How Does Maternity Leave Allowance Affect Fertility and Career Decisions?

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Abstract

The level of compensation during maternity leave varies significantly across countries, yet previous research provides limited insights on its consequences. In this paper, I assess how the generosity of maternity leave allowance affects first-time mothers' subsequent fertility decisions and career trajectory. I exploit the fact that the allowance is capped in Belgium so that women with pre-leave earnings above the maximum threshold face drastically lower replacement rates. Using a regression kink design, as well as a rich set of administrative data on mothers from 2002 to 2015, I find that subsequent fertility increases with the level of benefits: for each additional euro in daily allowance the probability of having a second child increases by 0.6 percentage point. Subsequently, I explore the consequences for their career and show that mothers who receive higher benefits are more likely to leave salaried employment for self-employment. I demonstrate that the transition to self-employment does not affect their earnings in the long run, suggesting that the career changes might reflect non pecuniary preferences. In fact, heterogeneity analysis reveals that those working in sectors with poor work-family balance are more likely to become self-employed.

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Introduction

Recent studies highlight the large drop in women's earnings following the birth of their first child (see e.g. Angelov, Johansson, & Lindahl, 2016; Lundborg, Plug, & Rasmussen, 2017). This so-called "child penalty" largely contributes to the remaining gender inequalities in labor market outcomes (Kleven, Landais, & Søgaard, 2019).

Maternity leave allowance protects mothers' finances in the short-run by providing wage replacement while they are away from work to recover from childbirth and care for their newborn.[1] In a majority of OECD countries, the wage replacement is, however, only partial, so that mothers do suffer a net income loss during maternity leave. Figure A1 in Appendix shows that maternity leave benefits completely replace the lost income in only 13 countries out of the 41 considered. In the remaining vast majority, the mean replacement rate for a woman with earnings at the level of the national average is around 66%. In addition, half of the OECD countries have caps on the benefit amount, which results in a much lower replacement rate for high-earning women.

In this paper, I assess how the generosity of maternity leave allowance affects first-time mothers' subsequent fertility decisions and career trajectory. My argument is that the first maternity leave acts as an information shock on the opportunity cost of childbearing.[2] As such, I build upon Becker's idea that the "cost of the mother's time" represents the largest component of the "total cost of producing and rearing children" (Becker, 1991). If mothers are fully compensated during maternity leave their opportunity cost of producing children is drastically reduced,[3] but since the wage replacement is only partial in most countries they suffer a net income loss for each child they bear. I expect this to be a particularly salient problem for high-earning women who must forego a higher wage while temporarily leaving the labor market to give birth (Willis, 1973). Having a first child will provide new mothers with information on the extent of this income loss,[4] which might affect their preference for additional children in the future. Through its effect on fertility, maternity leave allowance might also have implications for the mothers' career. Indeed,

[1] In the Appendix, I provide an event study analysis for Belgian women and take advantage of high-frequency data at quarterly level to show that maternity leave benefits indeed provide a short-term buffer against the child penalty in earnings. Figure A2 in Appendix shows that mothers' income loss during the two quarters following the birth of their first child is about three times larger when not accounting for maternity leave allowance.

[2] Kuziemko, Pan, Shen & Washington (2018) argue that women do not fully anticipate the cost of motherhood and that the event of the birth of a first child serves as an information shock which updates their attitudes towards employment and parenthood.

[3] However, the opportunity cost might not be entirely null, since absence from the workplace might result in missed promotion or loss in human capital.

[4] This is compatible with the recent findings of Spittal (2021), who shows that mothers in the United-Kingdom "learn through experience" and only adapt their labor supply after a reduction in the child tax credit when their first child becomes ineligible.

the need to conjugate family and work demands might push some to reconsider their career path.

Maternity leave mandates are built around two key parameters: the duration and the wage replacement rate. The former has received much more attention than the latter in the scientific literature (see Olivetti & Petrongolo, 2017 and Rossin-Slater, 2018 for comprehensive overviews). This is likely due to the difficulty of finding a credible causal inference design that isolates the benefit amount since it is not randomly assigned and because reforms often combine changes to both parameters.

