# The impact of parental leave duration on later career

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Preliminary and incomplete work, please do not quote. Comments welcome!

#### 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 administrative 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 (2005) to take into account these three problems simultaneously. We find that parental leave duration has a significant negative causal impact on later wages.

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

JEL Classification: C23, J38, J68

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# 1 Introduction

This paper estimates the causal impact of parental leave on return to work and later wages.

More generally, the causal impact of periods spent out of the labor market on later wages has been widely studied. Most of these studies focused on unemployment spells, and concluded that unemployment has a negative causal impact on wages. Several mechanisms are often put forward to explain this result. The first one is related to return to experience on wages: as no work experience is accumulated during unemployment spells, wages don't grow because the individual is not working. Moreover potential employers might interpret the existence and the length of those unemployment spells negatively, and thus they might lower wage offers. In the same vein, unemployed individuals might have a weaker bargaining power than employed people when they negotiate their wage during an interview.

A distinctive feature of unemployment is that individuals generally undergo the loss of their job rather than choose not to work. On the other hand, voluntary withdrawals from the labor market can also account for periods spent out of the work force. Employees may indeed decide to stop working temporarily. This can happen if one quits his job, or if an agreement of temporary leave is found between employee and employer. In particular, parents can take a maternity or paternity leave after the birth of a child. There are many reasons to believe that parental leave may not have the same impact than unemployment on subsequent career. Potential employers may interpret voluntarily withdrawing and being unemployed differently. Employers may also fear that parents of a young child might be less involved in their professional activities. We focus on those parental leaves, and investigate whether later career is affected by such temporary withdrawals.

[review of literature, to complete] first the link between fertility and employment decisions (perticara 06), then the impact of policies on duration of the leave, and then on wage.

We take advantage of a reform that took place in France in 1994. The so called Parental Education Benefit (*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 (they 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. If eligible, 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. Once the leave is over, the employer has to provide a job similar to the one the beneficiary had before the leave<sup>2</sup>. To compensate

<sup>&</sup>lt;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.

<sup>&</sup>lt;sup>2</sup>This Parental Leave law (*congé parental*) applies only to those who have at least one year of firm seniority at the time of the birth. It is in theory not related to the APE: parents can be eligible to the APE without being eligible to the Parental Leave law, and vice versa. However, in most cases

for inflation, the beneficiary's new wage must at least be equal to his old wage plus the mean increase in wages observed in the firm during the leave. In a nutshell, the APE gives financial support to working parents who want to leave their job to take care themselves of their young children, and guarantees that they won't have any trouble finding a job at the end of the leave. Although both mothers and fathers may in theory benefit from the APE, mothers represent more than 98% of all beneficiaries. Therefore we excluded males from our study and focused exclusively on women. 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 second-born children in July 1994. This extension has been a success from the very beginning: in 1996, more then 240 000 families with two children benefited from this policy.

We use this extension as an exogenous variation in the incentives workers face to take a parental leave. Figure 4 illustrates that this reform had indeed a huge impact on mothers' participation rate in the three years after the birth of their second child. Two previous papers studied the impact of the APE reform on return to work 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. Therefore we feel confident that our identification strategy does not rely on a weak instrumental variable.

To our knowledge, almost all articles on parental leave studied the return to work. As far as the APE is concerned, the return to work is theoretically guaranteed by the law. Piketty (2005) noted that participation rates four years after the birth are similar to those observed right before the birth. Hence it seems that mothers willing to work don't have much trouble finding a new job. However, there are still many things to learn on the conditions under which this return to work happens. It may be possible that women have a less interesting job than the one they had before the birth. This could lead to more frequent resignations. The simple fact of taking a parental leave may also scar them, and thus affect their subsequent wage growth rate. Most of these papers focused on return to work, and did not estimate the causal impact of parental leave on later career path (wages, upward mobility/promotion, change of employer). Some of them were published too soon after the policy took place to have information on subsequent career characteristics. Others lacked information on wages in their datasets. Fourteen years after the APE reform, we are able to fill in this gap by matching two longitudinal sources (the DADS and EDP samples) containing information on career and familial background respectively. We find that the parental leave duration has a causal negative impact on later wages.

parents are eligible to either both policies or none of them. As we focus on withdrawals from the labor market, we selected women who worked at least one day during the calendar year of the birth or the calendar year before. Therefore, women in our sample fullfilling APE eligibility conditions almost automatically satisfy Parental Leave eligibility conditions as well. As a consequence, slightly abusing notations, APE will refer to the combination of these two policies in the remaining of this paper.

