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**Parental Leave Duration  
and Wages :  
A Structural Approach**

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# Parental leave duration and wages: a structural approach

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February 21, 2012

## Abstract

We investigate the existence of causal mechanisms from parental leave duration to subsequent wages. Our instrumental variable is a French reform giving financial incentives to take a parental leave. Two longitudinal datasets provide us with information on wages and familial background from 1976 to 2005. In our context, panel data estimations potentially suffer from unobserved heterogeneity, endogeneity and selection. We implement an innovative procedure proposed by Semykina and Wooldridge (2010) to take into account these three problems simultaneously. We find that parental leave duration has a significant and negative causal impact on later wages.

Keywords: Parental leave duration, wages, selection, endogeneity, panel data

JEL Classification: J31, C33, J68

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## 1 Introduction

The causal impact of periods spent out of the labor market on later wages has been widely studied. Most papers focus on unemployment spells, and conclude that unemployment duration has a negative causal impact on wages. Apart from unemployment, several reasons can account for periods spent out of the work force. Using the Vietnam draft lottery, Angrist (1990) finds that being a Vietnam veteran lowers civilian earnings of white males. Employees may also quit their job, or find an agreement of temporary leave with their employer. In particular, parents can take a maternity or paternity leave after the birth of a child. Parental leave duration and unemployment are likely to have a different impact on subsequent career. Potential employers may interpret voluntarily withdrawing and being unemployed differently. They may also fear that parents of a young child might be less involved in their professional activities. This paper focuses on those parental leaves, and investigate whether later career is affected by such temporary withdrawals.

Two types of parental leave laws are usually implemented: benefits can be provided to eligible parents who want to reduce their labor supply, and/or guarantees that they will have a job once the leave is over. The first one is aimed at parents who would be deterred from raising their child by themselves because of the implied wage loss. The second one is targeted on parents who anticipate that they will have difficulties to find a new job if they quit their current employer and temporarily stop working. These two kinds of programs are expected to allow newly parents to reduce their labor supply after the birth of a child. Both types of policy exist in France, and this paper exploits a 1994 reform that made parents of a second-born child eligible to parental leave benefits.

Though some papers estimate a joint structural model of participation and fertility choices (Francesconi 2002, Keane and Wolpin 2002, Laroque and Salanié 2008), most studies rely on legislative changes to identify the impact of such policies on career development (for a comprehensive survey, see Del Boca and Wetzels 2008). Regarding return to work behavior, Piketty (2005) and Ekberg et al. (2005) show that participation rates of eligible parents drop when parental leave benefits are available. Moreover, the maximum duration of these benefits seems to have an effect on the number of months spent off work after the birth of a child (Lalive and Zweimüller 2005). Eventually, Piketty (2005) notes on French data that participation rates go back to their regular levels after benefits exhaustion. This indicates that parents

willing to work again seem to find a new job when they don't receive benefits any more.

However, career development does not boils down to return to work. It may be possible that women have a less interesting job than the one they had before the birth. This could result in more frequent resignations. The simple fact of taking a parental leave may also scar them, and thus affect their subsequent wage growth rate (Buding and England 2001). Only few papers go beyond return to work, and focus on the causal impact of parental leave on later wage. A series of articles based on the German Socio-Economic Panel claims that one year of withdrawal after the birth of a child decreases wages by 6% to 20% depending on the specification (Ondrich et al. 2002, Kunze and Ejrnaes 2004, Beblo et al. 2006, Buligescu et al. 2009). Moreover Lequien (2012) uses a difference-in-difference approach on French data. His results suggest a 10% wage penalty for each year spent on parental leave. Our paper also studies the French case, and it proposes an alternative econometric strategy: we estimate a structural model based on Semykina and Wooldridge (2010), instead of a non-parametric estimation. Matching two longitudinal sources on career and familial background respectively, we find that parental leave duration has a causal negative impact on later wages.

The next part presents the reform which created exogenous variations in time spent out of the labor market after the birth of a child. Section 3 presents the two datasets we use in this study, as well as descriptive statistics on the matched sample. The econometric framework is detailed in section 4. Results of the estimations are shown in section 5, followed by a discussion. The last section concludes.

## 2 The 1994 parental leave reform

We take advantage of a reform that took place in France in 1994. The so called *Allocation Parentale d'Education* (APE thereafter) is a monthly benefit for parents who choose to temporarily reduce their labor supply after the birth of a child (beneficiaries can either work part-time or totally stop working)<sup>1</sup>. Parents are eligible if they have worked at least two years in the five years previous to the birth. When eligible,

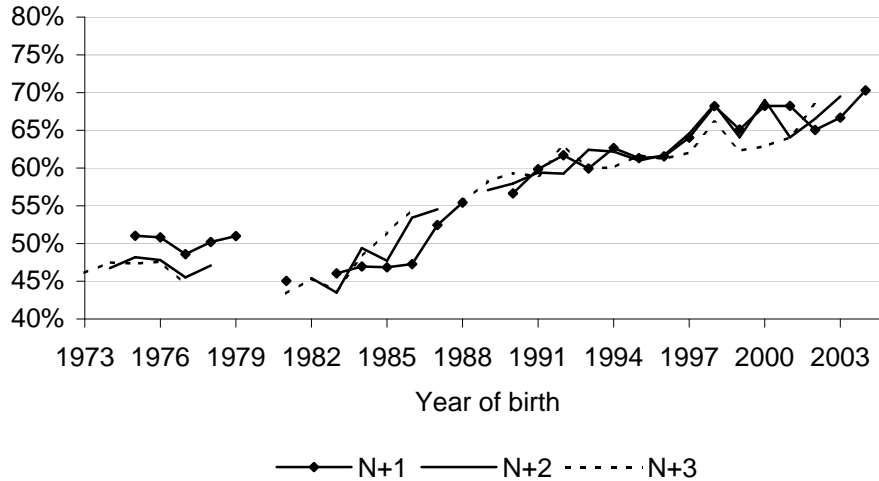
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<sup>1</sup>This policy comes on top of mandatory maternity leave for mothers. After having given birth, a woman working under the France law is supposed to stop working during a minimum number of weeks: 10 weeks for a first or second-born, 18 weeks for a third-born child. These periods are extended in case of multiple births.

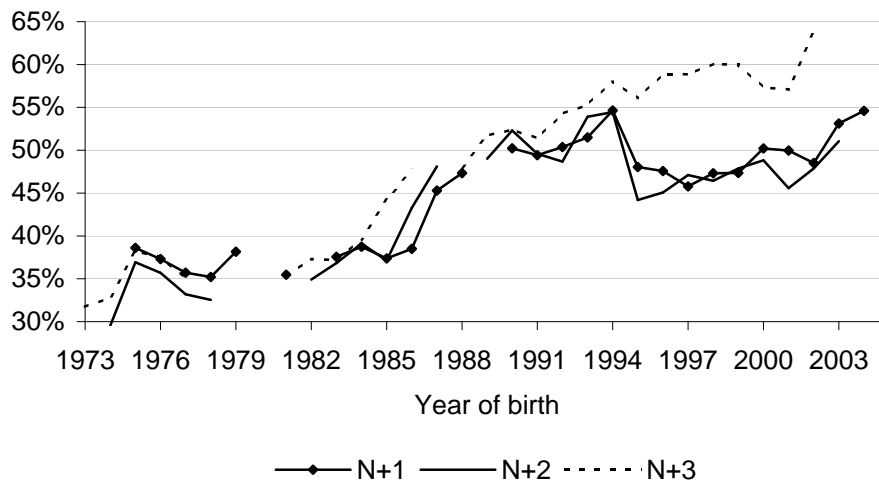
they receive the benefit until they come back to their previous level of labor supply. The length of the leave is up to the beneficiary, and can vary between six months and three years. Although both mothers and fathers may in theory benefit from the APE, mothers represent more than 98% of all beneficiaries (Piketty 2005). Therefore we excluded males from our study and focused exclusively on women's careers. In particular, this implies that explaining possible gender differences in wages is beyond the scope of this study.

The APE was created in 1985, and was at first available only for parents of a third-born child. Then this policy was extended to parents of a second-born child in July 1994. Judging from the number of beneficiaries, this extension has been a success from the very beginning (240 000 families with two children in 1996) until now (315 000 beneficiaries in 2002). Although the APE theoretically increases the incentives workers face to take a parental leave, these previous figures by themselves don't imply that the reform indeed affected beneficiaries' participation decision. It might be possible that they would have reduced their labor supply even in the absence of any financial compensation. In such a case, the reform would not have changed the distribution of parental leave durations. With Angrist et al.'s (1996) terminology on program evaluation, all beneficiaries would then be *always takers*, and there would be no *compliers*. As we wish to use this reform as an exogenous source of variation in leave durations, we need a major part of beneficiaries to be *compliers*.

