heterogeneous Effects on Employment by amount of experience (in months)

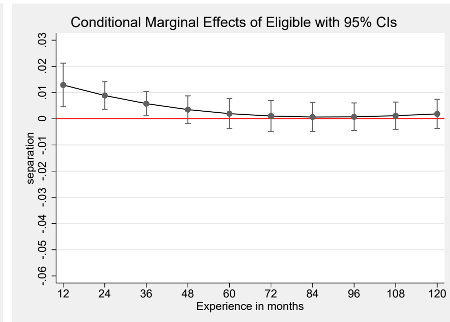
Notes: This figure shows the effects on employment by level of job protection, according to levels of experience in the firm (varying from 12 to 120 months). Results are estimated based on the interaction between the treatment variable and a cubic polynomial on tenure, as discussed in subsection 6.3 and as in Equation 3. We show results for selected (6th, 8th, 10th and 12th) months apart from the leave.



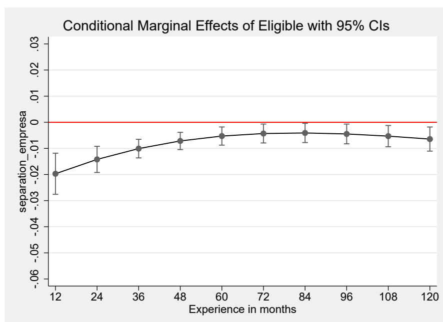
(a) **Total, 5th month**



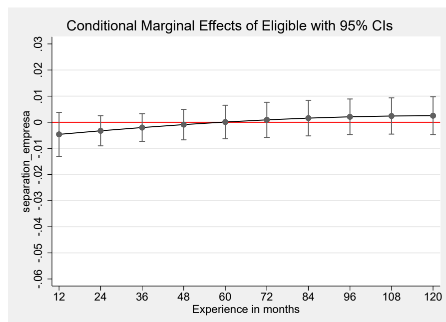
(b) **Total, 7th month**



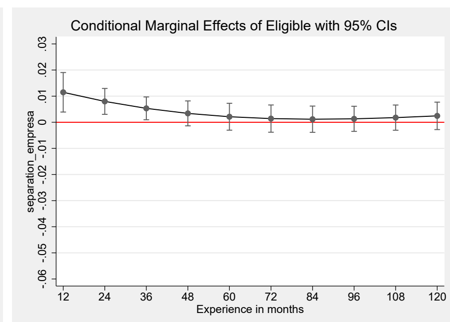
(c) **Total, 9th month**



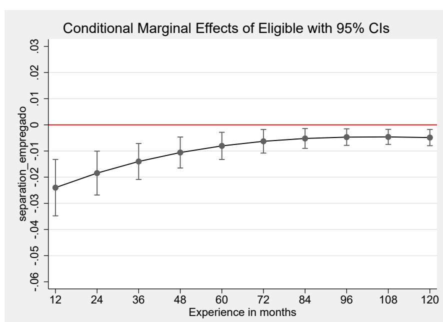
(d) **Fired, 5th month**



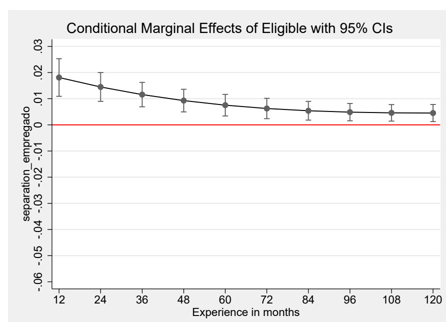
(e) **Fired, 7th month**



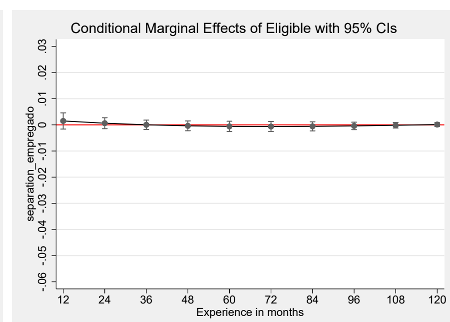
(f) **Fired, 9th month**



(g) **Voluntary, 5th month**



(h) **Voluntary, 7th month**



(i) **Voluntary, 9th month**

Figure 8: Heterogeneous Effects on Separation (and its causes) by amount of experience (in months)

Notes: This figure shows the effects on separation (also split into fired and voluntary quits) by level of job protection, according to levels of experience in the firm (varying from 12 to 120 months). Results are estimated based on the interaction between the treatment variable and a cubic polynomial on tenure, as discussed in subsection 6.3 and as in Equation 3. We show results for selected (5th, 7th and 9th) months apart from the leave.

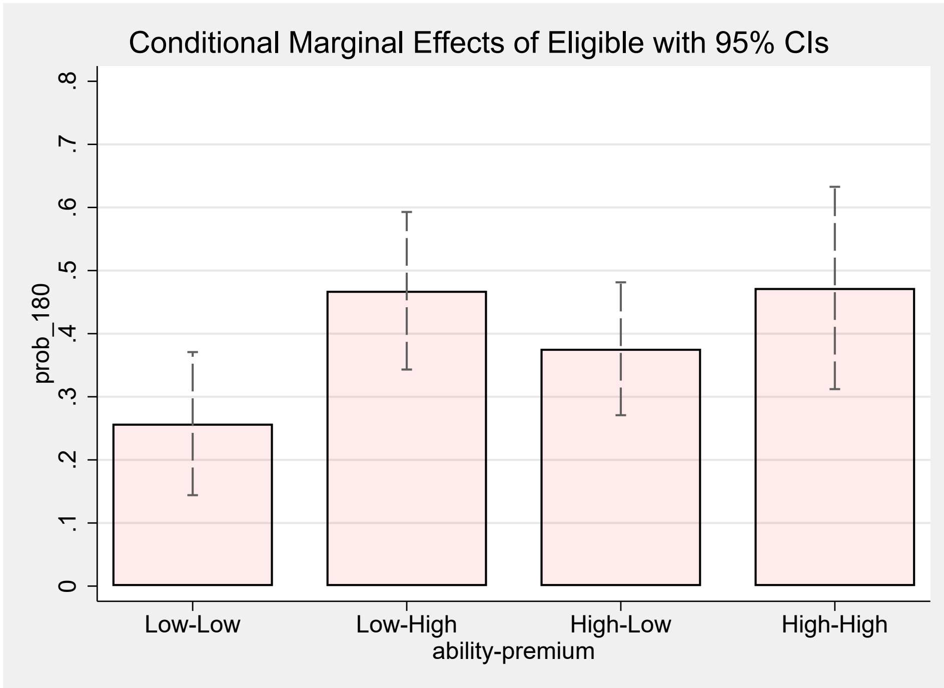
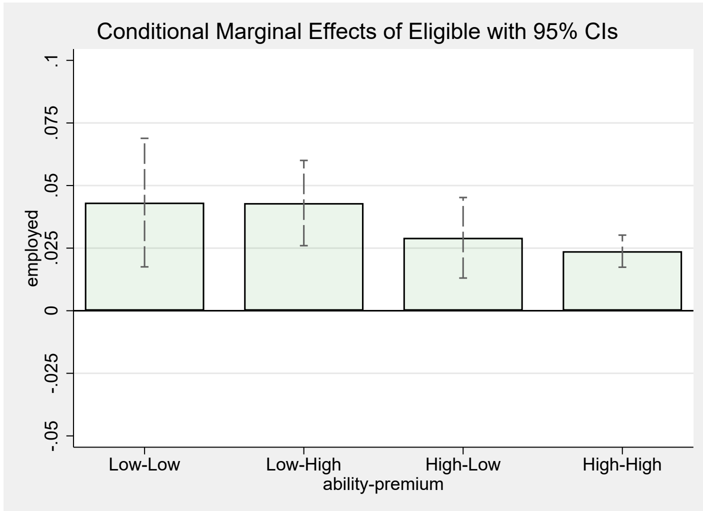
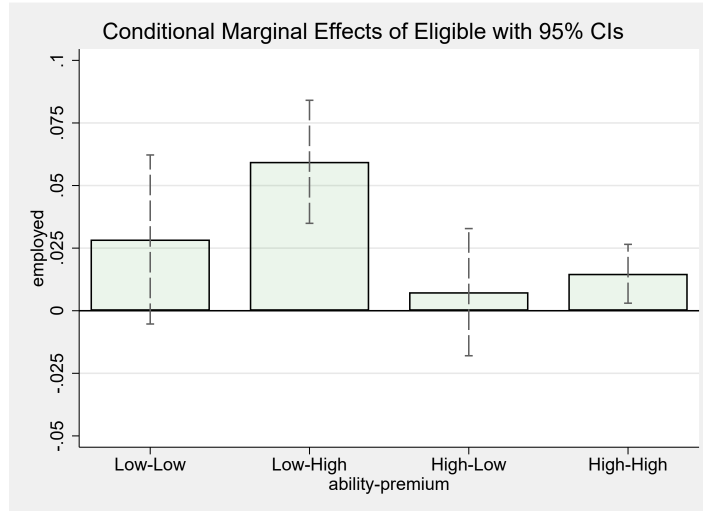


Figure 9: Take-up rate by workers' ability and firms' premium

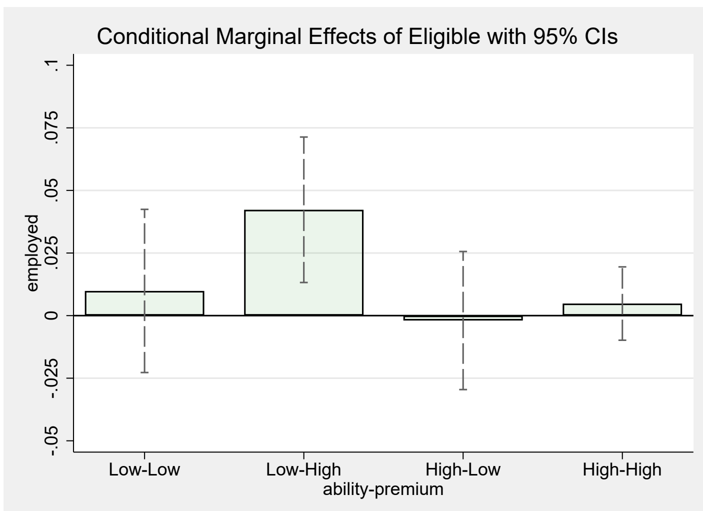
Notes: This figure shows the take-up rate by levels of workers' ability and firms' premium. Individuals and firms are divided into two groups each (Low and High), so that we have four groups for the pair ability-premium. For this, individuals/firms classified as Low (High) means that their ability/premium are below (above) the median. Results are estimated based on the interaction between the treatment variable and a set of dummies indicating each of those groups, as discussed in subsection 6.4 and as in Equation 4.