When estimating the impact of parental leave on later wages with a longitudinal dataset, three problems can arise. The first issue is that unobserved time-constant individual characteristics affecting wages are likely to be correlated with some explanatory variables (for instance, ability with education). A classical way to deal with heterogeneity is to add an idiosyncratic term  $c_i$  in the wage equation. Conditioning on that unobserved effect allows the explanatory variables to be correlated with the constant component of the unobserved heterogeneity. This solves the problem of omitted variables that are constant over time. For estimation purposes, the usual procedure consists in time-demeaning the equation of interest, and then pooling all the observations for an OLS estimation on the resulting equation. This within estimator is consistent on a balanced panel, as long as all explanatory variables are strictly exogenous (i.e. not correlated with past, present and future values of the error term) conditional on  $c_i$ .

However careers are often discontinuous, with periods spent out of the labor market. Apart from parental leave, these can be unemployment spells, or working spells out of the private sector<sup>3</sup>. 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 a subsample of women who chose to work, since we observe wages only for women 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 faced 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 first job after the birth is in the public sector. Moreover, endogeneity may stem from the link between  $l_{it}$  and motivation through the trade off made between time spent at

 $<sup>^{3}</sup>$ The DADS covers workers in the private sector, and doesn't contain civil servants and independent workers. See section 3.

<sup>&</sup>lt;sup>4</sup>Dustmann and Rochina-Barrachina (2007) survey these estimators in detail. They compare the exact set of assumptions needed for each estimator, and provide a discussion on their respective pros and cons/advantages and drawbacks. In particular they point out that Kyriazidou (1997) requires a "conditional exchangeability assumption which may be rather restrictive in practical applications".

the workplace and at home after the birth. This kind of correlation is indeed allowed in the fixed effect specification, as long as motivation keeps constant over time. But this assumption might be too strong, as some mechanisms could induce variations in motivation during the career. Changes in personal life like getting married or having children may increase the will to have spare time devoted to family, and thus lower motivation. Hence  $l_{it}$  might be linked to contemporaneous idiosyncratic changes in wages. Anyway, even if motivation were constant over time, the three aforementioned estimators require strict exogeneity for the length  $l_{it}$ , which is unlikely in our context. For instance, negative exogenous shocks to wages in the past may be related to poor work conditions, and thus affect the choice of parental leave length today. Dustmann and Rochina-Barrachina (2007) show that the previous estimators can be adapted to cases where strict exogeneity fails.

Our econometric specification is derived from Semykina and Wooldridge (2005). 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. Jäckle (2007) implements this method when studying the impact of health status on wages.

The econometric framework is detailed in the next part. Section 3 presents the two datasets, as well as descriptive statistics on the matched sample. Results of the estimations are shown in section 4 and the last section concludes.

# 2 The model

#### 2.1 No selection effect

Let's first ignore sample selection issues, and suppose that we work on a balanced panel. The equation of interest is the following:

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

$$\tag{1}$$

 $y_{it}$  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 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 (i.e. not correlated with  $u_{it'}$  for all t') conditional on  $c_i$ .

As explained above, it is likely that strict exogeneity of  $l_{it}$  will fail. A possible remedy is to find instrumental variables  $z_{it}$  sufficiently correlated with  $l_{it}$  and strictly exogenous conditional on  $c_i$  ( $z_{it}$  contains all strictly exogenous variables  $x_{it}$ , plus other strictly exogenous variable(s) correlated with  $l_{it}$ ). The procedure consists in timedemeaning equation (1) like in FE estimations and then applying a two stage least squares estimation (2SLS) to the time-demeaned equation. This FE-2SLS method produces consistent estimates on a balanced panel.