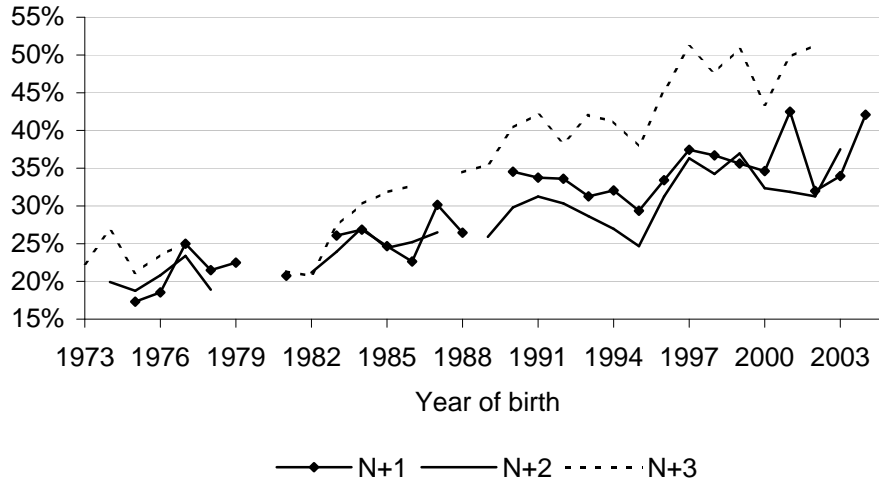
Figure 1, 2 and 3 illustrate that it is indeed the case and that the reform had a huge impact on mothers' participation rate in the three years after the birth of their second child. Participation rates 1, 2 and 3 calendar years after the birth of a first-born child are represented in Figure 1. Figures 2 and 3 plot the same curves for second and third-born children. A strong temporal trend is systematically visible: mothers tend to come back to work more and more frequently in the three years following the birth. The striking fact is that participation rates suddenly dropped by 10 percentage points for second-born children born after 1994, and this happened only in the first two calendar years following the birth. There is no similar decrease during the year of the birth nor 3 years after the birth. Moreover there is no such pattern with first and third-born children. This is exactly the kind of effect the APE reform was expected to produce: this reform was effective from 1994 onwards, it affected only mothers of a second-born child, and it gave incentives to withdraw

**Figure 1:** Participation rate after the birth of the first child

Scope: Women who had a first-born child, and were present in the DADS during the year of the birth or the during previous year. N corresponds to the calendar year of the birth, N+1 is the calendar year after the birth year N. Lecture: Among women who gave birth to a first-born child in 1986 and who were working either in 1984 or in 1985, 47% were working in 1987 and 53% were working in 1988.

**Figure 2:** Participation rate after the birth of the second child

Scope: Women who had a second-born child, and were present in the DADS during the year of the birth or during the previous year. N corresponds to the calendar year of the birth, N+1 is the calendar year after the birth year N.

**Figure 3:** Participation rate after the birth of the third child

Scope: Women who had a third-born child, and were present in the DADS during the year of the birth or during the previous year.  $N$  corresponds to the calendar year of the birth,  $N+1$  is the calendar year after the birth year  $N$ .

during at most 3 years from the labor market<sup>2</sup>. As a consequence, it is very likely that this reform accounts for most of this drop. Two points are worth emphasizing: the drop is particularly spectacular given the rising trend between 1976 and 2005, and women were fast to adapt their behavior to the new law.

Two previous papers studied the impact of the APE reform on leave duration using different datasets from ours: Piketty (2005) used Labor Force Surveys, Pailhé and Solaz (2006) worked on Family and Employers Survey. Both of them also found that the APE reform induced a significant share of eligible mothers to withdraw from the labor market in the three years following the birth of a second-born child. All this contributes to make us feel confident that our identification strategy does not rely on a weak instrumental variable.

<sup>2</sup>The absence of drop in the third calendar year after the birth is compatible with the APE legislation, since a withdrawal of three years after the birth implies that the return to work occurs during the third calendar year after the birth.

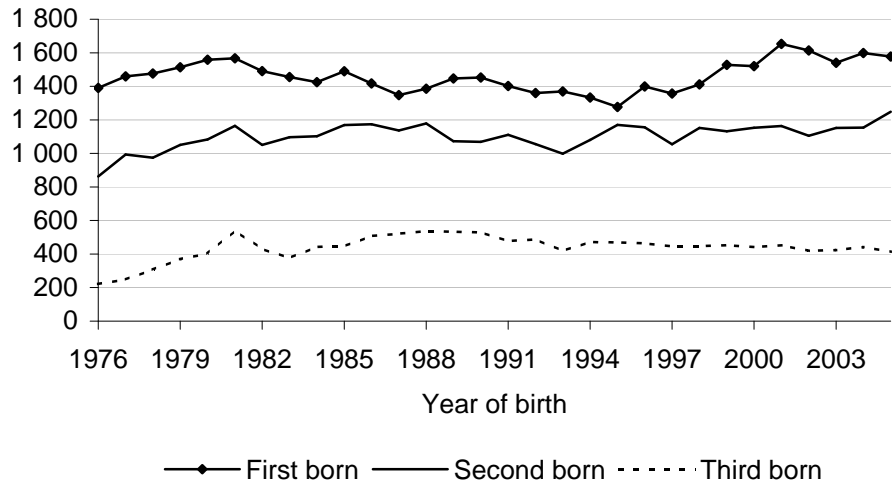
### 3 Data

We use information from two sources. The *Déclarations Annuelles de Données Sociales* (DADS thereafter) is a large-scale administrative dataset containing information on each employee subject to French payroll taxes. It basically includes all employees or self-employed persons working in private and state-owned firms. Only civil servants and independent workers are not present in the DADS. The DADS gathers yearly reports filled by employers. An observation consists in a unique individual-firm-year triplet. Each observation contains the number of days worked by the individual in the establishment during the calendar year, as well as the first day of the first spell of employment and the last day of the last spell of employment during that calendar year. It also provides us with date of birth, sex, occupation, a dummy variable for part- or full-time employment, the total net nominal earning and the annualized gross nominal earnings for the individual in that year. We exploit an extract of the DADS, covering all women born in October of even-numbered years. We follow them between 1976 and 2005 (except for 1981, 1983 and 1990, because the data are not available).

The Permanent Demographic Sample (*Echantillon Démographique Permanent*, or EDP) provides us with general information on individuals. This longitudinal dataset covers all French women and men born on one of the first four days of October. It compiles 1968, 1975, 1982, 1990 and 1999 census data with information from register of births, marriages and deaths from 1968 to 2005. In particular, it contains for each individual in the sample the dates of their children's birth.

The EDP and DADS use the same individual identifier NIR (a 13 digit number) which allows us to match these two datasets. However, we first had to exclude persons not born in France, because their identifier was not built with the same algorithm in the two sources. This removed 15% of individuals in the EDP and 10% of observations in the DADS. We also excluded DADS observations with an obviously wrong NIR (containing letters instead of numbers). When we matched these two samples, we selected women born on one of the first four days of October of even-numbered years. These women have worked at least one day in their life in the private sector. The matched sample contains 99,505 women and 1,285,407 observations. By construction, the EPD is representative of the French population, while the DADS may not be. Annex 8.1 provides information on possible sample selection issues by checking whether women's observable characteristics in the matched sample systematically



**Figure 4:** Number of births per year

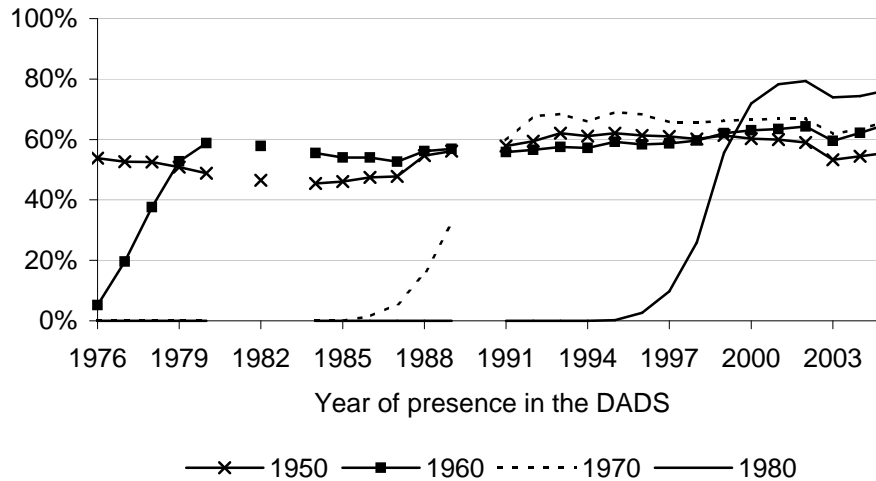
Notes: Number of births observed each year, with the mother belonging to the EDP/DADS sample.

differ from those of EDP.