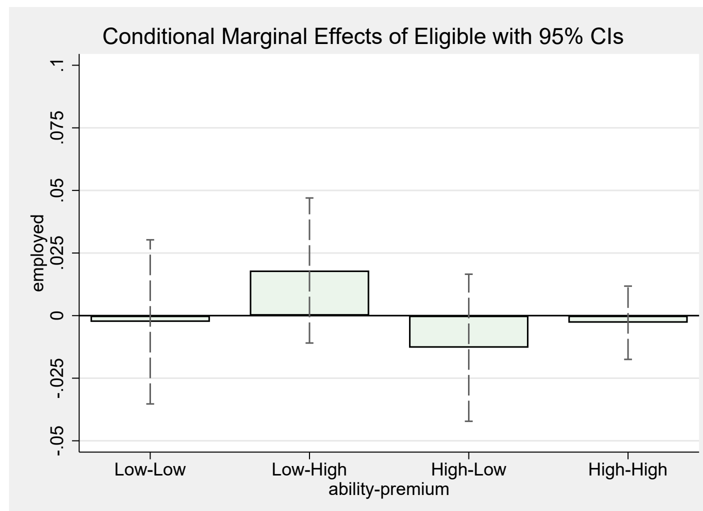
(a) **6th month**



(b) **8th month**



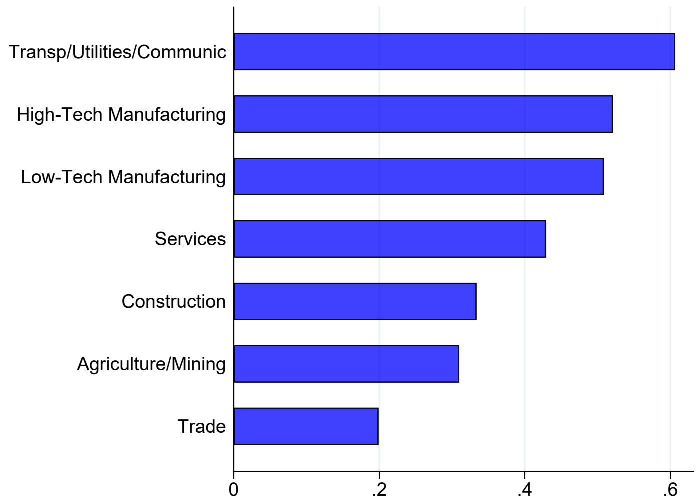
(c) **10th month**



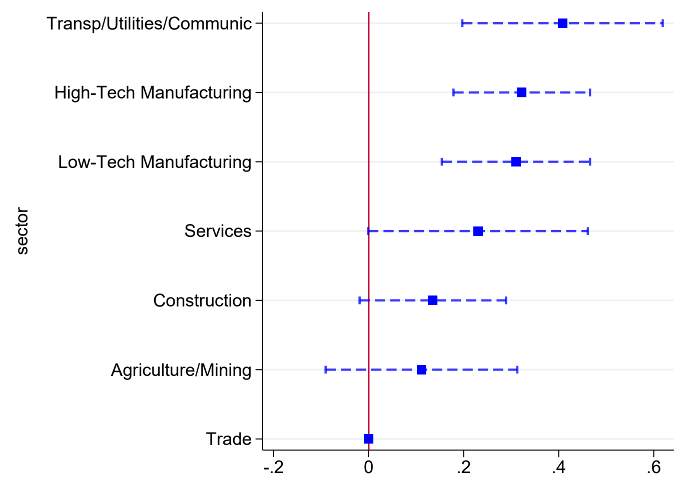
(d) **12th month**

Figure 10: Heterogeneous Effects on Employment by workers' ability and firms' premium

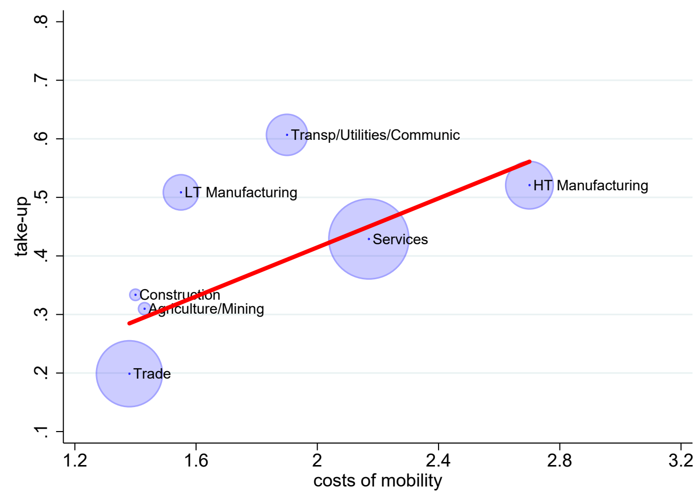
Notes: This figure shows the effects (for selected months) on employment by levels of workers' ability and firms' premium. Individuals and firms are divided into two groups each (Low and High), so that we have four groups for the pair ability-premium. For this, individuals/firms classified as Low (High) means that their ability/premium are below (above) the median. Results are estimated based on the interaction between the treatment variable and a set of dummies indicating each of those groups, as discussed in subsection 6.4 and as in Equation 4.



(a) **heterogeneous take-up by sector**



(b) **differential take-up by sector (baseline is "Trade")**



(c) **relation between take-up and cost of mobility**

Figure 11: Heterogeneous take-up by sector-specific human capital

Notes: This figure shows heterogeneous take-up across sectors. Workers are divided into seven groups following Dix-Carneiro [2014] classification. Results in Panel a are generated by interacting eligible status, E_i, with dummies for each sector, and Panel b displays results allowing to test if the differences in take-up are rates are significant (as discussed in 6.5). Panel c correlate the heterogeneous take-up with a measure of "costs of mobility" into each sector, based on Table 1 from Dix-Carneiro [2014].

Table 1: Average Characteristics of Workforce in EC Adopters and Sample Selection

	All Data		...matched EC-RAIS		...ML corrected		...window of 360 days	
	All workers (1)	Female (2)	All workers (3)	Female (4)	All workers (5)	Female (6)	All workers (7)	Female (8)
Female	0.3969	1.0000	0.3411	1.0000	0.3376	1.0000	0.3378	1.0000
Age	34.5091	34.4260	34.6945	33.6558	34.2485	32.9230	34.1668	32.8133
Black/Brown	0.2894	0.2279	0.2447	0.2060	0.2509	0.2213	0.2528	0.2261
Number of min. wages	2.8940	2.6017	6.2285	5.1428	6.3344	5.1876	6.3399	5.1332
Earning less than 2 MW	0.6058	0.6657	0.2753	0.3500	0.2751	0.3573	0.2827	0.3743
Earning 2-5 MW	0.2799	0.2328	0.3506	0.3292	0.3467	0.3193	0.3445	0.3127
Earning more than 5 MW	0.1142	0.1015	0.3742	0.3208	0.3783	0.3234	0.3728	0.3130
Less than High School	0.4201	0.2943	0.2305	0.1682	0.2122	0.1372	0.2139	0.1424
High School	0.4014	0.4479	0.3955	0.3684	0.4108	0.3951	0.4208	0.4084
College+	0.1785	0.2578	0.3741	0.4633	0.3770	0.4677	0.3653	0.4492
Hours per week	41.2979	39.8465	40.6915	39.5748	40.9987	40.0760	41.1316	40.2538
Full-time	0.9087	0.8504	0.8796	0.8221	0.9011	0.8541	0.9111	0.8685
Managers	0.0391	0.0433	0.0577	0.0609	0.0579	0.0606	0.0543	0.0558
Science and Arts	0.0882	0.1366	0.1275	0.1726	0.1173	0.1429	0.1192	0.1443
Middle level technicians	0.0957	0.1313	0.1129	0.1009	0.1189	0.1083	0.1211	0.1110
Administrative services	0.1862	0.2733	0.2817	0.4113	0.2742	0.4125	0.2634	0.4020
Service and sellers	0.2385	0.2803	0.1240	0.1436	0.1279	0.1528	0.1288	0.1547
Others (mainly industry)	0.3524	0.1352	0.2962	0.1108	0.3038	0.1229	0.3132	0.1321
# obs	61,126,896	24,260,887	3,232,347	1,102,683	2,800,747	945,522	2,461,783	831,571
workers	50,219,948	20,294,197	3,013,140	1,024,797	2,637,296	887,718	2,339,769	788,925
plants	3,185,547	2,177,521	44,525	39,744	26,257	25,895	16,210	16,104
firms	2,461,365	1,761,583	7,708	6,756	4,748	4,641	3,869	3,812

Notes: This Table shows basic descriptive statistics for individuals in our data (separately for all workers and women) containing EC adopters, relevant to understand the role of sample selection in our analysis. We start by showing summary statistics based on the raw RAIS data of 2009 (column 1-2) until the data for EC adopters used for the final analysis (column 7-8), in which we fix a window of . It also presents two intermediate sample analysis: in columns 3-4 we see summary statistics for all firms EC adopters found in RAIS and column 5-6 brings summary statistics for the remaining firms after we apply a correction in the sizes of maternity-leave (more details in Appendix B).

Table 2: Average Characteristics of Analysis Sample Across Intervals of the Running Variable (*leave starting dates relative to EC adoption dates, in days*)

	[-360 ; 360] (1)	[-360 ; -180] (2)	(-180 ; 0) (3)	[0 ; 180] (4)	(180 ; 360] (5)
Days of Leave-taking	138.680	123.042	135.441	146.539	147.672
Prob(leave>120 days)	0.324	0.058	0.268	0.458	0.477
Age	30.147	30.130	30.057	30.313	30.074
Black/Brown	0.239	0.231	0.233	0.242	0.251
Number of min. wages	4.928	5.045	4.891	4.948	4.837
Earning less than 2 MW	0.352	0.347	0.351	0.344	0.366
Earning 2-5 MW	0.342	0.338	0.345	0.346	0.339
Earning more than 5 MW	0.306	0.316	0.304	0.310	0.296
Less than High School	0.088	0.087	0.091	0.084	0.090
High School	0.422	0.427	0.418	0.414	0.429
College+	0.491	0.486	0.492	0.502	0.481
Hours per week	40.648	40.540	40.736	40.567	40.743
Full-time	0.891	0.886	0.894	0.888	0.897
Managers	0.065	0.066	0.072	0.065	0.056
Science and Arts	0.160	0.154	0.152	0.171	0.162
Middle level technicians	0.114	0.115	0.114	0.114	0.113
Administrative services	0.392	0.389	0.397	0.390	0.391
Service and sellers	0.143	0.150	0.142	0.139	0.142
Others (mainly industry)	0.126	0.126	0.122	0.121	0.137
workers	65,989	15,078	16,512	17,861	16,538
plants	17,990	6,684	7,877	8,165	7,401
firms	4,151	1,608	2,709	2,392	1,922

Notes: This table shows basic summary statistics for women in the analysis sample, according to their starting dates of the mandatory leave relative to EC adoption date. We split the data into four intervals of 180 days. Each column indicates the grouping of leave starting days relative to EC adoption, in which negative numbers indicate the maternity leaves taken (up to -360 days) before adoption and positive numbers indicate the maternity leaves starting (up to 360 days) after firms adopt EC Program. Results show that individual characteristics are balanced across these intervals, while extended leave-taking take-up is higher for eligible mothers (meaning those taking leaves after EC adoption,i.e., in the positive intervals).

Table 3: Covariates Balancing Tests for Differences Between Eligible (*leaves up to 180 days after EC adoption*) and Non-Eligible Mothers (*leaves within 180 and 360 days before EC adoption*)

	(1) Age	(2) Black/Brown	(3) # of min. wages	(4) < 2 MW	(5) 2-5 MW	(6) >5 MW
Eligible	0.1831***	0.0112*	-0.0967	-0.0030	0.0083	-0.0054
	(0.0671)	(0.0059)	(0.1062)	(0.0124)	(0.0134)	(0.0134)
Constant	30.1302***	0.2308***	5.0448***	0.3467***	0.3378***	0.3156***
	(0.2214)	(0.0217)	(0.2986)	(0.0441)	(0.0211)	(0.0315)

	(7) <High School	(8) High School	(9) College+	(10) Hours per week	(11) Full-time	(12) Managers
Eligible	-0.0034	-0.0131	0.0165	0.0269	0.0011	-0.0006
	(0.0064)	(0.0150)	(0.0194)	(0.1734)	(0.0080)	(0.0067)
Constant	0.0871***	0.4271***	0.4858***	40.5405***	0.8865***	0.0657***
	(0.0118)	(0.0432)	(0.0487)	(0.4166)	(0.0237)	(0.0116)

	(13) Science and Arts	(14) Mid. level tech.	(15) Adm. services	(16) Service and sellers	(17) Others (mainly industry)
Eligible	0.0169	-0.0008	0.0007	-0.0111	-0.0051
	(0.0141)	(0.0071)	(0.0085)	(0.0164)	(0.0078)
Constant	0.1544***	0.1148***	0.3888***	0.1505***	0.1257***
	(0.0185)	(0.0121)	(0.0356)	(0.0225)	(0.0168)

Notes: This table presents a series of balancing tests to check whether eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) are a credible group of control for non-eligible workers (taking maternity leave up to 180 days after EC adoption). To do so, we estimate various simple regressions in which the dependent variable is a particular worker's characteristic, and the independent variable is the indicator of eligibility, E_i, as defined in subsection 4.1. Sample contains 32,939 individuals (17,861 eligible and 15,078 non-eligible mothers). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at firm level.