Semykina and Wooldridge (2005) show that it can be applied to unbalanced panels, under a more restrictive condition. Let  $s_{it}$  be a binary variable equal to 1 if  $(y_{it}, x_{it}, z_{it})$  is observed and 0 otherwise. Then in addition to the usual rank conditions, the following assumption is needed:

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

$$\tag{2}$$

where  $z_i = (z_{i1}, ..., z_{iT})$  and  $s_i = (s_{i1}, ..., s_{iT})$ . 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, 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  $(z_i, c_i)$ , (2) 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, (2) 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' can affect the decision to participate during year t (t > t').

Semykina and Wooldridge (2005) propose a procedure to test whether condition (2) holds. 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 (2) holds. They also develop a method to test for contemporaneous selection bias (see Annex 6.4). If condition (2) indeed fails, FE-2SLS cannot be used to estimate (1).

In such a case, Semykina and Wooldridge (2005) provide an estimation strategy which overcomes the limitation faced by the above FE-2SLS on unbalanced panels. Their method allows for endogeneity of some explanatory variables, and constant unobserved heterogeneity to be correlated with explanatory and instrumental variables in both the selection and wage equations. Selection  $s_{it'}$  can be correlated with  $u_{it}$ (for all t and t'), and contemporaneous selection bias is corrected for. This procedure requires the instrumental variables  $z_{it}$  to be observed only when  $s_{it} = 1$ , and to be strictly exogenous conditional on  $c_i$ . However  $z_{it}$  and  $c_i$  can be arbitrarily correlated, so the most attractive feature of FE is also present here. Eventually additional parametric assumptions are needed. The remaining of this section presents the modeling of the selection and wage equations.

#### 2.2 The selection process

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

$$\begin{cases} s_{it} = \mathbb{1}[Z_{it}\gamma + d_i + v_{it} > 0] \\ v_{it}|Z_i, d_i \sim \mathcal{N}(0, 1), \quad t = 1, \dots, T \end{cases}$$
(3)

 $Z_i = (Z_{i1}, ..., Z_{iT})$ , where  $Z_{it}$  is a vector containing  $x_{it}$  and at least one other variable not present in equation (1). The econometric model is theoretically identified without any exclusion variable, but in that case identification relies solely on the non linearity of equation (3). The specification becomes more convincing when there is at least one variable affecting selection and not wages. 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 (2005), 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 (3) is not linear. Mundlak (1978) proposed a way to deal with  $d_i$  without time-demeaning. He modeled the relationship between  $d_i$  and the explanatory variables  $Z_i$  as follows:

$$\begin{cases} d_i = \mu + \overline{Z_i}\delta + a_i \\ a_i | Z_i \sim \mathcal{N}(0, \tau^2) \end{cases}$$
(4)

This equation decomposes/writes  $d_i$  into/as the sum of a term correlated with  $Z_i$  and a part which by construction is independent of  $Z_i$ . In all generality, no restriction should be imposed on the linear projection of  $d_i$  on  $Z_i$ , and therefore the time-averaged variables  $\overline{Z_i} = (Z_{i1} + \ldots + Z_{iT})/T$  in equation (4) should be replaced by  $Z_i$  (this more flexible specification was suggested by Chamberlain 1980). 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 périods t'. In other words, (4) assumes that all interactions between  $d_i$  and  $Z_i$  are captured by the time average  $\overline{Z_i} = (Z_{i1} + \ldots + Z_{iT})/T$ . Both approaches are valid within our framework, we chose to present Mundlak's here because it conserves on degrees of freedom. Unlike in the FE transformation,  $Z_i$  can contain time-constant variables like education.