My empirical strategy relies on a Regression Kink Design (RKD) to identify the impact of the allowance received by first-time mothers on their subsequent fertility and labor market outcomes, up to five years. I exploit the fact that from the 31$^{\text{st}}$ day of maternity leave the allowance is capped in Belgium, so that women with pre-leave earnings above the maximum threshold face drastically lower replacement rates. As shown in Figure 1, this translates into a discontinuous change in the marginal replacement at the threshold set by the social security administration. I leverage this discontinuity to identify the causal effects of the benefit amount by testing for a change in the slope of the relationship between my outcomes of interest and the assignment variable (i.e. the pre-leave earnings) at the kink. Thus, my empirical strategy allows to explore the effects of maternity leave allowance generosity, while holding constant other policy parameters, including the duration of leave.

By design, my analysis focuses on mothers in the upper-half of the income distribution, since they are the ones in the vicinity of the kink point, located around the 90$^{\text{th}}$ percentile. Those women tend to be older when giving birth for the first time. They were also more likely to work full-time before the birth of their first child. This is in fact a very interesting sub-sample, since those women are disproportionately affected by the "motherhood wage penalty" and therefore face a higher opportunity cost of maternity (Anderson, Binder, & Krause, 2002; Bertrand, Goldin, & Katz, 2010; Hotchkiss, Pitts, & Walker, 2017). As a result, they tend to have a lower fertility rate, what Raute (2019) calls the "baby gap" between low-earning and high-earning women. It therefore seems important to understand to what extent financial incentives play a role in the fertility decisions of those women. Furthermore, because they are highly productive women, the feedback effects of their fertility and labor supply decisions might provide important insights on gender differences in career trajectories.

I use a rich administrative dataset, which aggregates several registers on social security status and employment of Belgian mothers between 2002 and 2015, as well as detailed household's information, including about their co-parent. As such, I am able to paint a comprehensive picture of the consequences of maternity leave allowance by looking at the impact on both fertility and labor supply. I believe this is a truly positive feature of my paper, since those are joint decisions that cannot be fully understood if studied in isolation, as it has been done so far in the limited quasi-experimental literature on maternity leave benefits.[5] Furthermore, the data on employment allow me to distinguish between salaried and self-employment. I think this is another strength of my empirical design, which allows me to look beyond the mere employment status and highlight changes in revenue streams, as well as nonlinear career paths.

The first contribution of this paper is to demonstrate that the level of compensation during maternity leave positively affects subsequent fertility. More precisely, I estimate that for each additional euro in daily allowance the probability of having a second child increases by 0.6 percentage point. The second contribution of this study is to show that more generous maternity leave allowance increases the probability of leaving salaried employment for self-employment. Indeed, I estimate that an increase in maternity leave benefits of 1 euro per day decreases the probability of being salaried employee after five years by 0.7 percentage point, while it increases the odds of becoming self-employed by 0.6 percentage points. The third contribution is to explore the dynamics of these effects on a quarterly basis over a five-year period following the first childbirth. I demonstrate that the changes in career path precede the increase in subsequent fertility, suggesting that women transition to self-employment in anticipation of a second child. I argue that by switching to self-employment, these mothers seek a better balance between work and family demands. The fourth contribution of this research is to reveal that the increased transition to self-employment does not affect the mothers' earnings in the long run. I believe this supports my argument that the changes in career path reflect non pecuniary preferences. In fact, I find that the transition to self-employment is particularly important among women that earn less than their partner and work in sectors reported as less family-friendly because of their atypical time schedules.

My research expands on the handful of papers that manage to measure the effects of maternity leave allowance generosity[6] (Asai, 2015; Bana, Bedard, & Rossin-Slater,

[5]The structural literature has highlighted the interaction between fertility and female labor supply and as such the need to model jointly those decisions (e.g. Francesconi, 2002; Moffitt, 1984; Heckman & Walker, 1990). Some of the most recent papers in this literature build on dynamic life-cycle models that account for the effects of family policies (Adda, Dustmann, & Stevens, 2017), including paid leave benefits (Stichnoth, 2020).