Figure 4 represents the number of births by year. It shows that the reform was not followed by an increase in the number of second-born children. Therefore the decision to have a second child was not severely affected by the APE reform. This is crucial in our identification strategy, which imposes that women who gave birth to a second child before and after the reform had similar characteristics so that the sample selection bias created by selecting mothers with at least two children is constant over time.

Figure 5 is devoted to participation rate in the labor market at different ages. Each curve refers to a given birth cohort (1950, 1960, 1970 and 1980), and plots the proportion of women who appeared in the DADS between 1976 and 2005. The progressive rise of female labor market participation rate observed in most developed countries certainly accounts for the increase observed between the 1950 and 1980 cohorts (see for example Blau and Kahn 2007, for the labor supply of married women in the US).

Figures 6, 7, and 8 represent the cumulative frequency of the number of years spent out of the labor market after the birth of a child. Separate curves are plotted depending on whether the child was born before or after the APE reform took place

**Figure 5:** Participation rate by birth cohort

Scope: Women present in the EDP/DADS sample. Lecture: 80% of the 1980 cohort were present in the DADS (i.e. worked a least one day in the private sector) in 2002.

in 1994 (note that 1994 is only a milestone in Figures 6 and 8, because the APE reform in 1994 did not change incentives for mothers of a first- or third-born child). Mothers tend to come back to work more often and more rapidly when their child is born after 1994. This result is in line with the rising trend in participation rates after the birth observed in Figures 1 to 3 and 5. It certainly stems from the general change in women's (and here especially mothers') behavior toward the labor market. The gap between the pre-reform and post-reform curves is roughly constant after the birth of a first-born child. Therefore the behavior change seems to have evenly affected all working mothers when it comes to parental leave duration. A similar conclusion can be drawn from Figure 8 for mothers of three children. Moreover one can notice a negative shift for both curves between zero and three years of withdrawal in Figure 8. Such a negative shift is the kind of effect that the APE could create, since the APE gives incentives to delay the return to work during the first three years. As the APE was available for mothers of a third-born child since 1985, it could indeed have affected the two curves and thus is a plausible candidate to explain (at least part of) this downward change. Figure 7 shows a similar shift for mothers of a second-born child, but only for the post-reform curve. Furthermore the gap is not strongly marked for short withdrawals (less than 6 months), and then becomes

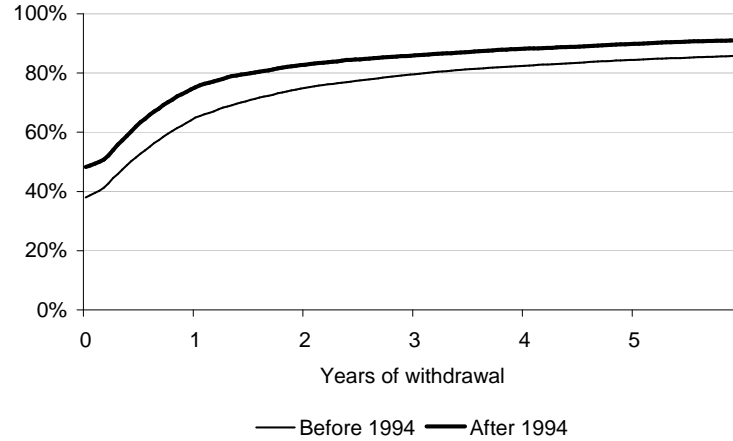
wider until the spell reaches three years. All this strengthens the hypothesis that the APE caused these shifts, because mothers of a second-born child became eligible to the APE in 1994, and withdrawals under the APE legislation can vary between 6 months and three years. Once again, these observations are in line with previous studies (Pailhé and Solaz 2006). It is worth noticing that these shifts occur around three years of withdrawal. Since the APE is available until the third anniversary of the child, it might imply that a significant proportion of APE beneficiaries choose to return to work right before the maximum length of three years elapses.

Giving birth may affect subsequent career path in different ways. There may be a wage penalty associated with the simple fact of having a baby<sup>3</sup>. We would then observe a decrease in mothers' wages after the birth. In all generality, this decrease could be time-constant, or could vary with the number of years since the birth. On top of this "scar" effect, the duration of the withdrawal from the labor market after the birth may also impact wages. Figure 9 pictures the mean wage between 1976 and 2005 of women who gave birth in 1993 (either of a first-, second- or third-born child). Women who left the labor market only during the mandatory maternity leave have a higher wage after the birth than mother who withdrew longer. The gap appears in 1995 and is roughly constant afterwards, whereas there is no significant difference in wages before the birth. This pattern is not specific to the 1993 birth cohort (results not presented here, and available upon request), and hence seems to be quite general. At this point, it is not possible to interpret this as a causal relationship running from the withdrawal duration to a decrease in wages. There may be other characteristics negatively affecting wages after the birth and common to all women who chose to withdraw longer.

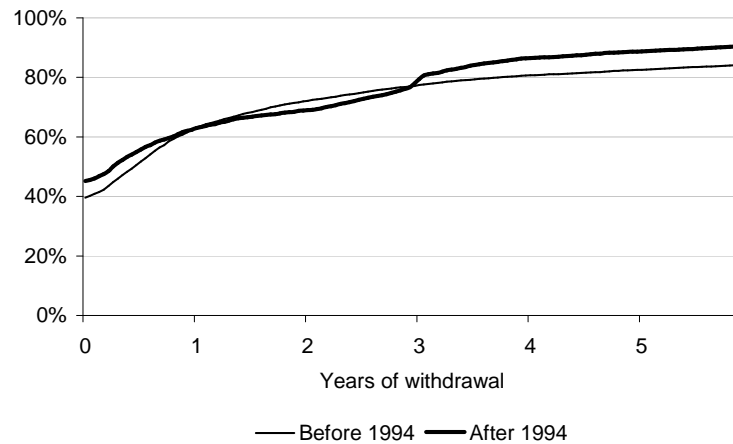
Figure 10 focuses on mothers who gave birth to a second-born child. All births occurred in 1996, so these mothers were potentially eligible to APE. A gap similar to Figure 9 is visible after the birth, its magnitude is constant until 2005. However this gap does not appear right after the birth, but rather three years after. This may be due to a composition effect. Piketty (2005) argues that low wages women tend to withdraw longer than high wages women when using the APE. Hence we would observe relatively more high wages women working in 1997 and 1998 among women who temporarily withdraw from the labor market after the birth. This would explain why wages are not decreasing (and are even increasing) in those two years, relatively

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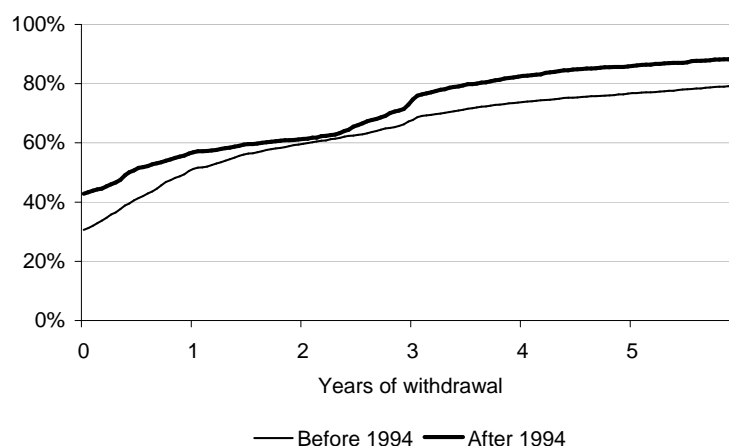
<sup>3</sup>See Felfe (2006).