Plugging (4) into equation (3) leads to:

$$\begin{cases} s_{it} = \mathbb{1}[\mu + Z_{it}\gamma + \overline{Z_i}\delta + w_{it} > 0] \\ w_{it}|Z_i \sim \mathcal{N}(0, 1 + \tau^2), \quad t = 1, \dots, T \end{cases}$$
(5)

where  $w_{it} = a_i + v_{it}$ . In fact, the effect of  $d_i$  in equation (3) 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):

$$\begin{cases} s_{it} = \mathbb{1}[\mu_t + Z_{it}\gamma_t + \overline{Z_i}\delta_t + w_{it} > 0] \\ w_{it}|Z_i \sim \mathcal{N}(0, 1), \quad t = 1, \dots, T \end{cases}$$
(6)

#### 2.3 The wage equation

First let's recall that the fixed effect transformation was applied to remove the unobserved heterogeneity  $c_i$  from equation (1) before running a 2SLS estimation. The residual resulting from the time-demeaning was a function of  $u_{it'}$  for all t'. Doing so, correlation between the selection indicator in period t and  $u_{it'}$  (for all t') became a problem, whereas only contemporaneous selection mattered 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:

$$\begin{cases} c_i = \eta + \overline{z_i}\theta + b_i \\ \mathbb{E}(b_i|z_i) = 0 \end{cases}$$
(7)

This specification assumes that  $c_i$  depends on  $z_i$  only through the time average  $\overline{z_i} = (z_{i1} + ... + z_{iT})/T$ . Note the no assumption is made on the law of  $b_i|z_i$ . The wage equation (1) can be rewritten using (7):

$$y_{it} = x_{it}\alpha + l_{it}\beta + \eta + \overline{z_i}\theta + b_i + u_{it}, \quad t = 1, \dots, T$$
(8)

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

$$\begin{cases} y_{it} = x_{it}\alpha + l_{it}\beta + \eta + \overline{z_i}\theta + \mathbb{E}(b_i + u_{it}|z_i, s_{it}) + e_{it} \\ \mathbb{E}(e_{it}|z_i, s_{it}) = 0, \quad t = 1, \dots, T \end{cases}$$
(9)

One important feature of (9) 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 (9) 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

$$\begin{cases} \mathbb{E}(u_{it}|z_i, w_{it}) = \mathbb{E}(u_{it}|w_{it}) = \rho_t w_{it}, & t = 1, \dots, T \\ \mathbb{E}(b_i|z_i, w_{it}) = \mathbb{E}(b_i|w_{it}) = \psi_t w_{it}, & t = 1, \dots, T \end{cases}$$
(10)

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. (10) 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 (10) and the law of iterated expectations to get:

$$\mathbb{E}(b_{i} + u_{it}|z_{i}, s_{it} = 1) = \mathbb{E}(b_{i} + u_{it}|z_{i}, w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t}) \\
= \mathbb{E}(b_{i} + u_{it}|w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t}) \\
= \frac{\mathbb{E}\left[(b_{i} + u_{it}) * \mathbb{1}(w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t})\right]}{\mathbb{P}\left[w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t}\right]} \\
= \frac{\mathbb{E}\left[\mathbb{E}(b_{i} + u_{it}|w_{it}) * \mathbb{1}(w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t})\right]}{\mathbb{P}\left[w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t}\right]} \quad (11) \\
= \Psi_{t} \frac{\mathbb{E}\left[w_{it} * \mathbb{1}(w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t})\right]}{\mathbb{P}\left[w_{it} > -\mu_{t} - Z_{it}\gamma_{t} - \overline{Z_{i}}\delta_{t}\right]} \\
= \Psi_{t} \frac{\phi(\mu_{t} + Z_{it}\gamma_{t} + \overline{Z_{i}}\delta_{t})}{\Phi(\mu_{t} + Z_{it}\gamma_{t} + \overline{Z_{i}}\delta_{t})}$$

where  $\phi$  and  $\Phi$  are respectively the probability density and cumulative distribution functions of a standard normal law. It shows that under (10),  $\mathbb{E}(b_i + u_{it}|z_i, s_{it} = 1)$ is proportional to the inverse Mills ratio

$$\lambda_{it}(\mu_t + Z_{it}\gamma_t + \overline{Z_i}\delta_t) = \frac{\phi(\mu_t + Z_{it}\gamma_t + Z_i\delta_t)}{\Phi(\mu_t + Z_{it}\gamma_t + \overline{Z_i}\delta_t)}$$