[6]Previous studies have highlighted the positive effect of maternity leave provision on fertility (Dahl, Løken, Mogstad, & Salvanes, 2016; Golightly, 2019; Lalive & Zweimüller, 2009). However, they explored reforms that affected several parameters of the parental leave system, including leave duration. The seminal paper by Lalive and Zweimüller (2009) finds strong positive effects on higher-order fertility after a reform in 1990 in Austria, which expanded the duration of paid maternity leave from one to two years. A more recent study by Golightly (2019) exploits the introduction of the first paid parental leave mandate in the United-States, which was implemented in 2004 in the State of California, and finds that it increased

2020; Cygan-Rehm, 2016; Ginja, Jans, & Karimi, 2020; Kluve & Schmitz, 2018; Raute, 2019; Tudor, 2020). Three of those papers use a German reform in 2007, which changes the parental leave system from a flat means-tested to an earnings-related benefit. Cygan-Rehm (2016) and then Kluve and Schmitz (2018) show that the reform reduced subsequent childbearing for low-income mothers, who received higher benefits under the old means-tested system. Conversely, Raute (2019) finds a positive effect on the fertility of women at the middle and upper end of the earnings distribution, who are better off after the reform. Those studies in the German context highlight the fact that compensating women according to their opportunity cost of childbearing increases fertility. Unfortunately, the main concern about these three studies is that they cannot rule out that some of the effect might be driven by the increased use of parental leave by the father/co-parent. Indeed, the 2007 reform also provides two earmarked "daddy months", which successfully increased the share of fathers taking parental leave (Raute, 2019). The rising involvement of fathers could have affected mothers' fertility decisions.[7] Compared to those studies, my RK design allows me to isolate completely the effect of the benefit amount. Another study by Tudor (2020) shows that a 2003 reform in Romania, which switched the earnings-related system to a fixed benefits system with substantial gains for most employed women, did not influence short term conception rates but significantly decreased the probability of abortion.

The three other studies on maternity leave allowance generosity (Asai, 2015; Bana et al., 2020; Ginja et al., 2020) examine the impact on labor market outcomes.[8] While Asai (2015) and Bana *et al.* (2020) do not find any effects, Ginja, Jans, & Karimi (2020) show that eligibility for higher parental leave benefits decreases mother's labor supply, but only in the short-run (up to 2 years). I extend these studies by showing that even though maternity leave allowance has no effect on the employment rate in the long run, it does affect the career path of young mothers. More particularly, I highlight the fact that the

the overall fertility rate by up to 15%. Interestingly, Golightly (2019) points out that the effect is driven by increases in rates of second and higher parity childbearing, suggesting that paid maternity leave does not lead otherwise childless women to have children but rather drives mothers to have additional children. The only paper that finds no effect on completed fertility is by Dahl, Løken, Mogstad and Salvanes (2016), who evaluate a series of expansions in paid maternity leave in Norway. Their study, unfortunately, cannot say anything about the benefit amount since the replacement rate was 100% for most women in Norway.

[7] The link between paternity leave and fertility has been highlighted by Farré and González (2019) in a recent study for Spain.

[8] More studies have explored the effect of maternity leave provision on mothers' labor supply, but they do not isolate the effect of the benefit amount. In a recent review of this literature, Rossin-Slater (2018) explains that the general conclusion emerging from empirical studies across countries is that provisions of maternity leave of less than one year typically appear to improve job continuity for women and increase employment rates several years after childbirth (see e.g. Ruhm, 1998; Baker & Milligan, 2008; Blau & Kahn, 2013; Kluve & Tamm, 2013; Thévenon & Solaz, 2013; Carneiro, Løken, & Salvanes, 2015; Geyer, Haan, & Wrohlich, 2015). On the contrary, longer maternity leave mandates seem detrimental to women's earnings, employment, and career advancement in the long-run (see e.g. Lalive & Zweimüller, 2009; Lequien, 2012; Lalive, Schlosser, Steinhauer, & Zweimüller, 2014; Schönberg & Ludsteck, 2014; Bičáková & Kalíšková, 2019).

propensity of young mothers to transition to self-employment increases with the level of benefits and I posit that the effect is mediated through a change in desired fertility.