**Figure 6:** Cumulative spell duration after the birth of the first child

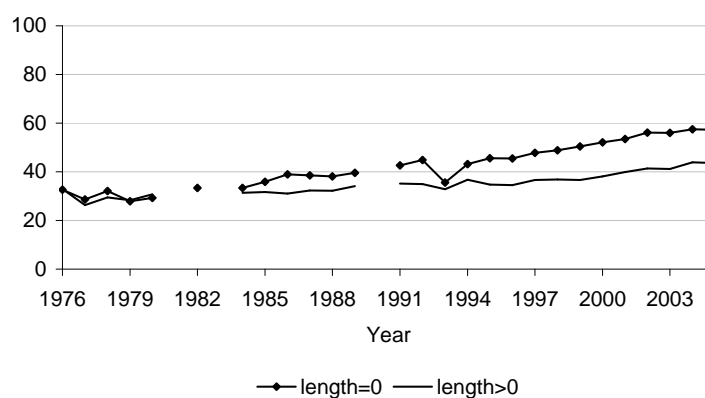
Scope: Women who had a first-born child between 1976 and 1999 included, and were present in the DADS during the year of the birth or during the previous year. The curves represent the cumulative frequency of the length of spell out of the labor market after the birth. The plain line is for women who gave birth before July 1994, the bold line for woman who gave birth between July 1994 and December 1999. As we have information until 2005, the length of withdrawal is defined up to 6 years in the latter curve.

**Figure 7:** Cumulative spell duration after the birth of the second child

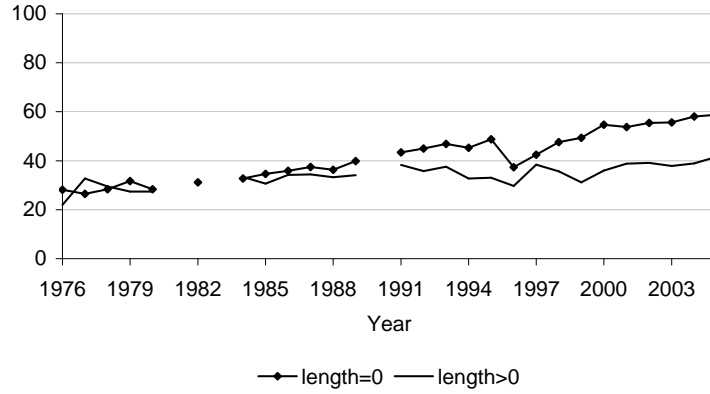
Scope: Women who had a second-born child between 1976 and 1999 included, and were present in the DADS during the year of the birth or during the previous year. The curves represent the cumulative frequency of the length of spell out of the labor market after the birth. The plain line is for women who gave birth before July 1994, the bold line for woman who gave birth between July 1994 and December 1999. As we have information until 2005, the length of withdrawal is defined up to 6 years in the latter curve.

**Figure 8:** Cumulative spell duration after the birth of the third child

Scope: Women who had a third-born child between 1976 and 1999 included, and were present in the DADS during the year of the birth or during the previous year. The curves represent the cumulative frequency of the length of spell out of the labor market after the birth. The plain line is for women who gave birth before July 1994, the bold line for woman who gave birth between July 1994 and December 1999. As we have information until 2005, the length of withdrawal is defined up to 6 years in the latter curve.

**Figure 9:** Mean daily wage per year, for women who gave birth in 1993

Notes: Annual wage divided by the number of days worked during the year, in €2005.  
 Scope: Women who gave birth in 1993 to a first-, second- or third-born child. “length=0” covers women who withdrew from the labor market only during the mandatory maternity leave after the birth. “length>0” corresponds to women who took a break longer than the mandatory maternity leave.

**Figure 10:** Mean daily wage per year, for women who gave birth to a second-born in 1996

Notes: Annual wage divided by the number of days worked during the year, in €2005. Scope: Women who gave birth to a second-born child in 1996. “length=0” covers women who withdrew from the labor market only during the mandatory maternity leave after the birth. “length>0” corresponds to women who took a break longer than the mandatory maternity leave.

to mothers whose withdrawal did not exceed the mandatory maternity leave.

A peculiar pattern is visible in both Figures 9 and 10. There is a drop in wages of about 20% the year of the birth for women who took only the mandatory maternity leave. Wage growth rates do not seem to differ before and after the birth. This decrease is common to all birth cohorts, and does not depend on whether women gave birth to a first-, second- or third-born child. This may partly be due to a (permanent) shift from full-time to part-time employment after the birth for some of these mothers.

## 4 The model

### 4.1 Econometric issues

The equation of interest is the following:

$$y_{it} = x_{it}\alpha + l_{it}\beta + c_i + u_{it}, \quad t = 1, \dots, T \quad (1)$$

$y_{it}$  is the (log of the) annual wage of individual  $i$  in year  $t$  divided by the number of days worked during that year.  $x_{it}$  are time-varying individual characteristics affecting

the wage (age, etc.), which are supposed to be strictly exogenous conditional (i.e. not correlated with  $u_{it'}$  for all  $t'$ ) on  $c_i$ .  $l_{it}$  is the length (in years) of the withdrawal after the birth of the second-born child: it is equal to 0 before the second birth, and to the actual length after the birth.  $c_i$  represents time-constant factors like ability or motivation.  $u_{it}$  is the error term, summing up all time-varying unobserved variables which determine wages.  $c_i$  can be arbitrarily correlated with  $x_{it}$  and  $l_{it}$ . For estimation purposes, one can implement a fixed-effect transformation (FE) to remove  $c_i$ , and then run an OLS estimation on the time-demeaned equation. This procedure gives consistent estimates on a balanced panel if  $x_{it}$  and  $l_{it}$  are strictly exogenous conditional on  $c_i$ .

However careers are often discontinuous, with periods spent out of the labor market (parental leave, unemployment spells, inactivity, etc.). Working on an unbalanced panel is problematic if the selection process is non random, because not correcting for that selection may result in inconsistent estimates. Our dataset contains women who chose to work in the private sector. If the decisions to participate (year after year) in the labor market and to work in the private sector are correlated with unobserved factors affecting wages, estimations are likely to be biased. Three panel estimators have been recently suggested to take into account unobserved heterogeneity and sample selection. They all allow individual effects to be correlated with explanatory variables in both the selection and primary equations<sup>4</sup>. Kyriazidou's (1997) estimator relies on individuals who have "close" selection effects in two different time periods. Differencing these two observations removes at the same time the individual and selection effects. Therefore the selection effect remains an unknown function, and requires no assumption. On the other hand, Rochina-Barrachina (1999) and Wooldridge (1995) parametrize this selection bias. The former removes the unobserved effect by differencing observations for individuals whose wage is observed twice. The latter applies the transformation proposed by Mundlak (1978) to deal with unobserved heterogeneity, and follows Heckman (1976) to correct for selection bias. He then estimates the wage equation in levels.

Apart from heterogeneity and sample selection, the third issue arising in our study is that parental leave length may suffer from measurement error and endogeneity. As the DADS covers only the private sector, the length  $l_{it}$  measured in the DADS may overestimate the actual length of withdrawal from the labor market if the mother's

<sup>4</sup>Dustmann and Rochina-Barrachina (2007) survey these estimators in detail.

first job after the birth is not in the private sector. Moreover, endogeneity may stem from the link between  $l_{it}$  and time-varying determinants of wages: changes in personal life like getting married or having children may increase the will to have spare time devoted to family, and thus simultaneously affect  $l_{it}$  and wages. Besides, negative exogenous shocks to wages in the past may be related to poor work conditions, which could affect the choice of parental leave length today. Hence strict exogeneity of  $l_{it}$  is unlikely in our context.

So three problems arise at the same time when estimating the impact of parental leave on later wages with a longitudinal dataset: heterogeneity in both selection and wage equations, non random selection, and no strict exogeneity of  $l_{it}$ . If only two of them were present, estimations would be quite straightforward. Assuming that  $l_{it}$  were strictly exogenous, the three aforementioned estimators would deal with the first two issues<sup>5</sup>. If there were no selection, a possible remedy would be to find instrumental variables  $z_{it}$  sufficiently correlated with  $l_{it}$  and strictly exogenous conditional on  $c_i$ . The procedure would consist in time-demeaning equation (1) like in fixed-effect estimations (FE) and then applying a two stage least squares estimation (2SLS) to the time-demeaned equation. This FE-2SLS method would produce consistent estimates on a balanced panel.

Our econometric specification is derived from Semykina and Wooldridge (2010). They provide an estimation strategy which overcomes the limitation faced by the above FE-2SLS on unbalanced panels. Their procedure is based on Wooldridge's (1995) estimator, and further allows some explanatory variables to be endogenous. Therefore it takes into account unobserved heterogeneity, endogenous variables, and corrects for selection bias while working on an unbalanced panel. Buligescu et al. (2009) and Himmler and Jäckle (2010) implement this method when studying the impact of parental leave duration (resp. health status) on wages. The remaining of this section presents the modeling of the selection and wage equations.