Running the probit regression (6) (for each period t separately) provides an estimate of this ratio  $\widehat{\lambda_{it}}(\mu_t + Z_{it}\gamma_t + \overline{Z_i}\delta_t) = \lambda_{it}(\widehat{\mu_t} + Z_{it}\widehat{\gamma_t} + \overline{Z_i}\widehat{\delta_t}).$ 

Eventually, the estimation strategy is the following:

- Compute the estimate of the inverse Mills ratio  $\widehat{\lambda_{it}}$  for period t from equation (6),  $t = 1, \dots, T$
- Replace  $\mathbb{E}(b_i + u_{it}|z_i, s_{it})$  by  $\Psi_t \widehat{\lambda_{it}}$  in equation (9), and estimate (9) on the selected sample  $(s_{it} = 1)$  by pooled 2SLS. The instrumental variables are 1,  $z_{it}$ ,  $\overline{z_i}$  and  $\widehat{\lambda_{it}}$ . The estimators' variance-covariance matrix needs to be computed according to the formula given in 6.3.

The presence of an 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.

In cases where condition (2) fails, this procedure corrects for selection bias and endogeneity of  $l_{it}$ . Moreover, it allows unobserved heterogeneity to be correlated with explanatory variables, both in the selection and primary equations. 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 conditionnal mean of  $u_{it}$ .

Eventually, using Mundlak's (1978) device instead of the usual FE transformation in the equation of interest allows us to add time-constant variables like education in equation (1). Obviously, their effect on wages (given by the vector of parameters  $\alpha$ ) is not identified in this procedure: they cannot be distinguished from the effect of unobserved time-constant variables passing through the time-averaged  $\overline{z_i}$  after the Mundlak's (1978) transformation. However, adding these variables is likely to capture a greater part of the unobserved heterogeneity constant over time in (7). Therefore, even if these coefficients cannot be causally interpreted, it is still an improvement compared to a situation with no time-constant variable in the wage equation.

# 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 individualfirm-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, full-time/parttime status, 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 these persons between 1976 and 2005 (except for 1981, 1983 and 1990, because the extraction of the DADS was not made in these three years).

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.



#### Figure 1: Number of births per year

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

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 6.1 provides information on possible sample selection issues by checking whether women's observable characteristics in the matched sample systematically differ from those of EDP.

Figure 1 represents the number of births by year. The extension of APE to secondborn children in 1994 does not seem to have increased the number of second-born births. Therefore the decision to have a second child was not severely affected by the APE reform. See Piketty (2005) for more information on that specific subject.

Figure 2 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<sup>5</sup> certainly accounts for the increase observed between the 1950 and 1980 cohorts.

After having given birth, a woman working under the French law is supposed to stop working during at least a given number of weeks, corresponding to the mandatory maternity leave. In most cases the actual length of the withdrawal is greater than this minimum leave. This length is a key variable in our study, as we wish to estimate the marginal impact of the withdrawal on later wages. Participation rates 1, 2 and

<sup>&</sup>lt;sup>5</sup>See XXX.



Figure 2: 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.

3 calendar years after the birth of a first-born child are represented in Figure 3. Figures 4 and 5 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 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. As the APE reform in 1994 affected only mothers of a second-born child, and gave incentives to withdraw during at most 3 years from the labor market, it is very likely that this reform accounts for most of these drops<sup>6</sup>. Two points are worth emphasizing: the drops are particularly spectacular given the rising trend between 1976 and 2005, and women were fast to adapt their behavior to the new law. Piketty (2005) found similar results using French Labor Force Surveys.

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 in 1994 (note that 1994 is only a milestone in Figures 6 and 8, because the APE reform in 1994 did not change anything for mothers of a first- or third-born child). Mothers

<sup>&</sup>lt;sup>6</sup>The absence of drop in the third calendar year after the birth is not problematic, since a withdrawal of three years after the birth implies that the return to work occurred during the third calendar year after the birth.