Two studies have explored the link between parental leave policies and entrepreneurship (Gerards & Theunissen, 2018; Gottlieb, Townsend, & Xu, 2021). The authors exploit reforms that changed the duration of parental leave in Canada and Germany to show that it affected the propensity of mothers to become entrepreneurs after childbirth. Their argument is that mothers use the paid time off work to incubate their businesses while the job-protected leave minimizes the risk for their career. I believe that these two papers do not account for an important mediator in the relationship between maternity leave and entrepreneurship: fertility choices. Both papers by Gerards et al. (2018) and Gottlieb et al. (2021) find that the probability to become entrepreneur is affected six years after the birth of the mother's first child. However, these two papers do not account for the fact that in this time interval, mothers decide (or not) to have a second child, and that this decision might be impacted by the maternity leave experience, as suggested by previous studies (see e.g. Dahl et al., 2016; Golightly, 2019; Lalive & Zweimüller, 2009).[9] My study suggests that making maternity leave more generous (in terms of duration or benefits) increases subsequent fertility and that young mothers are more likely to transition to self-employment when they want more children but they are employed in sectors with restrictive work schedule. In other words, changes to the maternity leave program affect subsequent fertility which in turn affect the decision to become self-employed. This argument is compatible with the theoretical model of Wellington (2006) who shows that women are choosing self-employment as a strategy to balance family and career, especially more educated women.

Taken together, my results reveal that mothers make decisions about their total fertility based, at least in part, on the generosity of maternity leave allowance. These decisions have in turn consequences for their career (but not their earnings), and particularly for those who used to earn less than their partner and those who worked in sectors with poor work-family balance. My findings should provide policy relevant information since, as discussed above, the level of compensation during maternity leave varies widely across countries. Belgium offers in that sense a particularly interesting case for research because the features of its maternity leave mandate are only slightly above the international standards set by the International Labor Organization and not among the top or bottom performers.

The remainder of the paper is organized as follows. Section 1 provides more details on the Belgian maternity leave program and benefit schedule. Section 2 introduces the

[9]In fact, Gerards et al. (2018) provide descriptive evidence in Figure 2 that the probability to give birth to a second child dropped after the 2001 reform in Germany.

empirical framework and shows tests of the identifying assumptions of the RKD. Section 3 presents the main results, as well as heterogeneity analyses. Section 4 provides various robustness checks. Section 5 concludes.

1 Institutional Background

In Belgium, a paid and job-protected maternity leave was introduced in 1971.[10] The legislation provides a maximum of 15 weeks[11] of paid leave for mothers of newborn children. Maternity leave is not universal and women are entitled to paid leave only if they have worked at least 120 days in the last 6 months.[12]

Mothers can to some extent decide how to distribute those weeks before or after giving birth. However, they must take at least one week before the planned delivery date and cannot come back to work earlier than 9 weeks after the actual childbirth. In other words, all mothers must stop working during a compulsory period of at least 10 weeks. Payments of benefits are made for 6 days per week, so that for a total leave duration of 15 weeks, the corresponding number of days is 90.

The replacement rate is 82% of pre-leave gross wage during the first 30 days and 75% thereafter. The benefits paid during the first 30 days are not capped, but the amount paid for the remaining 60 days is. Figure 1 (Panel A) illustrates this variation in the benefit schedule. One can observe that the daily allowance is a linear function of pre-leave earnings during the first 30 days (solid line), while it is a kinked function for the following 60 days (dashed line).