Table 4: First Stage Results: Take-up Rates of Eligible (*leaves up to 180 days after EC adoption*) relative to Non-Eligible Mothers (*leaves within 180 and 360 days before EC adoption*)

PANEL A: Indicator equal to 1 if taking extended leave	(1)	(2)	(3)	(4)	(5)	(6)
Eligible	0.3994***	0.4012***	0.3997***	0.4016***	0.4262***	0.4253***
	(0.0522)	(0.0513)	(0.0520)	(0.0511)	(0.0478)	(0.0477)
Constant	0.0582**	-0.0399	0.0548	-0.0468		
	(0.0270)	(0.1524)	(0.0383)	(0.1480)		
Observations	32,939	32,939	32,939	32,939	25,693	25,693
R-squared	0.1987	0.2143	0.2032	0.2179	0.7183	0.7196
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

PANEL B: Number of days in leave	(1)	(2)	(3)	(4)	(5)	(6)
Eligible	23.4966***	23.6062***	23.5154***	23.6269***	25.0880***	25.0315***
	(3.1390)	(3.0851)	(3.1254)	(3.0758)	(2.8436)	(2.8380)
Constant	123.0422***	116.6796***	122.8987***	116.2995***		
	(1.6152)	(9.0928)	(2.3321)	(8.8084)		
Observations	32,939	32,939	32,939	32,939	25,693	25,693
R-squared	0.1921	0.2079	0.1967	0.2116	0.7161	0.7174
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption). In Panel A we present estimates in which the dependent variable is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). We regress this indicator variable on a series of individual controls and fixed effects (as indicated at the bottom of the table) as a robustness check. Similarly, in Panel B, we present estimates in which the dependent variable is substituted by the total number of days on leave. The main variable of interest is the indicator of eligibility, E_i, as defined in subsection 4.1. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 5: Effects of Extended Maternity Leave on Employment

months relative to leave starting dates	Regression			Employment Rates	
	ITT		LATE-IV	Non Eligible	Eligible
	(1)	(2)	(3)	(4)	(5)
-60	0.0028	0.0119	0.0070	0.608	0.621
-48	0.0025	0.0105	0.0062	0.672	0.683
-36	0.0067	0.0137*	0.0167	0.735	0.749
-24	0.0099*	0.0154**	0.0247*	0.809	0.825
-12	-0.0055	-0.0034	-0.0137	0.933	0.930
-9	-0.0064**	-0.0056*	-0.0159*	0.965	0.960
-6	-0.0037	-0.0035	-0.0091	0.983	0.980
-3	-0.0013	-0.0014	-0.0032	0.994	0.993
1	-0.0008**	-0.0008**	-0.0020**	1.000	1.000
2	-0.0002	-0.0002	-0.0006	1.000	1.000
3	-0.0004	-0.0004	-0.0010	1.000	1.000
4	-0.0004	-0.0003	-0.0011	0.999	0.999
5	0.0100***	0.0107***	0.0250***	0.982	0.993
6	0.0336***	0.0345***	0.0836***	0.946	0.981
7	0.0383***	0.0397***	0.0954***	0.905	0.945
8	0.0264***	0.0284***	0.0658***	0.869	0.898
9	0.0192***	0.0213***	0.0477**	0.841	0.863
10	0.0123	0.0149*	0.0306	0.820	0.836
11	0.0037	0.0066	0.0092	0.808	0.815
12	-0.0010	0.0020	-0.0025	0.797	0.799
24	0.0051	0.0064	0.0130	0.749	0.756
36	0.0026	0.0065	0.0067	0.726	0.733
48	-0.0028	0.0021	-0.0072	0.710	0.713
60	-0.0001	0.0050	-0.0002	0.685	0.691
Observations	32,939	32,939	32,939	-	-
Plant FE	No	No	No	-	-
Month-ML FE	Yes	No	Yes	-	-
Controls	Yes	No	Yes	-	-

Notes: This table presents the main effects of extended maternity leave on employment over the months, based on the main econometric model as in Equation 1 detailed in subsection 4.1. The dependent variables are indicator variables equal to 1 if a mother is formally employed $r \in \{-60, ..., +60\}$ months before/after the maternity leave. Thus, each point estimate in this table is based on a separate (one for each r) regression allowing us to show the patterns of employment across different horizons in r. Column 1 shows the intention-to-treat effect of being eligible for an extension, and column 2 exhibits its sensitivity to the exclusion of control variables (education, race, age, occupation, wage, and hours worked per week) at the moment of the maternity leave. Accounting for imperfect compliance, column 3 complements this analysis by showing the local average treatment effect (LATE), in which eligibility E_i is first used as an instrument for the leave extension indicator and then (in a second stage) affects employment status. Columns 4-5 provides the baseline employment rates for eligible and non-eligible mothers over the months of analysis. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 6: Effects of Extended Maternity Leave on Separations

	Regression			Separation Rates	
months relative to	ITT		LATE-IV	Non Eligible	Eligible
leave starting dates	(1)	(2)	(3)	(4)	(5)
-60	0.0023**	0.0023**	0.0057**	0.010	0.012
-48	0.0004	0.0004	0.0009	0.012	0.012
-36	-0.0018	-0.0018	-0.0044	0.012	0.010
-24	0.0007	0.0006	0.0018	0.010	0.010
-12	-0.0006	-0.0007	-0.0015	0.005	0.004
-9	-0.0005	-0.0006	-0.0013	0.003	0.002
-6	0.0005	0.0005	0.0012	0.001	0.001
-3	0.0000	-0.0000	0.0000	0.000	0.000
1	0.0000	-0.0000	0.0000	-0.000	-0.000
2	0.0000	0.0000	0.0001	0.000	0.000
3	0.0000	-0.0001	0.0000	0.001	0.001
4	-0.0105***	-0.0110***	-0.0262***	0.017	0.006
5	-0.0229***	-0.0234***	-0.0571***	0.037	0.013
6	-0.0052	-0.0056*	-0.0130	0.042	0.037
7	0.0113***	0.0106***	0.0282***	0.039	0.050
8	0.0075***	0.0072***	0.0188***	0.031	0.038
9	0.0064***	0.0059***	0.0160***	0.025	0.031
10	0.0065***	0.0062***	0.0162***	0.019	0.025
11	0.0030*	0.0027	0.0075*	0.019	0.021
12	0.0005	0.0002	0.0013	0.018	0.018
24	0.0009	0.0007	0.0022	0.014	0.014
36	-0.0002	-0.0005	-0.0006	0.013	0.013
48	0.0006	0.0004	0.0016	0.013	0.013
60	-0.0002	-0.0005	-0.0004	0.011	0.010
Observations	32,939	32,939	32,939	-	-
Plant FE	No	No	No	-	-
Month-ML FE	Yes	No	Yes	-	-
Controls	Yes	No	Yes	-	-

Notes: This table presents the main effects of extended maternity leave on separations over the months, based on the main econometric model as in Equation 1 detailed in subsection 4.1. The dependent variables are indicator variables equal to 1 if a mother is separated from employment $r \in \{-60, ..., +60\}$ months before/after the maternity leave. Thus, each point estimate in this table is based on a separate (one for each r) regression allowing us to show the patterns of separations across different horizons in r. Column 1 shows the intention-to-treat effect of being eligible for an extension, and column 2 exhibits its sensitivity to the exclusion of control variables (education, race, age, occupation, wage, and hours worked per week) at the moment of the maternity leave. Accounting for imperfect compliance, column 3 complements this analysis by showing the local average treatment effect (LATE), in which eligibility E_i is first used as an instrument for the leave extension indicator and then (in a second stage) affects employment status. Columns 4-5 provides the baseline separation rates for eligible and non-eligible mothers over the months of analysis. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 7: Separation Causes and Other Labor Market Outcomes

PANEL A	Separations			
Months relative to leave starting dates	Total (1)	Fired (2)	Voluntary (3)	Other (4)
-12	-0.0006	-0.0003	-0.0001	-0.0002
-9	-0.0005	-0.0009***	0.0004*	0.0000
-6	0.0005	0.0002	0.0001	0.0002
-3	0.0000	-0.0001	0.0000	0.0001
1	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000	0.0000
3	0.0000	-0.0002*	-0.0003	0.0005
4	-0.0105***	-0.0043***	-0.0072***	0.0010
5	-0.0229***	-0.0108***	-0.0137***	0.0015
6	-0.0052	-0.0073***	0.0001	0.0020**
7	0.0113***	-0.0015	0.0113***	0.0016**
8	0.0075***	0.0028	0.0032***	0.0014***
9	0.0065***	0.0060***	0.0003	0.0001
10	0.0065***	0.0054***	0.0006	0.0005
11	0.0031*	0.0022	0.0007	0.0002
12	0.0005	0.0008	-0.0007	0.0004
PANEL B	Employed			Wage
Months relative to leave starting dates	Total (1)	Same Firm (2)	Other Firm (3)	(number of MW) (4)
-12	-0.0055	-0.0375**	0.0321*	-0.0781***
-9	-0.0064**	-0.0252	0.0188	-0.0633**
-6	-0.0037	-0.0193	0.0156	0.0093
-3	-0.0013	-0.0074	0.0061	0.0248
1	-0.0008**	-0.0012	0.0004	0.0182
2	-0.0002	-0.0004	0.0001	0.0195
3	-0.0004	-0.0005	0.0001	0.0048
4	-0.0004	-0.0006	0.0001	-0.0083
5	0.0100***	0.0120***	-0.0019	0.0523**
6	0.0335***	0.0424***	-0.0089***	0.1902***
7	0.0383***	0.0493***	-0.0110**	0.2216***
8	0.0264***	0.0379***	-0.0114	0.1572***
9	0.0192***	0.0356***	-0.0164	0.1329***
10	0.0123	0.0340**	-0.0217	0.1267***
11	0.0037	0.0334*	-0.0297	0.0901*
12	-0.0011	0.0343*	-0.0354*	0.0799
Observations	32,939	32,939	32,939	32,939
Plant FE	No	No	No	No
Month-ML FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table presents the main effects of extended maternity leave on various labor market outcomes over the months, based on the main econometric model as in Equation 1 detailed in subsection 4.1. Panel A presents results in which the indicator for separation is split into three cases: Fired, Voluntary, and Others. Panel B presents similar results but considering the main variable "Employed" split into two cases: employed at the same firm in which maternity leave is taken or at other firms. Besides, it shows effects on the number of minimum wages earned. Results are presented across selected horizons in r and within 12 months from the leave-taking. Thus, each point estimate in this table is based on a separate (one for each r) regression measuring the intention-to-treat effect of being eligible for an extension and its patterns. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 8: Take-up by Social/Economic Background: Education, Wage, Race and Managerial Position