## 4.2 The selection process

The selection process determining participation into the labor market during year  $t$  is specified using a probit model:

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<sup>5</sup>Dustmann and Rochina-Barrachina (2007) show that the previous estimators can be adapted to some cases where strict exogeneity fails.



$$\begin{cases} s_{it} = \mathbb{1}[Z_{it}\gamma + d_i + v_{it} > 0] \\ v_{it}|Z_i, d_i \sim \mathcal{N}(0, 1), \quad t = 1, \dots, T \end{cases} \quad (2)$$

The selection indicator  $s_{it}$  equals 1 if individual  $i$  worked at least one day during year  $t$ .  $Z_i = (Z_{i1}, \dots, Z_{iT})$ , where  $Z_{it}$  is a vector containing  $x_{it}$  and at least one other variable not present in equation (1)<sup>6</sup>. The fixed effect  $d_i$  sums up all persistent heterogeneity which could explain the propensity of individual  $i$  to select in or out of the sample. If we ignore  $d_i$  and consider it part of the error term, then the errors terms are automatically serially correlated. According to Semykina and Wooldridge (2010), estimation then imposes further assumptions which are far too unrealistic. We suppose that  $d_i$  and  $Z_i$  can be correlated, as it is likely to be the case. FE cannot be applied here to take  $d_i$  into account, since equation (2) is not linear. Mundlak (1978) proposed a way to deal with  $d_i$  without time-demeaning:

$$\begin{cases} d_i = \mu + \bar{Z}_i\delta + a_i \\ a_i|Z_i \sim \mathcal{N}(0, \tau^2) \end{cases} \quad (3)$$

This equation writes  $d_i$  as the sum of a term correlated with  $Z_i$  and a part which by construction is independant of  $Z_i$ . It assumes that all interactions between  $d_i$  and  $Z_i$  are captured by the time average  $\bar{Z}_i = (Z_{i1} + \dots + Z_{iT})/T$ <sup>7</sup>. Unlike in the FE transformation,  $Z_i$  can contain time-constant variables like education.

Plugging (3) into equation (2) leads to:

$$\begin{cases} s_{it} = \mathbb{1}[\mu + Z_{it}\gamma + \bar{Z}_i\delta + w_{it} > 0] \\ w_{it}|Z_i \sim \mathcal{N}(0, 1 + \tau^2), \quad t = 1, \dots, T \end{cases} \quad (4)$$

where  $w_{it} = a_i + v_{it}$ . In fact, the effect of  $d_i$  in equation (2) or the variance of  $w_{it}$  can be allowed to vary over time. Therefore a more general specification of the selection process is (after a rescaling of the error term):

<sup>6</sup>The econometric model is theoretically identified without any exclusion variable, but in that case identification relies solely on the non linearity of equation (2). The specification becomes more convincing when there is at least one variable affecting selection and not wages.

<sup>7</sup>In all generality, no restriction should be imposed on the linear projection of  $d_i$  on  $Z_i$ . However,  $d_i$  does not vary over time, and it seems legitimate to restrict the projection of  $d_i$  on  $Z_i$  to time-constant functions of  $Z_i$ . Mundlak's (1978) specification amounts to choosing a simple time-invariant function by imposing the same coefficient for  $Z_{it'}$  at all periods  $t'$ . Both approaches are valid within our framework, we chose to present Mundlak's here because it conserves on degrees of freedom.

$$\begin{cases} s_{it} = \mathbb{1}[\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t + w_{it} > 0] \\ w_{it}|Z_i \sim \mathcal{N}(0, 1), \quad t = 1, \dots, T \end{cases} \quad (5)$$

### 4.3 The wage equation

First let's recall that the residual resulting from the time-demeaning in the FE-2SLS procedure is a function of  $u_{it'}$  for all  $t'$ . So correlation between the selection indicator  $s_{it}$  and  $u_{it'}$  (for all  $t'$ ) becomes an issue, whereas only contemporaneous selection matters in equation (1). Once again, Mundlak's (1978) device can be used to avoid time-demeaning. The relationship between  $c_i$  and the strictly exogenous variables  $z_i$  is supposed to take the following form:

$$\begin{cases} c_i = \eta + \bar{z}_i\theta + b_i \\ \mathbb{E}(b_i|z_i) = 0 \end{cases} \quad (6)$$

This specification assumes that  $c_i$  depends on  $z_i$  only through the time average  $\bar{z}_i = (z_{i1} + \dots + z_{iT})/T$ . Note the no assumption is made on the law of  $b_i|z_i$ . The wage equation (1) can be rewritten using (6):

$$y_{it} = x_{it}\alpha + l_{it}\beta + \eta + \bar{z}_i\theta + b_i + u_{it}, \quad t = 1, \dots, T \quad (7)$$

To highlight the correction for contemporaneous selection bias, we can write:

$$\begin{cases} y_{it} = x_{it}\alpha + l_{it}\beta + \eta + \bar{z}_i\theta + \mathbb{E}(b_i + u_{it}|z_i, s_{it}) + e_{it} \\ \mathbb{E}(e_{it}|z_i, s_{it}) = 0, \quad t = 1, \dots, T \end{cases} \quad (8)$$

One important feature of (8) is that it is silent on correlation between  $e_{it}$  and  $s_{it'}$  for  $t \neq t'$ . Therefore we don't have to take into account selection in other periods, even if this selection indicator is correlated with  $e_{it}$ . In other words, selection does not have to be strictly exogenous. If we knew  $\mathbb{E}(b_i + u_{it}|z_i, s_{it})$ , applying pooled 2SLS to (8) would give consistent estimates of the parameters. In fact we only need to compute  $\mathbb{E}(b_i + u_{it}|z_i, s_{it} = 1)$ , because we do not observe  $(y_{it}, x_{it})$  when  $s_{it} = 0$ . The following linearity assumptions

$$\begin{cases} \mathbb{E}(u_{it}|z_i, w_{it}) = \mathbb{E}(u_{it}|w_{it}) = \rho_t w_{it}, \quad t = 1, \dots, T \\ \mathbb{E}(b_i|z_i, w_{it}) = \mathbb{E}(b_i|w_{it}) = \psi_t w_{it}, \quad t = 1, \dots, T \end{cases} \quad (9)$$

are classical and imply that the functions of  $w_{it}$  which best fit  $\mathbb{E}(u_{it}|w_{it})$  and  $\mathbb{E}(b_i|w_{it})$  are linear. (9) automatically holds in the special case where  $(u_{it}, w_{it})$  (resp.  $(b_i, w_{it})$ ) follow a bivariate normal distribution. The slopes of the linear fits are allowed to differ from one time period to another. Noting  $\Psi_t \equiv \rho_t + \psi_t$ , we use (9) and the law of iterated expectations to get:

$$\begin{aligned}
\mathbb{E}(b_i + u_{it}|z_i, s_{it} = 1) &= \mathbb{E}(b_i + u_{it}|z_i, w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t) \\
&= \mathbb{E}(b_i + u_{it}|w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t) \\
&= \frac{\mathbb{E}\left[(b_i + u_{it}) * \mathbf{1}(w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t)\right]}{\mathbb{P}\left[w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t\right]} \\
&= \frac{\mathbb{E}\left[\mathbb{E}(b_i + u_{it}|w_{it}) * \mathbf{1}(w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t)\right]}{\mathbb{P}\left[w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t\right]} \quad (10) \\
&= \Psi_t \frac{\mathbb{E}\left[w_{it} * \mathbf{1}(w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t)\right]}{\mathbb{P}\left[w_{it} > -\mu_t - Z_{it}\gamma_t - \bar{Z}_i\delta_t\right]} \\
&= \Psi_t \frac{\phi(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t)}{\Phi(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t)}
\end{aligned}$$

where  $\phi$  and  $\Phi$  are respectively the probability density and cumulative distribution functions of a standard normal law. It shows that under (9),  $\mathbb{E}(b_i + u_{it}|z_i, s_{it} = 1)$  is proportional to the inverse Mills ratio

$$\lambda_{it}(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t) = \frac{\phi(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t)}{\Phi(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t)}$$

Running the probit regression (5) (for each period  $t$  separately) provides an estimate of this ratio  $\widehat{\lambda}_{it}(\mu_t + Z_{it}\gamma_t + \bar{Z}_i\delta_t) = \lambda_{it}(\widehat{\mu}_t + Z_{it}\widehat{\gamma}_t + \bar{Z}_i\widehat{\delta}_t)$ .

Eventually, the estimation strategy is the following:

- Compute the estimate of the inverse Mills ratio  $\widehat{\lambda}_{it}$  for period  $t$  from equation (5),  $t = 1, \dots, T$
- Replace  $\mathbb{E}(b_i + u_{it}|z_i, s_{it})$  by  $\Psi_t \widehat{\lambda}_{it}$  in equation (8), and estimate (8) on the selected sample ( $s_{it} = 1$ ) by pooled 2SLS. The instrumental variables are 1,  $z_{it}$ ,  $\bar{z}_i$  and  $\widehat{\lambda}_{it}$ . The estimators' variance-covariance matrix needs to be computed according to the formula given in Semykina and Wooldridge (2005).