Formally, the average daily allowance $\bar{A}$ received by a woman who maxes out her maternity leave entitlement of 90 days, is a fraction τ_1 of her pre-leave daily earnings W during the first 30 days, and a fraction τ_2 of the capped pre-leave daily earnings W_{max} during the remaining 60 days:

$$\bar{A} = \begin{cases} (W \cdot \tau_1) \cdot (\frac{30}{90}) + (W \cdot \tau_2) \cdot (\frac{60}{90}) & \text{if } W < W_{max} \\ (W \cdot \tau_1) \cdot (\frac{30}{90}) + (W_{max} \cdot \tau_2) \cdot (\frac{60}{90}) & \text{if } W \geq W_{max} \end{cases} \tag{1}$$

Panel B of Figure 1 simulates the benefit function of Equation (1) and illustrates the

[10] "*Loi sur le travail du 16 mars 1971*"

[11] 19 weeks for multiple births.

[12] Part-time workers are required to have worked at least 400 hours. Unemployment insurance recipients are also entitled to maternity leave, given that they can demonstrate sufficient active days of job search.

effect of a cap placed at the January 2007 threshold (i.e. 110.655 euros), right in the middle of my sample window. One can observe the change in elasticity at this threshold. The elasticity of maternity leave allowance to the pre-leave income is 0.77 below the kink,[13] while it is 0.27 above the kink.[14] The marginal replacement rate faced by women above the kink is therefore 50 points lower than those below the kink.

To give a sense of the income loss resulting from the cap, Panel B of Figure 1 features the situation of a mother whose pre-leave daily earnings were 175 euros. Her average daily allowance is about 103 euros, that is a replacement rate of only 59%. In the absence of the kink (i.e. if the benefit schedule was linear), she would receive a daily allowance of about 135 euros (32 euros more per day). If she maxes out her leave entitlement, this mother loses 2880 euros compared to a situation when there is not cap on the benefit amount.

Figure A3 in Appendix shows that the daily earnings' threshold has been evolving over time, from 99 euros in January 2003 to 121 euros at the end of 2010, reflecting government's decisions, as well as automatic adjustment to inflation. It is important to notice that the schedule applies based on the start date of the maternity leave, so that a change in the earnings' threshold does not affect ongoing spells.

The features of the Belgian maternity leave system that have been described above are very close to the standards set by the International Labor Organization. Indeed, since 2000 the ILO's Maternity Protection Convention (No. 183) mandates a minimum leave period of 14 weeks for women around childbirth. The ILO also recommends that the cash benefit paid to women during maternity leave should amount to at least two-thirds of their previous earnings. Thus, Belgium offers a particularly interesting set-up, slightly above international standards, but not among the top performers. In that sense, this study might offer potentially good external validity.

2 Empirical Strategy

In this section, I start by describing the data collected on Belgian mothers who had a child during the period 2003-2010 and provide descriptive statistics on the sample. Then, I explain in depth the estimation strategy based on a Regression Kink Design (RKD). Finally, I discuss several tests that provide support for the validity of the RKD in my particular context.

[13] It corresponds to the following calculation: ((0.82*30/90)+(0.75*60/90))

[14] It corresponds to the following calculation: (0.82*30/90)

2.1 Data and Sample

I leverage a rich set of administrative data from the Belgian Crossroads Bank for Social Security. The latter puts together several administrative registers linked at the individual level (via personal identification numbers) and contains information on household composition, labor market outcomes of each member, as well as social security status. Most importantly, the data allows me to match children with their parents, as well as workers to their firms.

I obtained a large sample of 60% of all births during the years 2003 to 2010, with stratification at the provincial level to ensure representativity. I am able to follow the career of the mothers of those children over the period 2002 to 2015. I can therefore build a balanced panel that spans the period from 4 quarters before the birth of the child to 20 quarters after.

I restrict my sample to mothers who had a first child between 2003 and 2010. The objective is to focus the analysis on maternity leave for firstborns, which, as discussed in the introduction, should act as an information shock on the opportunity cost of childbearing. Then, I remove mothers who are not entitled to paid maternity leave because they do not have sufficient work history.[15] Finally, I do not take into account women who were self-employed before motherhood, since they receive a flat amount of maternity leave benefit. To summarize, I have a large sample of women who were salaried employee before becoming mother for the first time in the period 2003-2010 and who are entitled to paid maternity leave, which comprises 219,388 women.