Figure 3: 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 4: 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 5: 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.

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 3 to 5. It certainly stems from the general change in women's (and here especially mothers') behavior toward the labor market, often symbolized by the rise in female participation rate (Blanchet and Pennec 1997). The gap between the pre-reform and post-reform curves is roughly constant after the birth of a firstborn 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. 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



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

Notes: 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. See Annex 6.2 for details on how the length was computed. Lecture: 80% of working women who had a third-born child before 1994 were working three years after the birth of this child.

noticing that these shifts occur after 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. 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 7: Cumulative spell duration after the birth of the second child

Notes: 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. See Annex 6.2 for details on how the length was computed.



60%

40%

20%

0%

0

1

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

Notes: 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. See Annex 6.2 for details on how the length was computed.

3

Years of withdrawal

Before 1994 — After 1994

4

5

2



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  $\in 2005$ . 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 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 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.



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  $\in 2005$ . 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.

# 4 Results

We implement the estimation strategy described in section 2 on two different samples, with two slightly different sets of variables.

Our first sample is composed of mothers of at least two children. The length  $l_{it}$  of the withdrawal from the labor market is the length of the spell (in years) following the birth of the second-born child. Our instrumental variable in  $z_{it}$  correcting for the endogeneity of  $l_{it}$  is whether this birth occurred before or after the APE reform in July 1994. The reform is indeed correlated with the choice of  $l_{it}$  (see Figure 7), and there is no evident reason to think that it had a direct impact on wages. 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. Several authors used a similar exclusion variable. Local unemployment rates are also used are exclusion variables.

Other explanatory variables are age, square age, the number of children, education, and annual dummies as a proxy for macro economic environment.

An implicit assumption is that the APE reform in 1994 did not have an impact on the decision to have a second child, as we want the selection bias (created by selecting mothers of at least two children) to be constant over time. Figure 1 shows that the reform was not followed by an increase in the number of second-born children, which supports this hypothesis. However, the total number of birth increases in the 1990ies, mainly driven by the rise in first-born children. Piketty (2005) noted the same phenomena, and argued that most of this increase was probably due to better macroeconomic conditions. He estimated that the APE reform explained only a small

wage	Coef.	Std. Err.	t	P >  t	[95% Conf. Interval]	
length age age2 nbchild intercept	0279408 .072178 0725249 0638052 2.146096	$\begin{array}{c} .0015316\\ .0017541\\ .0023988\\ .0028148\\ .0297398\end{array}$	-18.24 41.15 -30.23 -22.67 72.16	0.000 0.000 0.000 0.000 0.000	0309426 .0687401 0772265 069322 2.087806	0249389 .075616 0678234 0582883 2.204385
Number of individuals Number of observations		$15 \ 048 \\ 170 \ 102$				

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

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 15 048 of them. Wages are observed 170 102 times between 1984 and 2005. Coefficients of time dummies are not reported. The dependent variable *wage* is the log of the daily wage per year, in  $\in$  2005.

part of the increase between 1994 and 2001.

The second sample contains all women in the matched EDP/DADS sample. In this specification,  $l_{it}$  is the sum of all spells out of the labor market after the birth of a child.  $l_{it}$  is equal to 0 if a woman does not have any child. We instrument  $l_{it}$  with a dummy equal to 1 if the second birth occurred after 1994 or if the third birth occurred after the creation of the APE in 1985. Once again, the exclusion variable for selection is whether there is a child under three in the household.

The remaining of this section presents the results of different estimations on the first sample. The instrumental variable is whether the birth occurred before or after July 1994. For computational purposes, we selected women who gave birth to a second child between 1986 and 2002. Wages are observed between 1984 and 2005. Table 1 presents the FE estimation results of equation (1). This estimation 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. One year of withdrawal from the labor market is associated with a 2.8% decrease in wages.