The presence of at least one exclusion variable in the probit estimations guarantees that even if the inverse Mills ratio is well approximated by a linear function on a large part of its range, there won't be any collinearity issue in the second step.

This procedure corrects for selection bias and endogeneity of  $l_{it}$  on an unbalanced panel. Moreover, it allows unobserved heterogeneity to be correlated with explanatory and instrumental variables, both in the selection and primary equations. Selection  $s_{it}$  can be correlated with  $u_{it'}$  (for all  $t$  and  $t'$ ), and contemporaneous selection bias is corrected for in the wage equation. It also allows for correlation between the idiosyncratic errors in the two equations. Both error terms can be serially correlated and heteroscedastic. Joint normality of the error terms is not required: the error term in the selection equation is supposed to be normally distributed, while there is only a linearity assumption on the conditional mean of  $u_{it}$ .

## 5 Results

We implement the estimation strategy described in section 4. The estimation sample is composed of women who gave birth to a second child between 1986 and 2002, and their wages are observed between 1984 and 2005.  $l_{it}$  is the length (in years) of the withdrawal from the labor market following the birth of the second-born child. Our instrumental variable  $z_{it}$  correcting for the endogeneity of  $l_{it}$  is whether this birth occurred before or after the APE reform in July 1994. The first exclusion variable in the selection equation is a dummy equal to one if the woman has at least a child under the age of three. Local unemployment rate is also used as an exclusion variable. Region of residence and a part-time job indicator are among explanatory variables in the wage equation. As this latter variable might be considered as endogenous when determining wages, we systematically run estimations with and without this variable in the set of regressors. Finally, covariates common to both wage and selection equations are age, square age, number of children, and annual dummies as a proxy for macro economic environment<sup>8</sup>.

The remaining of this section presents the results of different estimations on this sample. Table 1 presents the FE estimation results of equation (1). This estimation

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<sup>8</sup>Individual variables constant over time cannot be included in the regression, because their effect cannot be separated from the effect of the constant unobserved heterogeneity. Hence we don't include year of birth, education and socio-professional group. Sex is not included either since our sample contains only women.

**Table 1:** FE estimation of equation (1)

	Dependant variable	
	<i>wage</i>	
	(1)	(2)
<i>length</i>	-0.030*** (0.0019)	-0.032*** (0.0020)
<i>age</i>	0.065*** (0.0021)	0.084*** (0.0022)
<i>age2</i>	-0.055*** (0.0028)	-0.082*** (0.0030)
<i>nbchild</i>	-0.049*** (0.0034)	-0.11*** (0.0035)
<i>part – time</i>	-0.56*** (0.0036)	
<i>intercept</i>	2.40*** (0.053)	1.96*** (0.056)
<i>temporal FE</i>	yes	yes
<i>regional FE</i>	yes	yes

Notes: Total sample consists of women in the EDP/DADS matched sample, who gave birth to a second-born child between 1986 and 2002. Their wage is observed more than one year for 17 389 of them. Wages are observed 204 177 times between 1984 and 2005. *part – time* is a dummy variable equal to 1 if and only if the woman worked part-time during the corresponding year. The dependent variable *wage* is the log of the average daily wage earned in the corresponding year, in €2005.

allows for unobserved heterogeneity to be correlated with all explanatory variables, and ignores potential sample selection issues. Moreover strict exogeneity is assumed for all variables. Whether or not including a part-time job indicator in the covariates, one year of withdrawal from the labor market is associated with a 3% decrease in wages.

Unobserved heterogeneity and endogeneity are taken into account in a FE-2SLS estimation. On the other hand, sample selection is not accounted for and it might lead to inconsistent estimates. Columns 1 and 2 of Table 2 show the results of the first step estimation. The instrumental variable  $z$  has a large (+0.11 year) and highly

**Table 2:** FE-2SLS estimation

	First stage <i>length</i>		Second stage <i>wage</i>	
	(1)	(2)	(3)	(4)
<i>length</i>			-0.15** (0.064)	-0.21*** (0.069)
<i>z</i>	0.11*** (0.0084)	0.11*** (0.0084)		
<i>age</i>	-0.0053** (0.0026)	-0.0045* (0.0026)	0.065*** (0.0021)	0.085*** (0.0023)
<i>age2</i>	0.032*** (0.0036)	0.032*** (0.0036)	-0.052*** (0.0032)	-0.078*** (0.0034)
<i>nbchild</i>	0.26*** (0.0046)	0.26*** (0.0046)	-0.014 (0.019)	-0.059*** (0.020)
<i>part – time</i>	0.0083* (0.0044)		-0.56*** (0.0036)	
<i>intercept</i>	0.076 (0.12)	-0.10 (0.066)	2.27*** (0.10)	1.93*** (0.059)
<i>temporal FE</i>	yes	yes	yes	yes
<i>regional FE</i>	yes	yes	yes	yes

Notes: Total sample consists of women in the EDP/DADS matched sample, who gave birth to a second-born child between 1986 and 2002. Wages are observed 204 177 times between 1984 and 2005. The dependent variable *wage* is the log of the average daily wage earned in the corresponding year, in €2005.

significant effect on withdrawal duration, in line with statistics presented in section 3. The second step of the estimation (columns 3 and 4) indicates that parental leave duration has a negative and significant impact on wages. Its magnitude is larger than in the FE estimation: wages decrease by 15% with each year away from the labor market (column 3).

Results of the procedure testing for selection bias in FE-2SLS are presented in section 8.2. They show that there is indeed a significant selection bias (the null hypothesis of no contemporaneous selection bias is rejected at the 1% confidence level), and therefore motivate the use of a method correcting for selection bias.

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Table 3 shows estimation results of equation (8) by pooled 2SLS. The three potential issues identified in section 4.1 are now taken into account. Different specifications are presented in columns 1 to 4. In each case, *length* is instrumented by  $z$ , and the presence of a child under 3 is the exclusion variable in the selection equation. They differ in two dimensions: a part-time job indicator can be included in the set of covariates, and local unemployment rate can be used as another exclusion variable.

We find a negative causal impact of parental leave duration on later wages in all specifications, and these estimates are significant at the 1% confidence level. According to Table 3, each extra year of withdrawal decreases later wages by 7.7% when taking into account part-time jobs (columns 1 and 3). The loss is even bigger when this variable is not included in the regressors (-17%, columns 2 and 4).

**Table 3:** Final step of the estimation

	Dependant variable			
	<i>wage</i>			
	(1)	(2)	(3)	(4)
<i>length</i>	-0.077*** (0.020)	-0.17*** (0.023)	-0.077*** (0.020)	-0.17*** (0.024)
<i>age</i>	0.027*** (0.0055)	0.035*** (0.0067)	0.027*** (0.0056)	0.035*** (0.0067)
<i>age2</i>	-0.021*** (0.0068)	-0.027*** (0.0082)	-0.021*** (0.0068)	-0.026*** (0.0082)
<i>nbchild</i>	0.048*** (0.011)	0.067*** (0.013)	0.046*** (0.012)	0.068*** (0.013)
<i>part – time</i>	-0.57*** (0.0057)		-0.57*** (0.0057)	
<i>temporal FE</i>	yes	yes	yes	yes
<i>regional FE</i>	yes	yes	yes	yes
Exclusion variables :				
<i>Child under 3</i>	yes	yes	yes	yes
<i>Unemployment rate</i>	yes	yes	no	no

Notes: Total sample consists of women in the EDP/DADS matched sample, who gave birth to a second-born child between 1986 and 2002. Wages are observed 204 177 times between 1984 and 2005. Coefficients on Mills ratios and time-averaged variables are not reported. The dependent variable *wage* is the log of the average daily wage earned in the corresponding year, in €2005.



## 6 Discussion

### 6.1 Causal impact magnitude

Our results suggest that parental leave duration has a negative causal impact on wages. According to Table 3, each extra year of withdrawal decreases later wages by 7% or 17% depending on the specification. This effect is large: it corresponds to a 11% wage loss for the average withdrawal duration in our sample (1.5 year). This does not necessarily mean that mothers' wage level decreases by 11% from their return to work until they retire. This decrease could be explained by a (time-constant) wage gap after the birth, and/or a lower wage growth rate. The cumulative effect of a 0.5% wage growth rate during the 25 years between the birth of a child and the end of one's career would create a wage differential of 13% after 25 years.