	Extended Leave	Test for Diff.	Take-up Ratio
	(1)	(2)	(3)
PANEL A: Education			
Eligible x Less than HS	0.3011***		0.7498
	(0.0484)		
Eligible x HS	0.3400***	0.0390	0.8466
	(0.0495)	(0.0501)	
Eligible x College+	0.4717***	0.1706*	1.1746
	(0.0821)	(0.0919)	
PANEL B: Wage			
Eligible x Lowest tercile wage distribution	0.3149***		0.7841
	(0.0455)		
Eligible x Middle tercile wage distribution	0.4512***	0.1362**	1.1235
	(0.0576)	(0.0580)	
Eligible x Highest tercile wage distribution	0.4445***	0.1296	1.1068
	(0.0793)	(0.0815)	
PANEL C: Race			
Eligible x Black/Brown	0.2940***		0.7321
	(0.0522)		
Eligible x Non-Black/Brown	0.4349***	0.1409***	1.0829
	(0.0543)	(0.0407)	
PANEL A: Manager			
Eligible x Non-Manager	0.4002***		0.9965
	(0.0518)		
Eligible x Manager	0.4235***	0.0233	1.0545
	(0.0752)	(0.0592)	
Observations	32,939	32,939	-
Plant FE	No	No	-
Month-ML FE	Yes	Yes	-
Controls	Yes	Yes	-

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption).The dependent variable (in column 1) is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). The main variable of interest is the indicator of eligibility, E_i, as defined in subsection 4.1, which is interacted with individual demographic characteristics. In Panel A we observe heterogeneous take-up rate by level of education. Panel B shows heterogeneous effect in different wage tertiles. Panel C shows heterogeneity by race and Panel D by Managerial Position in the firm. Column (2) presents analogous results as in column (1), in which the econometric model is adapted to allow testing for the significance of difference in take-up rates. Finally, column (3) shows the ratio between take-up rates among each group (by education, wage, race, managerial position) relative to the overall take-up rate (around 40%). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 9: Learning from Peers: Heterogeneous Take-up Rate by the Order of Maternity-Leave in the Firm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	Extended Leave		Extended Leave		Extended Leave		Extended Leave		Extended Leave		Extended Leave	
Panel A: sample of women taking leave until 48 months after EC adoption												
Elilgible x first	0.3868***		0.3902***		0.3814***		0.3849***		0.4010***		0.3987***	
	(0.0918)		(0.0786)		(0.0917)		(0.0785)		(0.0503)		(0.0500)	
Elilgible x (2nd-5th)	0.3931***	0.0063	0.4075***	0.0173	0.3872***	0.0058	0.4017***	0.0168	0.4289***	0.0279**	0.4272***	0.0285**
	(0.0696)	(0.0341)	(0.0664)	(0.0227)	(0.0693)	(0.0341)	(0.0661)	(0.0227)	(0.0517)	(0.0113)	(0.0509)	(0.0111)
Elilgible x (6th-9th)	0.4076***	0.0207	0.4321***	0.0419	0.4011***	0.0197	0.4259***	0.0410	0.4459***	0.0449**	0.4445***	0.0458**
	(0.0529)	(0.0853)	(0.0487)	(0.0580)	(0.0524)	(0.0850)	(0.0484)	(0.0578)	(0.0529)	(0.0220)	(0.0520)	(0.0219)
Elilgible x (10th more)	0.4705***	0.0837	0.4730***	0.0828	0.4637***	0.0823	0.4664***	0.0815	0.4718***	0.0707***	0.4707***	0.0720***
	(0.0498)	(0.0747)	(0.0505)	(0.0571)	(0.0500)	(0.0746)	(0.0508)	(0.0571)	(0.0532)	(0.0220)	(0.0522)	(0.0218)
Elilgible		0.3868***		0.3902***		0.3814***		0.3849***		0.4010***		0.3987***
		(0.0918)		(0.0786)		(0.0917)		(0.0785)		(0.0503)		(0.0500)
Observations	145,303	145,303	145,303	145,303	145,303	145,303	145,303	145,303	134,511	134,511	134,511	134,511
Panel B: women taking leave in our final sample												
Elilgible x first	0.3669***		0.3720***		0.3687***		0.3737***		0.3814***		0.3765***	
	(0.0664)		(0.0630)		(0.0658)		(0.0627)		(0.0458)		(0.0457)	
Elilgible x (2nd-5th)	0.3917***	0.0248	0.3947***	0.0227	0.3904***	0.0217	0.3937***	0.0200	0.3994***	0.0180	0.3982***	0.0217*
	(0.0429)	(0.0494)	(0.0426)	(0.0416)	(0.0430)	(0.0482)	(0.0427)	(0.0411)	(0.0453)	(0.0115)	(0.0451)	(0.0117)
Elilgible x (6th-9th)	0.4521***	0.0852	0.4479***	0.0758	0.4482***	0.0795	0.4445***	0.0709	0.4466***	0.0652***	0.4476***	0.0712***
	(0.0416)	(0.0582)	(0.0415)	(0.0522)	(0.0428)	(0.0574)	(0.0425)	(0.0518)	(0.0440)	(0.0216)	(0.0440)	(0.0227)
Elilgible x (10th more)	0.4860***	0.1191	0.4774***	0.1054	0.4866***	0.1179	0.4778***	0.1041	0.5100***	0.1286**	0.5115***	0.1350**
	(0.0944)	(0.0747)	(0.0881)	(0.0703)	(0.0930)	(0.0745)	(0.0872)	(0.0700)	(0.0739)	(0.0608)	(0.0746)	(0.0629)
Elilgible		0.3669***		0.3720***		0.3687***		0.3737***		0.3814***		0.3765***
		(0.0664)		(0.0630)		(0.0658)		(0.0627)		(0.0458)		(0.0457)
Observations	32,939	32,939	32,939	32,939	32,939	32,939	32,939	32,939	25,683	25,683	25,683	25,683
Plant FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Month-ML FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption). The dependent variable is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). The main variable of interest is the indicator of eligibility, E_i, which is interacted with a set of variables indicating how many mothers took maternity leave previously in the same firm, as defined in equation 2 and discussed in subsection 6.2. In particular, we estimate heterogeneous effect comparing women who are the first to take leave in a given firm, among the 2nd-5th leaves, 6th-9th leaves in the firm, or 10th or more. In odd columns we omit the dummy, E_i, in order to compare the magnitudes, while in even columns in present a variation of the model which allow us to test the statistical significance of the differences observed. Panel A (Panel B) presents estimates based on our main analysis sample and focused on mothers with (without) College degree. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 10: Learning from Peers and Education (College *v.s* Non-College): Heterogeneous Take-up Rate by the Order of Maternity-Leave in the Firm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	Extended Leave		Extended Leave		Extended Leave		Extended Leave		Extended Leave		Extended Leave	
Panel A: women without College												
Elilgible x first	0.2682***		0.2774***		0.2689***		0.2786***		0.2764***		0.2663***	
	(0.0459)		(0.0485)		(0.0434)		(0.0454)		(0.0495)		(0.0495)	
Elilgible x (2nd-5th)	0.2960***	0.0278	0.3010***	0.0236	0.2958***	0.0269	0.3005***	0.0220	0.3116***	0.0352***	0.3097***	0.0434***
	(0.0485)	(0.0383)	(0.0461)	(0.0395)	(0.0481)	(0.0361)	(0.0460)	(0.0367)	(0.0529)	(0.0112)	(0.0525)	(0.0118)
Elilgible x (6th-9th)	0.3968***	0.1286***	0.3883***	0.1109**	0.3930***	0.1241***	0.3846***	0.1061**	0.4090***	0.1326***	0.4110***	0.1447***
	(0.0531)	(0.0444)	(0.0508)	(0.0458)	(0.0553)	(0.0466)	(0.0523)	(0.0443)	(0.0552)	(0.0263)	(0.0543)	(0.0276)
Elilgible x (10th more)	0.5714***	0.3032***	0.5472***	0.2699***	0.5692***	0.3003***	0.5454***	0.2668***	0.5431***	0.2667***	0.5476***	0.2813***
	(0.0802)	(0.0792)	(0.0720)	(0.0700)	(0.0811)	(0.0809)	(0.0733)	(0.0703)	(0.0683)	(0.0635)	(0.0687)	(0.0652)
Elilgible		0.2682***		0.2774***		0.2689***		0.2786***		0.2764***		0.2663***
		(0.0459)		(0.0485)		(0.0434)		(0.0454)		(0.0495)		(0.0495)
Observations	16,643	16,643	16,643	16,643	16,643	16,643	16,643	16,643	13,356	13,356	13,356	13,356
Panel B: women with College												
Elilgible x first	0.4533***		0.4548***		0.4550***		0.4563***		0.5047***		0.5043***	
	(0.1008)		(0.0958)		(0.0997)		(0.0953)		(0.0602)		(0.0582)	
Elilgible x (2nd-5th)	0.5145***	0.0612	0.5152***	0.0603	0.5113***	0.0563	0.5130***	0.0567	0.5181***	0.0134	0.5177***	0.0134
	(0.0482)	(0.0613)	(0.0509)	(0.0535)	(0.0503)	(0.0581)	(0.0523)	(0.0517)	(0.0494)	(0.0194)	(0.0491)	(0.0183)
Elilgible x (6th-9th)	0.5152***	0.0619	0.5150***	0.0602	0.5119***	0.0569	0.5130***	0.0567	0.4964***	-0.0082	0.4998***	-0.0045
	(0.0433)	(0.0881)	(0.0457)	(0.0783)	(0.0449)	(0.0836)	(0.0470)	(0.0756)	(0.0514)	(0.0274)	(0.0526)	(0.0269)
Elilgible x (10th more)	0.4169***	-0.0363	0.4218***	-0.0331	0.4215***	-0.0335	0.4251***	-0.0312	0.4758***	-0.0288	0.4748***	-0.0295
	(0.1297)	(0.0819)	(0.1264)	(0.0770)	(0.1258)	(0.0795)	(0.1233)	(0.0756)	(0.1139)	(0.0737)	(0.1141)	(0.0755)
Elilgible		0.4533***		0.4548***		0.4550***		0.4563***		0.5047***		0.5043***
Observations	16,296	16,296	16,296	16,296	16,296	16,296	16,296	16,296	10,938	10,938	10,938	10,938
Plant FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Month-ML FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption). The dependent variable is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). The main variable of interest is the indicator of eligibility, E_i, which is interacted with a set of variables indicating how many mothers took maternity leave previously in the same firm, as defined in equation 2 and discussed in subsection 6.2. In particular, we estimate heterogeneous effect comparing women who are the first to take leave in a given firm, among the 2nd-5th leaves, 6th-9th leaves in the firm, or 10th or more. In odd columns we omit the dummy, E_i, in order to compare the magnitudes, while in even columns in present a variation of the model which allow us to test the statistical significance of the differences observed. Panel A considers an extended sample with mothers taking leave up to 48 months after EC adoption. Panel B show similar results considering our main analysis sample. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 11: Heterogeneous Take-up Rate by Workers' Ability and Firms' Premium