Unobserved heterogeneity and endogeneity are taken into account with a FE-2SLS estimation (see Table 2). Parental leave duration does not have a significant impact on wages. Results of the first step estimation are not reported here; our instrumental

wage	Coef.	Std. Err.	t	P >  t	[95% Con	f. Interval]
length age age2 nbchild intercept	.0718489 .0720012 0746732 0931585 2.175744	.0550827 .0017837 .0027088 .0164465 .034344	$1.30 \\ 40.37 \\ - 27.57 \\ - 5.66 \\ 63.35$	$\begin{array}{c} 0.192 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \end{array}$	0361112 .0685051 0799824 125393 2.108431	.179809 .0754972 069364 060924 2.243057
Number of individuals Number of observations		$15 \ 048 \\ 170 \ 102$				

 Table 2: FE-2SLS estimation (second step)

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 170 102 times between 1984 and 2005. Coefficients of time dummies are not reported. The dependent variable *wage* is the log of the daily wage per year, in  $\in$  2005.

variable has a large (+0.10 year) and highly significant (t value=10.45) impact on the endogenous variable *length*. On the other hand, sample selection is not accounted for and it might lead to inconsistent estimates.

Results of the procedure testing for selection bias are presented in section 6.4. They show that there is indeed a significant selection bias (the null hypothesis of no selection bias is rejected at the 1% confidence level), and therefore motivate the use of a method correcting for selection bias.

Table 3 shows estimation results of equation (9) by pooled 2SLS. The three potential issues identified in section 1 are now taken into account. We find a negative causal impact of parental leave duration on later wages. This estimate is highly significant. It implies that, on top of a possible wage penalty when women give birth, the length of the parental leave is associated with wage losses. According to Table 3, there is a a 18% wage loss for the average withdrawal length in our sample (1.5 year). This effect is massive, and larger than one would have expected. At this stage, one must be very cautious when interpreting the magnitude of the effect. It represents the mean effect on wages mothers face during the remaining of their career. This does not necessarily mean that mothers' wage level decreases by 13% from their return to work until they retire. This decrease could be explained by a (time-constant) wage gap after the birth, or/and a lower wage growth rate. The cumulative effect of a 1% difference in wage growth rate during the 25 years between the birth of a child and the end of one's career could explain an important part of the 13% effect. Moreover,

wage	Coef.	Std. Err.	t	P> t	[95% Con	f. Interval]	
length	1369813	.019937	-6.87	0.000	1760574	0979052	
age2 nbchild	08989999 0125946	.0083917 .0136212	-10.71 -0.92	0.000 0.355	1063475 0392919	0734522	
age mean age2	.0860215	.0070839 .0026667	12.14 -2.89	0.000	.0721371 0129202	.0999059 0024668	
mean nbchild mean age	1325322 .0169813	.0119533	-11.09 6.33	0.000	1559603 .0117256	109104 .0222371	
mean excl mean z	.1313879 .0877421	.0610592 .0193666	$2.15 \\ 4.53$	0.031 0.000	.0117131 .0497839	.2510626 .1257003	
Number of individuals		$15\ 048$					
Number of observations Joint Wald test on Mills ratios		$\begin{array}{l} 170 \ 102 \\ F(\ 21,\ 149 \ 775) = 2.05 \end{array}$			Prob > F = 0.0031		

Table 3: Final step of the estimation

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 170 102 times between 1984 and 2005. Coefficients of time dummies and Mills ratios are not reported. The dependent variable *wage* is the log of the daily wage per year, in  $\notin$ 2005.

experience is not taken into account in our model, so this coefficient contains the effect of not increasing experience during the withdrawal.

Bayet (1997) can help us put these results into context. He studied wage differentials between French workers with interrupted or uninterrupted careers. By his definition a career is interrupted if the sums of spells out of the labor market during the career exceeds two years. He found that long breaks have a massive effect on wages. For example, focusing on female clerical workers with 25 years of total experience, and 10 years of tenure with their current employer (the average tenure in his sample), wages are 23% lower in case of interrupted careers. As Bayet (1997) does a ceteris paribus analysis, his results cannot be causally interpreted. However the magnitude of his coefficients is comparable to what is seen in Figures 9 and 10.