Experience is not taken into account in our model, but is known to contribute to wage growth. Bardaji et al. (2003) and Koubi (2003) estimate on French data that returns to one year of experience on wages are close to 2%. Ours results certainly incorporate this wage loss due to a lower experience. Moreover, human capital may depreciate while out of work, which would result in lower wages. The magnitude of this loss would increase with the duration of the absence from work. This phenomenon is not specific to withdrawals after the birth of a child, and exists after most non-working periods (Albrecht et al. 1999). Once again, this contributes to the causal effect that we estimate.

For different reasons, Buligescu et al. (2009) and Lequien (2012) constitute a relevant benchmark to put our results into perspective. The former uses a similar econometric framework on German data, and finds a causal impact of 10% to 14% for a one-year leave. The latter works on the same dataset, and also exploits the APE reform as a source of identification. However, Lequien (2012) uses a difference-in-difference (DiD) approach, while we impose more structure and specify a selection equation. These two complementary approaches<sup>9</sup> give qualitatively similar results,

<sup>9</sup>Each strategy has its own advantages and drawbacks. DiD are generally more robust to misspecification because they need very few structural hypotheses. Instead of having to specify how variables interact with each other, they only require that those unknown structural interactions do not change in a short period of time surrounding the 1994 reform. But DiD do not control for sample selection, since they do not take into account participation decisions at the individual level. DiD estimations could be biased if the set of women who give birth to a child just before the reform are not similar to those whose delivery occurs just after the reform. On the other hand, the structural model presented here controls for individual selection year after year, but the selection equation has

since Lequien (2012) claims that a one-year leave decreases wages by 10%<sup>10</sup>. This is a comforting hint that the structural assumptions made in section 4 do not seem too strong in our context.

Eventually, our results are in line with studies implementing the same econometric strategy or working on the same country with a different methodology.

## 7 Conclusion

This paper uses a structural model to test whether parental leave duration has a causal impact on later wages. Identification comes from a legislative change giving up to three years of benefits to mothers who decrease their labor supply after the birth of their second child. This monetary incentive has been having a massive impact on participation rate of eligible women from its implementation in 1994 until now. This exogenous drop in participation allows us to identify the parameter of interest. Our estimations suggest that parental leave duration has a negative and significant causal impact on wages. Each extra year of withdrawal from the labor market decreases later wages by 7% to 17% depending on the specification.

Wages are obviously an important dimension of career development, but the latter cannot be reduced to that one factor. Integration into the workplace of newly mothers also includes a job as fulfilling as before the leave, prospects of promotion, etc (Green 2010). Even if wages are correlated with these dimensions, consequences of parental leave duration deserve further research on a broader set of outcomes.

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to be correctly specified.

<sup>10</sup>An important difference between the two papers is estimations precision. Estimates are statistically significant at the 1% confidence level in all specifications of our structural model, whereas they reach the 5% confidence level only in one specification of the DiD approach. This may be due to the presence of covariates and individual fixed effects in the structural model, which decreases the part of unexplained variations in wages.

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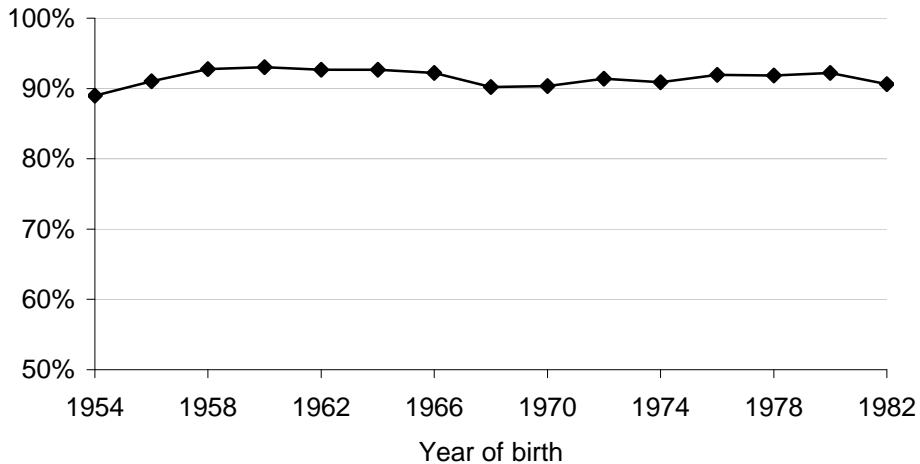
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## 8 Annex

### 8.1 Matching the EPD and DADS files

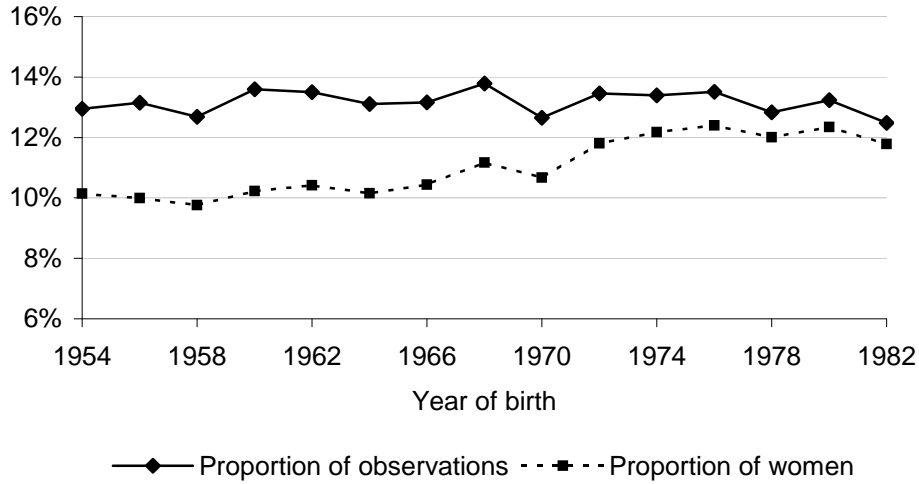
Figure 11 represents the share of EDP women also present in the EDP/DADS sample. This proportion is remarkably stable across birth cohorts, around 0.9. The selection between the initial DADS sample and the matched sample is plotted in Figure 12. The plain line represents the proportion of DADS observations corresponding to women present in the EDP. As expected, this proportion is roughly constant, close to 13% for even-numbered years of birth (4 days of birth selected out of 31 days in October). This ratio of 13% is also constant across years of presence in the DADS: Figure 13 pictures the proportion of observations sorted by year of presence in the DADS. The dotted line in Figure 12 represents a similar ratio, in terms of number of individuals in the DADS instead of number of observations. This curve is below the first one, between 10% and 13%. This is probably due to some wrong NIR remaining in the DADS sample<sup>11</sup>.

**Figure 11:** Proportion of EDP women present in the EDP/DADS sample



Notes: The curve represents the proportion of women in the EDP sample who are also present in the EDP/DADS matched sample, by birth cohort. Only even-numbered cohorts are plotted.

<sup>11</sup>An individual career generally consists in several observations in the DADS, since there is one observation per individual-firm-year. If the NIR is wrongly coded in one of these observations, it creates a new (fictitious) individual with a career reduced to only one observation. This could explain part of the difference between the two curves in Figure 12.

**Figure 12:** Proportion of DADS women and observations present in the EDP/DADS sample

Notes: The plain line represents the proportion of DADS observations corresponding to women present in the EDP. The dotted line represents a similar ratio, in terms of number of individuals in the DADS instead of number of observations.

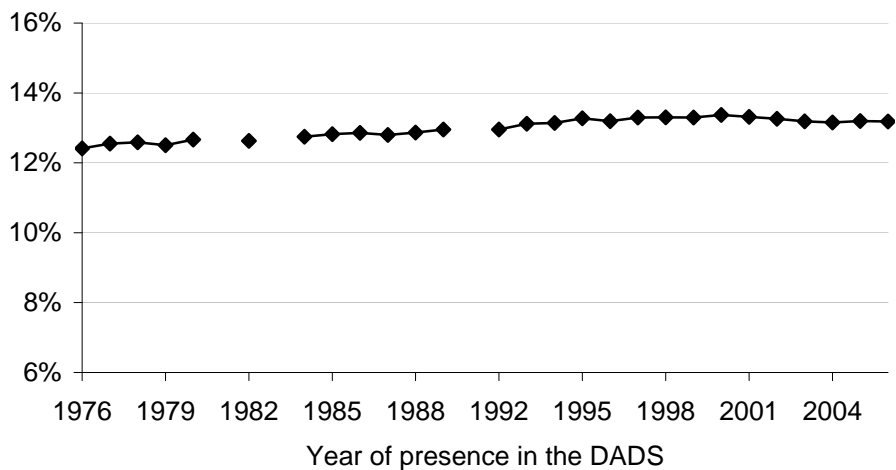
By construction, the EPD is representative of the French population, while the DADS may not be. To find out if the matching led to sample selection issues, we can check whether women's observable characteristics in the matched sample systematically differ from those of EDP. Figure 14 compares the number of children per woman between the EDP and the EDP/DADS matched sample. The proportion of women with no child is slightly higher in the matched sample (the gap is at most 29% vs. 25% for the 1970 cohort), whereas it is the opposite for mothers with two children. Overall, there is no huge difference.