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Extended Leave		Extended Leave		Extended Leave	
Eligible		0.3482***		0.2852***		0.2574***
		(0.0472)		(0.0557)		(0.0578)
High ability x Eligible	0.4553***	0.1071*				
	(0.0678)	(0.0591)				
Low ability x Eligible	0.3482***	*(baseline)*				
	(0.0472)					
High premium x Eligible			0.4710***	0.1858**		
			(0.0723)	(0.0917)		
Low premium x Eligible			0.2852***	*(baseline)*		
			(0.0557)			
Low ability x Low premium x Eligible					0.2574***	*(baseline)*
					(0.0578)	
Low ability x High premium x Eligible					0.4680***	0.2106**
					(0.0637)	(0.0869)
High ability x Low premium x Eligible					0.3761***	0.1187***
					(0.0537)	(0.0401)
High ability x High premium x Eligible					0.4724***	0.2150**
					(0.0818)	(0.1003)
Observations	32,882	32,882	32,920	32,920	32,882	32,882
Plant FE	No	No	No	No	No	No
Month-ML FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption). The dependent variable is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). The main variable of interest is the indicator of eligibility, E_i, which is interacted with a set of variables indicating groups of premium-ability, as discussed in subsection 6.4. To create measures of firm premium and worker's ability, we first estimate an AKM model as described in 4. Then we classify firms (workers) as low/high premium (ability) according to these measures being below/above the median in our sample data. Finally, we create four groups of premium-ability (low-low, low-high, high-low, and high-high) and interact dummies for these groups with the dummy for eligibility status, E_i. Columns 1 and 2 (3 and 4) present heterogenous take-up rates by workers' ability (firm's premium). Columns 5 and 6 present the more general result in which we combine these two groups (for ability and premium) into the four potential groups as described above. Besides, odd columns highlight the differences in magnitudes, while even columns are modified versions of the original model allowing to test for the significance in differences observed in take-up rates for each group. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

Table 12: Heterogeneous Take-up Rate by Workers' Substitutability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Overall	***Split by Firm Size (number of employees)***					***Type of Task***	
Dep. Variable		*size<=15*	*size<=25*	*size <=50*	*size <=100*	*size >100*	*Non-Routine*	*Routine*
Eligible x zero sub	0.3277***	0.2659**	0.2979***	0.3053***	0.3115***	0.3774***	0.2992***	0.3944***
	(0.0580)	(0.1098)	(0.1016)	(0.0900)	(0.0790)	(0.0395)	(0.0729)	(0.0540)
Eligible x sub [1-2]	0.3555***	0.2996***	0.3181**	0.3320***	0.3362***	0.3934***	0.3502***	0.3499***
	(0.0677)	(0.1137)	(0.1236)	(0.1086)	(0.0946)	(0.0406)	(0.0892)	(0.0502)
Eligible x sub [3-9]	0.3773***	0.4222***	0.3861***	0.3880***	0.3647***	0.4051***	0.4443***	0.2967***
	(0.0755)	(0.1322)	(0.1285)	(0.1216)	(0.1089)	(0.0356)	(0.0921)	(0.0475)
Eligible x 10 or more	0.4177***	0.7544***	0.6279***	0.5723***	0.4801***	0.4052***	0.4866***	0.3561***
Difference in take-up								
Eligible	0.3277***	0.2659**	0.2979***	0.3053***	0.3115***	0.3774***	0.2992***	0.3944***
	(0.0580)	(0.1098)	(0.1016)	(0.0900)	(0.0790)	(0.0395)	(0.0729)	(0.0540)
Eligible x zero sub	*(baseline)*	*(baseline)*	*(baseline)*	*(baseline)*	*(baseline)*	*(baseline)*	*(baseline)*	*(baseline)*
Eligible x sub [1-2]	0.0279	0.0336	0.0201	0.0267	0.0246	0.0160	0.0510	-0.0444
	(0.0252)	(0.0357)	(0.0374)	(0.0325)	(0.0295)	(0.0498)	(0.0318)	(0.0599)
Eligible x sub [3-9]	0.0496	0.1563**	0.0882	0.0828	0.0532	0.0277	0.1451***	-0.0977
	(0.0378)	(0.0637)	(0.0550)	(0.0534)	(0.0509)	(0.0451)	(0.0407)	(0.0671)
Eligible x 10 or more	0.0901*	0.4885***	0.3300**	0.2671**	0.1686	0.0278	0.1874***	-0.0383
Observations	32,939	2,260	4,314	7,375	10,343	22,596	14,958	12,367
Plant FE	No	No	No	No	No	No	No	No
Month-ML FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the first stage regression to estimate the difference in take-up rates between eligible workers (taking maternity leave at some point between 180 and 360 days before a firm join EC Program) and non-eligible workers (taking maternity leave up to 180 days after EC adoption). The dependent variable is an indicator equals 1 if a mother decides to take the leave extension (from 120 to 180 days). The main variable of interest is the indicator of eligibility, E_i, which is interacted with a set of variables indicating groups according to the number of substitutes within the firm at the time of the leave: zero substitutes, 1 or 2 substitutes, from 3 up to 9 substitutes and 10 or more substitutes within the firm. Columns 1 presents the results for the full sample analysis, and we also show heterogeneous estimates in subsamples split according to firm sizes (columns 2-6) or type of task performed (column 7-8). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results are clustered at the firm level.

A Appendix: Labor Market in Brazil

Table A.1: Descriptive Statistics for Women in the Labor Market in Brazil

	People aged 25-44				People aged 25-44 Legally employed in priv. sec.				Additionally, who had Child in the last 12 months	
	Women		Men		Women		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Head of Family	0.319	0.466	0.572	0.495	0.318	0.466	0.580	0.494	0.308	0.462
Urban	0.869	0.337	0.853	0.355	0.971	0.169	0.949	0.221	0.973	0.163
Black or Mulatto	0.541	0.498	0.562	0.496	0.447	0.497	0.522	0.500	0.467	0.499
Age in years	34.419	5.632	34.315	5.658	33.520	5.535	33.841	5.574	31.440	4.308
Worked on reference week	0.620	0.485	0.856	0.351	1.000	0.000	1.000	0.000	1.000	0.000
Employed in private sector	0.719	0.450	0.853	0.354	1.000	0.000	1.000	0.000	1.000	0.000
Legally employed	0.689	0.463	0.755	0.430	1.000	0.000	1.000	0.000	1.000	0.000
Legally employed in private sector	0.384	0.486	0.436	0.496	1.000	0.000	1.000	0.000	1.000	0.000
>30 min. from home to work	0.334	0.472	0.354	0.478	0.406	0.491	0.426	0.494	0.349	0.477
Average number of hours of work per week	0.620	0.485	0.856	0.351	1.000	0.000	1.000	0.000	1.000	0.000
Full time	0.408	0.492	0.720	0.449	0.864	0.342	0.926	0.262	0.881	0.324
Contributed to social security	0.683	0.465	0.664	0.472	1.000	0.000	1.000	0.000	1.000	0.000
Number of years worked on this job	5.205	5.705	6.229	6.553	3.935	4.258	4.677	4.996	3.917	3.574
Age when started working	16.261	4.441	14.801	3.732	16.933	3.893	15.446	3.410	16.958	3.578
Economically active	0.726	0.446	0.933	0.250	1.000	0.000	1.000	0.000	1.000	0.000
Did Household chores in the ref. week	0.923	0.267	0.542	0.498	0.891	0.311	0.565	0.496	0.935	0.246
Tried to find work last month	0.013	0.113	0.016	0.126	0.014	0.117	0.013	0.115	0.005	0.069
Student	0.072	0.258	0.056	0.230	0.082	0.275	0.061	0.240	0.046	0.209
Literate	0.970	0.170	0.950	0.219	0.997	0.054	0.989	0.102	0.998	0.041
Years of schooling	10.855	3.991	10.054	4.164	12.358	3.013	11.086	3.431	12.489	2.940
Monthly income from main job	1,720.737	2,758.719	2,219.650	3,097.427	1,921.605	2,751.511	2,253.463	2,851.250	1,816.086	2,263.994
Monthly income from all occupations	1,771.645	2,829.786	2,275.167	3,167.356	1,952.890	2,796.593	2,292.162	2,894.385	1,836.766	2,282.714
Monthly income from all sources	1,274.716	2,526.570	2,044.396	3,103.970	2,006.279	2,844.597	2,309.695	2,925.040	1,870.325	2,276.200
Monthly household income per capita	3,695.737	4,182.499	3,787.712	4,195.140	4,630.138	4,275.417	4,073.062	4,004.291	4,702.002	4,428.078
Had a child in the last 12 months	0.053	0.224	-	-	0.035	0.183	-	-	1.000	0.000

Source: PNAD 2015.

Table A.2: Female and Male Employment by Child Age in Brazil

	(1)	(2)
	Fraction Working	Fraction Working ≥ 35
Panel A: Women 25-44		
All	0.6452	0.4537
Conditional on age of youngest child:		
1 month	0.2942	0.1799
3 months	0.2880	0.1971
6 months	0.3510	0.2295
1 year	0.4171	0.2801
3 years	0.4948	0.3284
6 years	0.5477	0.3595
Panel B: Men 25-44		
All	0.8800	0.7765
Conditional on age of youngest child:		
1 month	0.89120	0.80191
6 months	0.92708	0.81822
1 year	0.92872	0.82438
6 years	0.92775	0.82585

Source: PNAD 2015

B Appendix: matching RAIS to Receita data

We first divide the list of adopters from *Receita Federal*, based on the years in which the firms decide to participate in EC program (see Table B.1). We then match, per each year from 2010 to 2014, these firms to RAIS to keep all jobs reported by EC firms in RAIS (see Table B.2 for matching numbers).

Table B.3 summarize the firms in RAIS matched and unmatched to adopters from *Receita Federal*. In general, we cannot find in RAIS smaller firms (such as micro-entrepreneurs and individual micro-entrepreneurs). After we find EC firms in RAIS, we restrict our data to the highest paying job for all women who took maternity leave in these companies. In Table B.4 we show the number of firms and workers we have after applying the restrictions step by step.

RAIS is an annual cumulative data for all jobs reported by firms in a given year. The instructions to fill out dates of maternity leaves says that if a worker starts the year on leave (which indeed was taken in the previous year), the information on start dates must be reported as of January 1st. On the other hand, if a worker is on leave at the end of the year (even continuing on leave in the next one), the end dates of maternity leave for that year must be reported as of December 31st.

Therefore, to calculate the correct start and end dates for each maternity leave, it is worth to merge two consecutive years in order to pick information on the actual start/end dates. To do so, we first split the data for each year based on the date in which maternity leave starts/ends, so that we have those leaves starting on January first, starting and ending within a given year, and ending on December 31th (see Table B.5). Then, we match the correspondent years to recover the correct information on the start and end dates of leave (see Table B.6).

Finally, after we fix the start and end dates of each maternity leave, we then calculate the length of each maternity leave starting at some point between 2009 and 2015 (see Table B.7). Furthermore, we restrict our datasets to maternity leave lasting a total of 120 days (standard maternity leave period), 135 days (standard period plus two weeks) or 180 days (extended maternity leave).[41] These are the regular leave taking spells, and these restrictions eliminate reporting errors as well as shorter leaves due to adoption or abortion (see Table B.8). Finally, we restrict our sample to workers taking maternity leave within a margin of 360 days distant from the time in which the companies decided to become an EC firm.

[41] In fact, we allow a 2-days margin of error to each one of them, i.e., we consider maternity leave periods lasting 118-122, 133-137 or 178-182 days.