We plan to test other model specifications, and allow the duration of the withdrawal to have a different impact depending on the number of years since the return to work.

Eventually, these are early estimations, and robustness checks need to be implemented.

# 5 Discussion and conclusion

# References

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### 6 Annex

### 6.1 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>7</sup>.





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.

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

<sup>&</sup>lt;sup>7</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:



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

Notes:

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. Figure 15 plots the mean age at which mothers gave birth.



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.

Figure 15: Mother's age at the birth of her children, comparison EPD vs. EDP/DADS

#### A FAIRE

Notes: For each mother's cohort, mean age at which they gave birth to their  $i^{th}$  child. The scope is women in the EDP or DADS/EDP samples who had at least i children.

#### 6.2 Length of withdrawal

Construction of the length of withdrawal from the labor market. translate the french draft.

## 6.3 Variance Covariance matrix

See Semykina and Wooldridge (2005).

#### 6.4 Testing for selection bias

Table 4 presents the results of the procedure testing 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

$$y_{it} = x_{it}\alpha + l_{it}\beta + c_i + \rho_t \widehat{\lambda_{it}} + \epsilon_{it}, \quad t = 1, \dots, T$$
(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 2 is required.

The Wald test of joint significance of the  $\rho_t$  rejects the null hypothesis of no contemporaneous selection bias at the 1% confidence level.

The FE-2SLS estimation requires selection  $s_i = (s_{i1}, ..., s_{iT})$  to be strictly exogenous (see equation (2)). Note that this procedure 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.

wage	Coef.	Std. Err.	t	P> t	[95% Cont	f. Interval]
length	0648363	.0198672	-3.26	0.001	1037784	0258943
nbchild	.0380564	.0131532	2.89	0.004	.0122746	.0638381
age	.0436939	.0060244	7.25	0.000	.0318855	.0555024
age2	0368569	.0079706	-4.62	0.000	0524803	0212335
mills1	267986	.047589	-5.63	0.000	3612661	1747059
mills2	2812795	.0422488	-6.66	0.000	364092	198467
mills3	2600923	.0432104	-6.02	0.000	3447898	1753948
mills4	3903357	.0423921	-9.21	0.000	4734292	3072423
mills5	3675029	.0395697	-9.29	0.000	4450641	2899417
mills6	3493455	.0420161	-8.31	0.000	431702	266989
mills7	4624634	.0462238	-10.00	0.000	5530674	3718594
mills8	5927996	.0495207	-11.97	0.000	6898659	4957333
mills9	5238072	.0538436	-9.73	0.000	6293469	4182675
mills10	5532578	.0562357	-9.84	0.000	6634864	4430291
mills11	7503328	.0631391	-11.88	0.000	8740929	6265728
mills12	671709	.0623369	-10.78	0.000	7938965	5495215
mills13	7418261	.0603838	-12.29	0.000	8601854	6234669
mills14	6707448	.0619943	-10.82	0.000	792261	5492286
mills15	7234668	.0652687	-11.08	0.000	851401	5955325
mills16	6592944	.0681926	-9.67	0.000	7929598	525629
mills17	744345	.0773228	-9.63	0.000	8959068	5927831
mills18	417756	.0639203	-6.54	0.000	5430474	2924646
mills19	3718563	.0668428	-5.56	0.000	502876	2408366
mills20	3024215	.0663553	-4.56	0.000	4324857	1723573
mills21	4661167	.0675477	-6.90	0.000	5985181	3337154
intercept	2.761555	.1183295	23.34	0.000	2.529615	2.993494

Table 4: Testing for selection bias

Notes: Total sample consists of women in the EDP/DADS matched sample, who gave birth to a second born child between 1991 and 2004. Wages are observed 172 456 times between 1984 and 2005, among a total of 328 230 possible observations. Coefficients of time dummies are not reported. *partial* is a dummy variable equal to 1 iff the woman worked part-time during the corresponding year. The dependent variable *wage* is the log of the daily wage per year, in €2005. Mills ratios are numbered chronologically (mills1 for 1984, up to mills21 for 2005, 1990 is missing).