## 8.2 Testing for selection bias

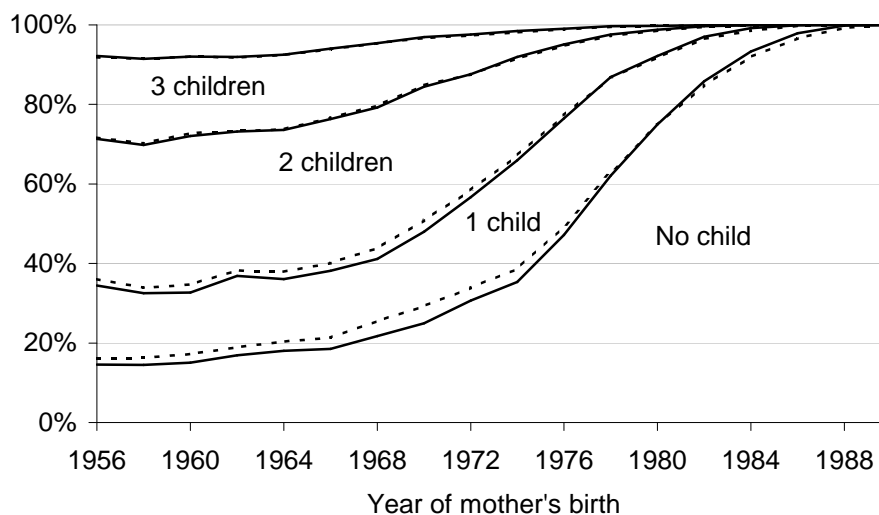
We saw in section 4.1 that a FE-2SLS estimation of equation (1) can give consistent estimates on a balanced panel. Semykina and Wooldridge (2010) show that it can also be applied to unbalanced panels, under a restrictive condition:

$$\mathbb{E}(u_{it}|z_i, s_i, c_i) = 0, \quad t = 1, \dots, T \quad (11)$$

where  $z_i = (z_{i1}, \dots, z_{iT})$  and  $s_i = (s_{i1}, \dots, s_{iT})$ . A major feature of FE-2SLS is that no restriction is imposed on the relationship between  $s_i$  and  $(c_i, z_i)$ . In particular,

**Figure 13:** Proportion of DADS observations present in the EDP/DADS sample

Notes: This ratio of 13 in the DADS: The curve represents for each year, the proportion of DADS observations that given year present in the EDP/DADS sample.

**Figure 14:** Number of children, comparison EDP vs. EDP/DADS

Notes: The curves represent the proportion of women with resp. 0, 1, 2, or 3 children, as a function of the woman year of birth. Dotted lines refer to the EDP, whereas plain lines refer to the matched sample EDP/DADS. Only even-numbered cohorts are plotted.



it allows attrition to be correlated with unobserved heterogeneity, which will be the case if some constant characteristics determining wages also have an impact on selection. Given the strict exogeneity of  $(z_i, c_i)$ , (11) automatically holds in the two polar cases where selection is totally random (i.e. not correlated with observed and unobserved determinants of wages) or completely determined by  $(z_i, c_i)$ . However neither of these situations seems likely to occur. For instance, one's level of education is a plausible candidate to explain both participation and wages, which rules out randomness. Moreover, assuming that all possible parameters related to the decision to participate into the labor market are included in  $(z_i, c_i)$  seems unrealistic: among other things, it would imply that there would be no unobserved time-varying variable influencing participation. But even if none of these two extreme situations holds, (11) remains valid as long as determinants of  $s_{it}$  not included in  $(z_i, c_i)$  are not part of the unexplained changes in wages  $u_{it'}$  for all  $t'$ .

This last assumption seems too strong in our context, since idiosyncratic shocks on wages in year  $t'$  could affect the decision to participate during year  $t$  ( $t > t'$ ). If condition (11) indeed fails, FE-2SLS cannot be used to estimate (1). Semykina and Wooldridge (2010) propose two procedures to test whether condition (11) holds.

The first one tests past or future selection bias : adding the selection indicators  $s_{it'}$  (for  $t' \neq t$ ) to equation (1) and estimating the augmented equation by FE-2SLS should lead to non significant coefficients on the  $s_{it'}$  if assumption (11) holds.

They also develop a method to test for contemporaneous selection bias in the FE-2SLS estimation of equation (1). This procedure (described in detail in Semykina and Wooldridge 2005) boils down to estimating

$$y_{it} = x_{it}\alpha + l_{it}\beta + c_i + \rho_t \widehat{\lambda}_{it} + \epsilon_{it}, \quad t = 1, \dots, T \quad (12)$$

by FE-2SLS. If the  $\rho_t$  are jointly significant, then there is indeed contemporaneous selection. In that case, estimation of  $\beta$  by FE-2SLS is biased, and the procedure described in section 4 is required. Note that this method does not test for past or future selection bias. Therefore accepting the null hypothesis of no contemporaneous bias does not imply that FE-2SLS is consistent.

Table 4 shows that the Wald test of joint significance of the  $\rho_t$  rejects the null hypothesis of no contemporaneous selection bias at the 1% confidence level. Therefore the procedure described in section 4 is required to produce a consistent estimate of  $\beta$ .

**Table 4:** Testing for selection bias

	(1)	(2)
<i>mills</i> <sub>1</sub>	-.2760801*** (.0446099)	-.3381206*** (.0448014)
<i>mills</i> <sub>2</sub>	-.2538073*** (.0434802)	-.3065577*** (.0443483)
<i>mills</i> <sub>3</sub>	-.2533781*** (.0450312)	-.3134802*** (.0455259)
<i>mills</i> <sub>4</sub>	-.2784707*** (.043574)	-.3676864*** (.0448777)
<i>mills</i> <sub>5</sub>	-.2903211*** (.0422251)	-.4023698*** (.045117)
<i>mills</i> <sub>6</sub>	-.2888452*** (.0434322)	-.4055856*** (.0449973)
<i>mills</i> <sub>7</sub>	-.4391497*** (.0490407)	-.5795309*** (.0523085)
<i>mills</i> <sub>8</sub>	-.5178682*** (.0507555)	-.6619586*** (.0537436)
<i>mills</i> <sub>9</sub>	-.4386951*** (.0591959)	-.6033393*** (.0619414)
<i>mills</i> <sub>10</sub>	-.3857685*** (.0577071)	-.5626253*** (.0620861)
<i>mills</i> <sub>11</sub>	-.4950894*** (.0600658)	-.6997221*** (.0647957)
<i>mills</i> <sub>12</sub>	-.4029094*** (.0599825)	-.6006247*** (.0646308)
<i>mills</i> <sub>13</sub>	-.4273978*** (.0608473)	-.6426625*** (.0649924)
<i>mills</i> <sub>14</sub>	-.4414156*** (.0631861)	-.6398817*** (.067327)
<i>mills</i> <sub>15</sub>	-.4152668*** (.0644735)	-.6112592*** (.0689118)
<i>mills</i> <sub>16</sub>	-.3297608*** (.0622768)	-.506142*** (.0666462)
<i>mills</i> <sub>17</sub>	-.4879121*** (.0699378)	-.6823519*** (.0742196)
<i>mills</i> <sub>18</sub>	-.2889029*** (.0568053)	-.4675414*** (.0606741)
<i>mills</i> <sub>19</sub>	-.2865194*** (.0614204)	-.4610958*** (.0655767)
<i>mills</i> <sub>20</sub>	-.2656346*** (.0600736)	-.4817236*** (.0643062)
<i>mills</i> <sub>21</sub>	-.294866*** (.0691163)	-.524047*** (.0727939)
Joint Wald test on Mills ratios	F( 21, 17388) = 7.45 Prob > F = 0.0000	F( 21, 17388) = 10.83 Prob > F = 0.0000

Notes: Total sample consists of women in the EDP/DADS matched sample, who gave birth to a second-born child between 1986 and 2002. Coefficients from the FE-2SLS estimation of equation 12 (second step). A part-time job indicator is included in the set of covariates (column 1) or not (column 2). Mills ratios are numbered chronologically (*mills*<sub>1</sub> for 1984, up to *mills*<sub>21</sub> for 2005, 1990 is missing).