Table B.1: Adopters of EC Program

Year	# Companies	% joing EC Program	% EC Program (2010-2014)
2010	10,898	55.83%	59.94%
2011	4,714	24.15%	25.93%
2012	1,035	5.30%	5.69%
2013	777	3.98%	4.27%
2014	757	3.88%	4.16%
2015	709	3.63%	-
2016	629	3.22%	-
Total	**19,519**		
Total 2010-2014	**18,181**		

Table B.2: Matching between RAIS and the list of EC from *Receita Federal*

Year	EC	Found in...	contracts (plant-worker)	firms	plants	workers
2010	10,898	both	2,234,725	5,249	35,739	2,030,453
		RAIS only	64,512,577	2,615,997	3,323,397	52,145,558
		EC only	-	5,649	-	-
2011	4,714	both	801,186	1,682	7,590	707,164
		RAIS only	70,169,939	2,776,793	3,533,610	56,107,757
		EC only	-	3,032	-	-
2012	1,035	both	286,350	671	2,010	275,675
		RAIS only	73,040,135	2,886,396	3,643,395	58,521,225
		EC only	-	364	-	-
2013	777	both	245,164	592	1,500	239,044
		RAIS only	75,155,346	3,011,451	3,784,342	60,292,532
		EC only	-	185	-	-
2014	757	both	310,768	610	1,861	294,319
		RAIS only	75,796,511	3,111,787	3,893,181	61,274,041
		EC only	-	147	-	-
		Total Matching	3,878,193	8,804	48,700	3,546,655

Table B.3: Matching and non-matching by firm's type

Type	**Matched** abs.	**Matched** percent	**Unmatched** abs.	**Unmatched** percent(%)
MEI	33	0.37%	1,845	17.22%
ME	3,005	34.13%	5,576	52.04%
EPP	1,177	13.37%	389	3.63%
LTDA	2,811	31.93%	1,369	12.78%
SA	700	7.95%	166	1.55%
Others	1,078	12.24%	1,370	12.79%
Total	8,804	100.00%	10,715	100.00%

Table B.4: Sequence of filters applied to the original datasets

Found in RAIS	**All contracts in all the 8804 firms**				**...only women**			
Year	**contracts**	**firms**	**plants**	**workers**	**contracts**	**firms**	**plants**	**workers**
2008	3,107,934	7,360	40,241	2,892,040	1,021,670	6,440	36,267	949,874
2009	3,232,347	7,708	44,525	3,013,140	1,102,683	6,756	39,744	1,024,797
2010	3,561,495	8,300	46,494	3,274,692	1,243,454	7,171	41,901	1,136,294
2011	3,782,447	8,091	47,695	3,477,501	1,338,268	7,092	43,156	1,228,614
2012	3,850,871	7,815	49,103	3,593,947	1,407,778	6,902	44,741	1,306,805
2013	3,951,463	7,478	50,486	3,684,198	1,458,017	6,644	46,330	1,353,398
2014	3,898,887	7,169	50,442	3,632,819	1,455,440	6,342	46,442	1,353,360
2015	3,705,945	6,830	50,053	3,450,161	1,400,190	6,042	46,098	1,294,113
2016	3,495,395	6,452	50,566	3,216,730	1,333,888	5,731	46,592	1,212,223
Year	**...took maternity leave**				**...highest wage**			
2008	34,065	2,237	11,194	33,774	34,017	2,237	11,194	33,774
2009	39,897	2,425	12,764	39,281	39,864	2,425	12,764	39,281
2010	45,149	3,046	14,704	44,364	45,108	3,046	14,704	44,364
2011	50,125	3,050	15,863	49,430	50,026	3,050	15,863	49,430
2012	55,036	3,041	16,808	54,497	54,990	3,041	16,808	54,497
2013	60,175	3,141	18,131	59,499	60,127	3,141	18,131	59,499
2014	64,642	3,113	18,913	63,813	64,357	3,113	18,913	63,813
2015	66,597	2,943	19,283	65,989	66,507	2,943	19,283	65,989
2016	64,116	2,732	19,103	62,732	64,007	2,732	19,103	62,732

Table B.5: Separating maternity leaves taken within the year from those at the start/end of the year

Found in...	**starting at 1-Jan**				**ending at 31-Dec**				**within**			
	contracts	**firms**	**plants**	**workers**	**contracts**	**firms**	**plants**	**workers**	**contracts**	**firms**	**plants**	**workers**
2008	7,265	1,034	3,945	7,255	8,620	1,257	4,585	8,608	18,184	1,776	7,650	18,011
2009	9,004	1,261	4,773	8,909	10,052	1,424	5,251	10,031	20,864	1,800	8,613	20,478
2010	10,616	1,396	5,615	10,424	12,184	1,600	6,232	12,173	22,372	2,378	9,684	21,922
2011	12,460	1,586	6,402	12,431	13,545	1,688	6,752	13,535	24,081	2,306	10,108	23,656
2012	14,110	1,661	7,086	14,070	15,488	1,728	7,429	15,478	25,479	2,298	10,649	25,190
2013	15,843	1,721	7,681	15,839	16,844	1,833	7,956	16,840	27,515	2,348	11,481	27,062
2014	17,307	1,797	8,274	17,304	17,877	1,858	8,297	17,872	29,254	2,334	11,937	28,919
2015	18,974	1,824	8,902	18,970	18,488	1,726	8,558	18,481	29,123	2,264	11,939	28,820
2016	19,621	1,717	9,106	19,604	16,481	1,561	7,848	16,472	27,982	2,113	11,702	27,199
							Total LM 2009-2015		**178,688**			

Table B.6: Eliminating duplicate maternity leaves by joining leaves ending on December 31th and beginning on January first

(A) Ending at 31/12 of...	contracts	(B) starting at 01/01 of...	contracts	Matching	
2008	8,620	2009	9,004	both A and B	7,877
				only A	743
				only B	1,127
2009	10,052	2010	10,616	both A and B	9,354
				only A	698
				only B	1,262
2010	12,184	2011	12,460	both A and B	11,043
				only A	1,141
				only B	1,417
2011	13,545	2012	14,110	both A and B	12,661
				only A	884
				only B	1,449
2012	15,488	2013	15,843	both A and B	13,890
				only A	1,598
				only B	1,953
2013	16,844	2014	17,307	both A and B	15,763
				only A	1,081
				only B	1,544
2014	17,877	2015	18,974	both A and B	17,112
				only A	765
				only B	1,862
2015	18,488	2016	19,621	both A and B	17,571
				only A	917
				only B	2,050
				Total LM 2009-2015	**97,394**

Table B.7: Eliminating inaccurate-size for the maternity leaves

Maternity Leaves in 2009-2015	contracts	accurate size	% of accurate size
within	178,688	163,161	91.31%
beggining/end of the year	97,394	93,419	95.92%
Total	276,082	256,580	92.94%

Table B.8: Additional filters

contracts	**firms**	**plants**	**workers**
256,580	5,114	34,083	238,464
Window of 360 days			
66,632	4,154	18,062	65,989
First maternity leave			
65,989	4,150	17,978	65,989

C Appendix: The gradual take-up of leave extensions near adoption dates

Let t_i^{ml} be the calendar time (in days) in which worker i takes maternity leave and t_i^e the calendar time (in days) when firm e (where i works at the time of maternity leave) joined EC Program. We define a running variable as $R_i \equiv t_i^{ml} - t_i^e$.

It is convenient to normalize the calendar time to represent the elapsed time since maternity leave. Precisely, for each worker i we consider the number of months between calendar time, t, and the moment of leave-taking l (i.e., $r = t - l$). We also set the relative time r as the number of months since the month in which the maternity leave started and evaluate its effects on the outcome over r.[42]

We estimate the following equations:

$$D_i = g_r(R_i) + \pi I(R_i \geq 0) + \nu_{ir} \tag{5}$$

$$y_{ir} = f_r(R_i) + \delta_r I(R_i \geq 0) + \eta_{ir} \tag{6}$$

where D_i indicates if the worker take extended maternity leave of 180 days; y_{ir} is the employment indicator (equal 1 if employed and zero otherwise) for women i at r months after the leave event (i.e, when $r = 0$). $I(R_i \geq 0)$ is a dummy variable that takes value one if the woman took the maternity leave after the company, where she was working, adopted EC Program and zero for women who took maternity leave at the same firms but before that time; functions $f_r()$ and $g_r()$ are polynomial distances from the cutoff; and η_{ir} and ν_{ir} are the errors.

We are primarily interested in the patterns of δ_r across different horizons in r. These coefficients measure employment differences between women taking maternity leave after their companies joined EC (and hence are treated) and those taking the leave before that. Therefore, plotting δ_r versus r in a graph we can investigate the impacts of extended maternity leave for each month before and after the leave-taking. Equation 2 estimates the extended leave-taking take up, whereas Equation 3 captures the effects of maternity leave extension from 120 to 180 days on employment.

We further restrict observations around the threshold, by limiting the running variable to 360 days before and after the cutoff (i.e., $R_i \in [-12; 12]$)[43]. Regressions use triangular weights and add individual controls (such as age, race, education, and occupation) for precision.

C.1 Validity of the Research Design and Leave-Taking Take Up

Manipulation of the running variable could occur both by the timing of EC adoption and the time of birth. While it is unlikely that mothers can delay births in order to meet the EC entitlement, firms could plausibly anticipate the adoption of EC depending on the number of pregnant women in

[42] Note that each worker i may have a different relative time, r, but we omit the subscript i in r for the ease of notation.

[43] We normalize the running variable dividing it by 30, so that each unity mena approximately one month

their workforce. We empirically investigate this possibility by plotting the histogram of the running variable in Figure C1 and performing the McCrary test as shown in Figure C2. We find evidence of a small heaping in the distribution of the running variable around the threshold.

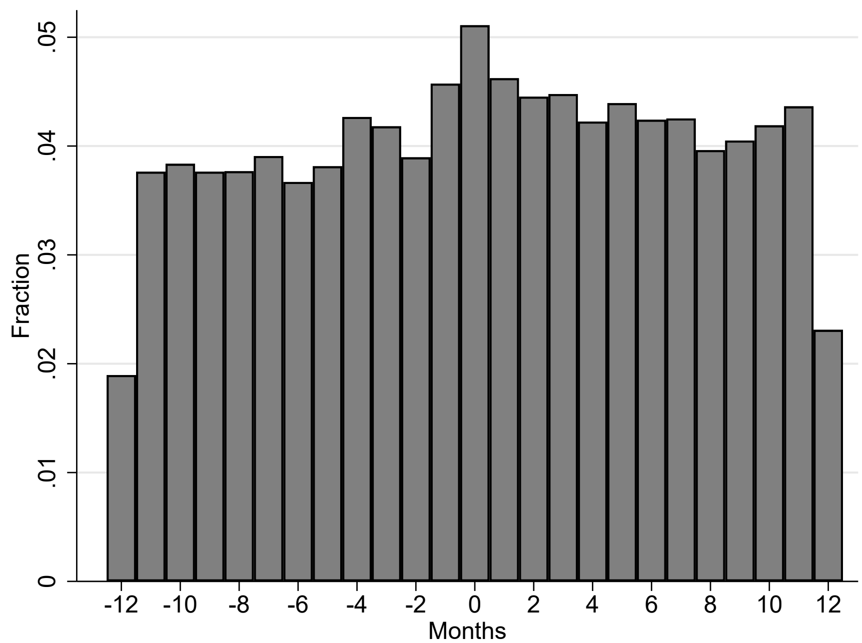


Figure C1: Density of running variable: t_i^{ml} - t_i^{e}

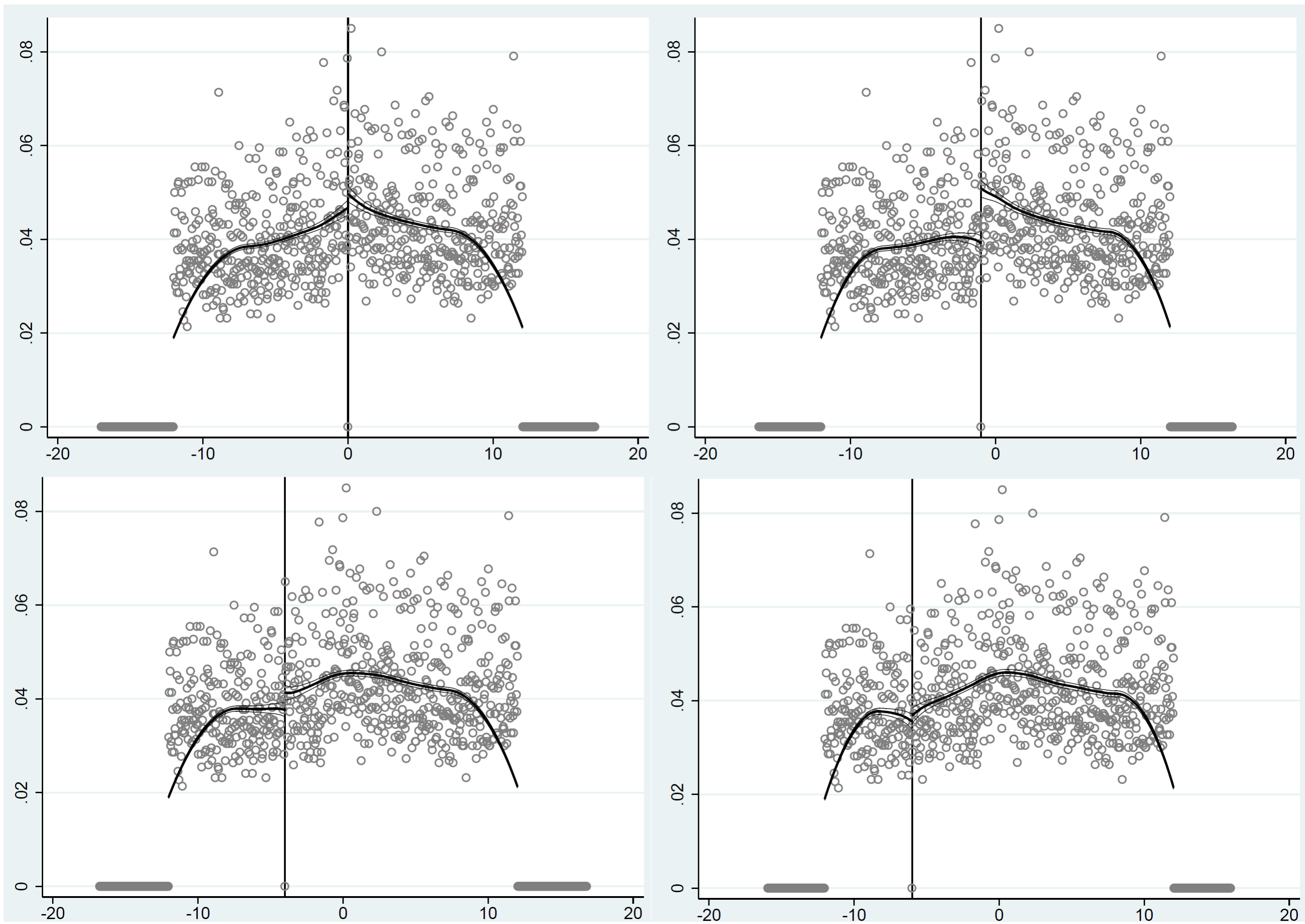


Figure C2: McCrary manipulation test for various cut-offs (in months): Upper-Left (c=0), Upper-Right (c=-1), Bottom-Left (c=-4) and Bottom-Right (c=-6)

A second concern would be if there were a jump in the baseline characteristics of workers around the cutoff qualifying for the extra 60 days in the standard maternity. If this occurs, it would evidence that the assignment to the treatment does not provide us with a treatment variation as good as random around the threshold. We do not find any evidence of discontinuity over a large set of worker's characteristics[44].

Finally, we show visual evidence on the leave extension take-up in Figure C3. In sum, there is no discontinuity in the probability of taking extended maternity leave around the cutoff. More comments and details on this subject can be found in section 3.3 of the paper.

[44] These results are available upon request.

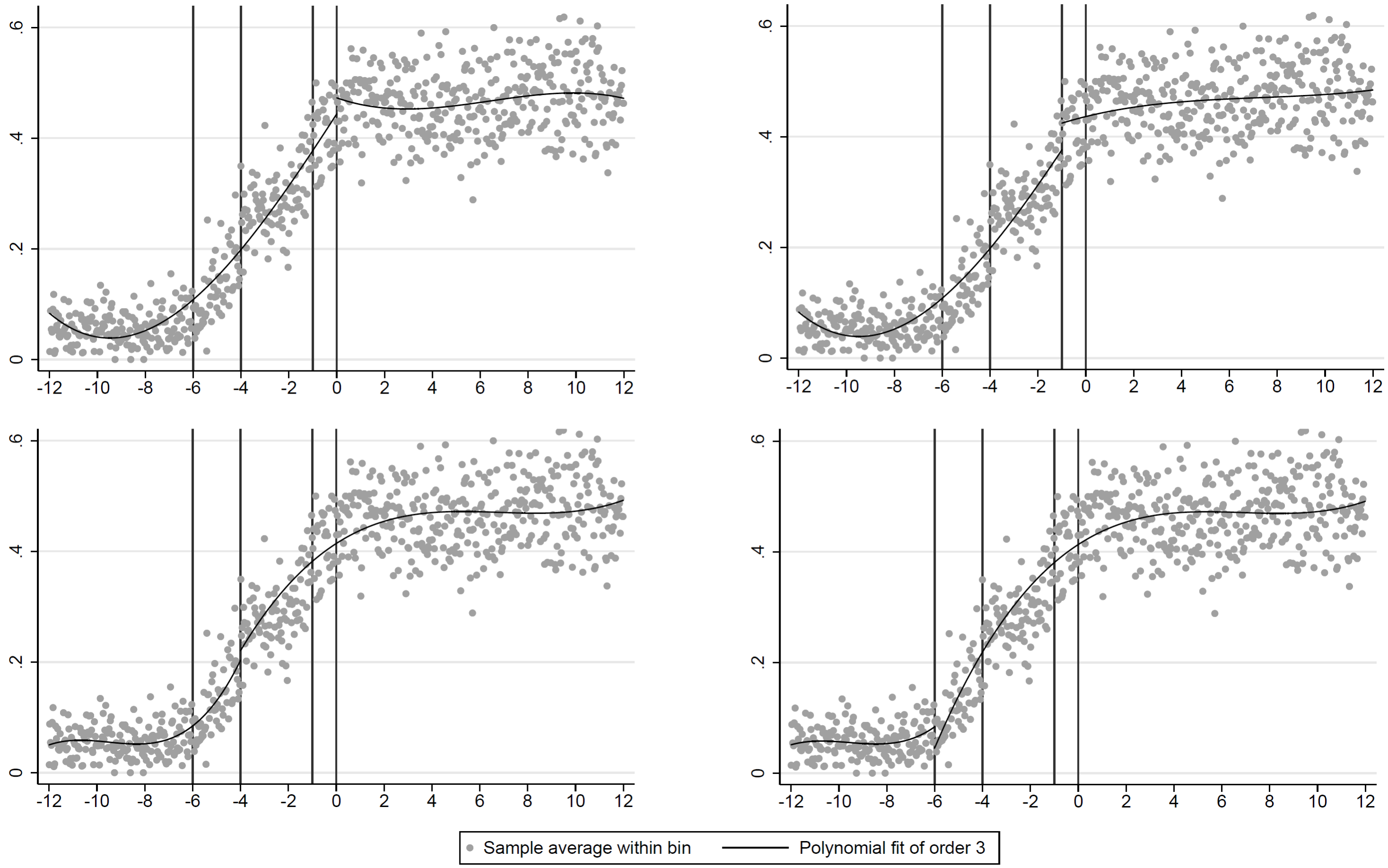


Figure C3: Probability of taking extended maternity leave for various cutoffs (in months): Upper-Left (c=0), Upper-Right (c=-1), Bottom-Left (c=-4) and Bottom-Right (c=-6)

D Appendix: Robustness Analysis

Table D.1: Main results using a window of 60 days

Time since leave-taking	(1)	(2) ITT	(3)	(4)	(5) LATE-IV	(6)
	Empoyed	Separation	Hiring	Empoyed	Separation	Hiring
-60	-0.0049	-0.0001	0.0012	-0.0118	-0.0002	0.0029
-48	-0.0131	-0.0018	0.0008	-0.0314	-0.0043	0.0018
-36	-0.0082	-0.0024	0.0029	-0.0196	-0.0058	0.0070
-24	0.0055	0.0008	0.0007	0.0132	0.0019	0.0017
-12	-0.0054	-0.0012	-0.0050*	-0.0128	-0.0028	-0.0119*
-9	-0.0097*	-0.0007	0.0019	-0.0233*	-0.0016	0.0046
-6	-0.0046	0.0020**	-0.0008	-0.0109	0.0047*	-0.0020
-3	-0.0032	-0.0005	0.0008	-0.0078	-0.0012	0.0019
1	-0.0011	-0.0002	0.0009	-0.0025	-0.0006	0.0021
2	0.0001	0.0003	-0.0004	0.0002	0.0008	-0.0009
3	-0.0006	0.0007	0.0002	-0.0015	0.0016	0.0004
4	-0.0011	-0.0097***	-0.0003	-0.0027	-0.0233***	-0.0007
5	0.0083**	-0.0178**	0.0013**	0.0199**	-0.0427**	0.0032**
6	0.0275***	0.0053	-0.0015	0.0659***	0.0127	-0.0035
7	0.0207	0.0138***	0.0009	0.0497*	0.0332**	0.0022
8	0.0078	0.0058	-0.0000	0.0187	0.0139	-0.0000
9	0.0020	0.0110***	0.0004	0.0048	0.0263**	0.0009
10	-0.0086	0.0070*	-0.0010	-0.0206	0.0167*	-0.0024
11	-0.0166	0.0026	-0.0024	-0.0397	0.0062	-0.0057
12	-0.0215	-0.0029	0.0009	-0.0516	-0.0068	0.0021
24	0.0073	-0.0024	0.0011	0.0176	-0.0057	0.0028
36	-0.0006	-0.0027	-0.0038	-0.0016	-0.0066	-0.0093
48	0.0139	0.0027	-0.0022	0.0335	0.0066	-0.0054
60	0.0252	0.0007	0.0043	0.0605	0.0018	0.0104
Observations	11,366	11,366	11,366	11,366	11,366	11,366
Plant FE	No	No	No	No	No	No
Month-ML FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table D.2: Main results using a window of 120 days

Time since leave-taking	(1)	(2)	(3)	(4)	(5)	(6)
	ITT			LATE-IV		
	Empoyed	Separation	Hiring	Empoyed	Separation	Hiring
-60	-0.0028	0.0026*	0.0026	-0.0068	0.0062	0.0062
-48	-0.0065	0.0004	0.0029	-0.0157	0.0010	0.0069
-36	0.0016	-0.0023	0.0017	0.0039	-0.0056	0.0042
-24	0.0094	0.0009	-0.0027	0.0225	0.0021	-0.0065
-12	-0.0086**	-0.0007	0.0007	-0.0207**	-0.0018	0.0017
-9	-0.0083**	-0.0004	0.0013	-0.0200**	-0.0010	0.0031
-6	-0.0066*	0.0009	0.0017	-0.0159**	0.0021	0.0040
-3	-0.0012	0.0001	-0.0009	-0.0028	0.0002	-0.0022
1	-0.0012*	-0.0001	0.0006*	-0.0028*	-0.0002	0.0013*
2	-0.0005	-0.0000	-0.0002	-0.0013	-0.0000	-0.0004
3	-0.0007	0.0004	0.0000	-0.0016	0.0009	0.0001
4	-0.0010	-0.0088***	0.0003	-0.0025	-0.0210***	0.0007
5	0.0080**	-0.0222***	0.0012**	0.0192**	-0.0531***	0.0029**
6	0.0314***	-0.0002	-0.0014**	0.0752***	-0.0004	-0.0033*
7	0.0302***	0.0133***	-0.0003	0.0723***	0.0319***	-0.0007
8	0.0166*	0.0068**	0.0004	0.0397*	0.0164**	0.0010
9	0.0102	0.0044*	-0.0007	0.0243	0.0105*	-0.0017
10	0.0051	0.0066***	-0.0018	0.0121	0.0157***	-0.0043
11	-0.0033	0.0024	-0.0017	-0.0079	0.0058	-0.0040
12	-0.0074	0.0004	0.0002	-0.0178	0.0008	0.0006
24	0.0067	0.0018	0.0005	0.0162	0.0044	0.0013
36	0.0022	-0.0005	0.0002	0.0052	-0.0011	0.0004
48	-0.0010	-0.0004	-0.0001	-0.0024	-0.0010	-0.0002
60	0.0086	0.0019	0.0020	0.0214	0.0047	0.0050
Observations	22,174	22,174	22,174	22,174	22,174	22,174
Plant FE	No	No	No	No	No	No
Month-ML FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table D.3: Changing the econometric model, keeping a window of 180 days. Dependent variable: Employed

Time since leave-taking	(1) Employed	(2) Employed	(3) Employed	(4) Employed	(5) Employed	(6) Employed
-60	0.0119	0.0027	0.0117	0.0028	0.0163***	0.0063
-48	0.0105	0.0025	0.0103	0.0025	0.0180***	0.0097
-36	0.0138*	0.0067	0.0135*	0.0067	0.0235***	0.0162***
-24	0.0154**	0.0101*	0.0151**	0.0099*	0.0215***	0.0152**
-12	-0.0035	-0.0055	-0.0035	-0.0055	0.0117***	0.0091**
-9	-0.0055*	-0.0065**	-0.0054*	-0.0064**	0.0053*	0.0040
-6	-0.0035	-0.0038	-0.0034	-0.0037	0.0026	0.0022
-3	-0.0014	-0.0014	-0.0013	-0.0013	0.0011	0.0012
1	-0.0008**	-0.0008**	-0.0008*	-0.0008**	-0.0003	-0.0004
2	-0.0002	-0.0002	-0.0002	-0.0002	0.0003	0.0002
3	-0.0004	-0.0004	-0.0004	-0.0004	-0.0002	-0.0002
4	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
5	0.0107***	0.0103***	0.0104***	0.0100***	0.0128***	0.0126***
6	0.0346***	0.0338***	0.0343***	0.0336***	0.0402***	0.0394***
7	0.0397***	0.0385***	0.0395***	0.0383***	0.0439***	0.0424***
8	0.0284***	0.0263***	0.0285***	0.0264***	0.0289***	0.0270***
9	0.0212***	0.0188**	0.0216***	0.0192***	0.0230***	0.0213***
10	0.0149*	0.0118	0.0153*	0.0123	0.0155**	0.0133*
11	0.0066	0.0032	0.0070	0.0037	0.0085	0.0061
12	0.0021	-0.0015	0.0025	-0.0010	0.0050	0.0024
24	0.0064	0.0047	0.0069	0.0051	0.0020	0.0000
36	0.0065	0.0024	0.0066	0.0026	0.0009	0.0000
48	0.0020	-0.0033	0.0026	-0.0028	-0.0054	-0.0065
60	0.0049	-0.0003	0.0051	-0.0001	-0.0031	-0.0052
Observations	32,939	32,939	32,939	32,939	25,693	25,693
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Table D.4: Changing the econometric model, keeping a window of 180 days. Dependent variable: Separation

Time since leave-taking	(1) Separation	(2) Separation	(3) Separation	(4) Separation	(5) Separation	(6) Separation
-60	0.0023**	0.0024**	0.0022**	0.0023**	0.0017	0.0014
-48	0.0004	0.0005	0.0003	0.0004	-0.0002	-0.0004
-36	-0.0018	-0.0017	-0.0019	-0.0018	-0.0005	-0.0005
-24	0.0006	0.0008	0.0005	0.0007	-0.0003	-0.0002
-12	-0.0007	-0.0006	-0.0007	-0.0006	-0.0017*	-0.0016*
-9	-0.0006	-0.0005	-0.0006	-0.0005	-0.0002	-0.0001
-6	0.0005	0.0005	0.0005	0.0005	-0.0001	-0.0002
-3	-0.0000	0.0000	-0.0000	0.0000	-0.0004	-0.0004
1	-0.0000	0.0000	-0.0000	0.0000	0.0001	0.0001
2	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001
3	-0.0001	-0.0000	-0.0000	0.0000	0.0003	0.0003
4	-0.0110***	-0.0107***	-0.0108***	-0.0105***	-0.0131***	-0.0129***
5	-0.0234***	-0.0229***	-0.0233***	-0.0229***	-0.0272***	-0.0267***
6	-0.0056*	-0.0051	-0.0057*	-0.0052	-0.0045	-0.0038
7	0.0106***	0.0116***	0.0104***	0.0113***	0.0140***	0.0145***
8	0.0073***	0.0078***	0.0071***	0.0075***	0.0061**	0.0060**
9	0.0059***	0.0065***	0.0058***	0.0064***	0.0059***	0.0064***
10	0.0062***	0.0065***	0.0062***	0.0065***	0.0044**	0.0047**
11	0.0027	0.0031*	0.0026	0.0030*	0.0020	0.0023
12	0.0002	0.0006	0.0001	0.0005	0.0006	0.0006
24	0.0006	0.0009	0.0006	0.0009	-0.0019	-0.0017
36	-0.0005	-0.0002	-0.0005	-0.0002	-0.0009	-0.0010
48	0.0004	0.0008	0.0002	0.0006	-0.0010	-0.0011
60	-0.0005	-0.0001	-0.0005	-0.0002	-0.0012	-0.0012
Observations	32,939	32,939	32,939	32,939	25,693	25,693
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Table D.5: Changing the econometric model, keeping a window of 180 days. Dependent variable: Hiring

Time since leave-taking	(1) Hiring	(2) Hiring	(3) Hiring	(4) Hiring	(5) Hiring	(6) Hiring
-60	0.0011	0.0013	0.0011	0.0012	-0.0004	-0.0005
-48	0.0017	0.0018	0.0016	0.0017	0.0006	0.0005
-36	0.0023*	0.0027**	0.0023*	0.0027**	0.0007	0.0009
-24	-0.0020	-0.0015	-0.0020	-0.0014	-0.0018	-0.0013
-12	0.0012	0.0017	0.0011	0.0016	-0.0012	-0.0009
-9	0.0007	0.0011	0.0007	0.0010	-0.0011	-0.0007
-6	0.0011	0.0013	0.0012	0.0013	-0.0010	-0.0008
-3	-0.0004	-0.0004	-0.0004	-0.0004	-0.0017**	-0.0019**
1	0.0006***	0.0006***	0.0006***	0.0006***	0.0007**	0.0007**
2	-0.0002	-0.0001	-0.0002	-0.0002	-0.0005*	-0.0005**
3	-0.0000	-0.0000	-0.0000	-0.0000	0.0001	0.0001
4	-0.0001	-0.0000	-0.0000	-0.0000	0.0001	0.0001
5	0.0006*	0.0006*	0.0006*	0.0006*	0.0001	0.0002
6	-0.0005	-0.0004	-0.0005	-0.0005	-0.0008	-0.0007
7	-0.0007	-0.0006	-0.0006	-0.0006	-0.0010	-0.0009
8	0.0002	0.0002	0.0002	0.0003	0.0002	0.0003
9	-0.0005	-0.0004	-0.0005	-0.0004	-0.0017**	-0.0016*
10	-0.0021**	-0.0020**	-0.0021**	-0.0021**	-0.0025**	-0.0025**
11	-0.0018**	-0.0016*	-0.0019**	-0.0017**	-0.0016	-0.0015
12	-0.0002	0.0000	-0.0002	0.0000	0.0011	0.0013
24	0.0006	0.0008	0.0006	0.0008	0.0022	0.0024
36	-0.0003	-0.0000	-0.0002	0.0000	-0.0019	-0.0018
48	-0.0013	-0.0011	-0.0014	-0.0011	-0.0022	-0.0021
60	-0.0004	-0.0001	-0.0005	-0.0001	0.0005	0.0006
Observations	32,939	32,939	32,939	32,939	25,693	25,693
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

Table D.6: Take-up estimation for the restricted sample considering a window of 60 days

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pr(period>120)	Pr(period>120)	Pr(period>120)	Pr(period>120)	Pr(period>120)	Pr(period>120)
Treated	0.3986***	0.4006***	0.4155***	0.4170***	0.4160***	0.3960***
	(0.0501)	(0.0489)	(0.0480)	(0.0460)	(0.0505)	(0.0373)
Constant	0.0648***	-0.2017	0.0266	-0.2110		
	(0.0251)	(0.2272)	(0.0827)	(0.2044)		
Observations	11,366	11,366	11,366	11,366	7,103	7,103
R-squared	0.1925	0.2112	0.2146	0.2312	0.7323	0.7438
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Days of Leave	Days of Leave	Days of Leave	Days of Leave	Days of Leave	Days of Leave
Treated	23.3963***	23.5109***	24.4411***	24.5258***	24.4114***	23.2184***
	(3.0338)	(2.9603)	(2.9031)	(2.7904)	(3.0201)	(2.2586)
Constant	123.4970***	107.2232***	121.2149***	106.6157***		
	(1.4993)	(13.5344)	(4.9990)	(12.1976)		
Observations	11,366	11,366	11,366	11,366	7,103	7,103
R-squared	0.1855	0.2042	0.2070	0.2237	0.7282	0.7398
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

The estimations are restricted to those women who took maternity leave from twelve to six months before their firms joined EC Program (the *Control Group*) and from zero to six months after that (the *Treatment Group*).

Clustered at firm level.

Table D.7: Take-up estimation for the restricted sample considering a window of 120 days

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Prob(period>120)	Prob(period>120)	Prob(period>120)	Prob(period>120)	Prob(period>120)	Prob(period>120)
Treated	0.3992***	0.4016***	0.4150***	0.4174***	0.4223***	0.4156***
	(0.0509)	(0.0499)	(0.0466)	(0.0454)	(0.0473)	(0.0419)
Constant	0.0594**	-0.1174	0.0589	-0.1068		
	(0.0264)	(0.2094)	(0.0595)	(0.2108)		
Observations	22,174	22,174	22,174	22,174	16,010	16,010
R-squared	0.1969	0.2141	0.2055	0.2222	0.7250	0.7291
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Days of Leave	Days of Leave	Days of Leave	Days of Leave	Days of Leave	Days of Leave
Treated	23.4724***	23.6155***	24.4317***	24.5735***	24.8528***	24.4611***
	(3.0705)	(3.0114)	(2.8128)	(2.7452)	(2.8224)	(2.5041)
Constant	123.1157***	112.1746***	123.2223***	112.9395***		
	(1.5742)	(12.4832)	(3.5879)	(12.5623)		
Observations	22,174	22,174	22,174	22,174	16,010	16,010
R-squared	0.1902	0.2077	0.1989	0.2159	0.7222	0.7264
Plant FE	No	No	No	No	Yes	Yes
Month-ML FE	No	No	Yes	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes

The estimations are restricted to those women who took maternity leave from twelve to six months before their firms joined EC Program (the *Control Group*) and from zero to six months after that (the *Treatment Group*).

Clustered at firm level.