I observe for each maternity leave, the starting and end months, the exact number of days of the claim, as well as the quarterly allowance received by the mother. For each woman, I assign the relevant pre-leave earnings by looking into the last wage payment received over the four quarters that precede the maternity leave start. I was able to find the pre-leave earnings for more than 82% of the sample.[16] My final sample is therefore composed of 180,327 women for which I have a complete work history.

I follow those mothers for 20 quarters (i.e. 5 years) after the start of their maternity leave. I can observe their quarterly earnings from both salaried and self-employment.[17]

[15] I also do not include civil servants who are entiled to a 15-week maternity leave, but with a replacement rate of 100% paid directly by the public administration.

[16] The missing 18% are women for which I cannot infer their pre-leave earnings based on the limited work history available in my sample. It very likely concerns women who were receiving unemployment or sickness benefits before the birth. Those women are entiled to maternity leave but their last wage payment might be older than 12 months.

[17] Self-employment earnings are reported on a yearly basis, therefore I divide the amount by 4 and impute the value for each quarter of any given year during which the individual had positive self-employment earnings.

For salaried employees, I also have precise information on their volume of work (recorded as full-time equivalent[18]) and their sector of employment (based on the first 3 digits of the NACE classification). Finally, I am also able to track the place where they live and the composition of their household, including the number of children, their partner[19] and whether they are married or not.

Table 1 presents the means and standard deviations of key variables for women in my sample. I also report descriptive statistics for my "kink sample", that is women with pre-leave daily earnings within 22 euros of the kink point, a sub-sample of 37,906 individuals. As discussed in the next sub-section, this is the preferred bandwidth for my estimations. From Figure A4 in Appendix, one can observe the distribution of those pre-leave earnings relative to the kink point located around the 90$^{\text{th}}$ percentile. The 22 euros bandwidth includes most women in the fourth quartile of the earnings distribution.

One can observe from Table 1 that the age of mothers at first birth is on average 28.4 years, slightly below the OECD average of 29.1.[20] The data on maternity leave claims show that the average duration is 84.7 days, close to the maximum of 90 days. The average benefit amount is 4808 euros. One can also see that women in the "kink sample" are slightly older, have of course higher pre-leave earnings and consequently receive higher benefits. The descriptive statistics also reveal that mothers within the 22 euros bandwidth receive a higher hourly wage and work more hours per week.

2.2 Regression Kink Design

I am interested in identifying the causal impacts of the maternity leave allowance on mothers' subsequent fertility and labor market participation. The challenge is that women with high benefits cannot be directly compared to those with low benefits, since it is likely that there are unobserved variables, which are correlated with both the benefit amount and my outcomes of interest. One can think, for instance, that women who are more career-oriented worked longer hours before entering motherhood, therefore had higher earnings and will consequently receive higher benefits. At the same time, those women might be willing to have less children in total.

[18]It is computed as the number of hours worked by an individual during a given quarter, divided by the average time for a reference worker in the same sector. The outcome therefore measures the amount of part-time work, but also account for the fact that a person has not been working during the whole quarter.

[19]While I can follow the career of all parents during the whole 2002-2015 period, I can match them only at the moment of the birth of their common children. My sample includes only 60% of all births in Belgium, which implies that I am not always able to match the parents at the birth of their first child. In that case, I match them based on the birth of a subsequent common child. This concerns about 20% of the co-parents, which are "imputed" based on their next observed child.

[20]Source: OECD Family Database, 2017.

To circumvent this issue, I leverage quasi-experimental variation stemming from a kink in the maternity leave benefit schedule, created by the earnings' threshold set by the social security administration. As explained in Section 1, women below and above the kink face drastically different marginal replacement rates. Following Card, Lee, Pei and Weber (2015b), I make use of this change in slope of the benefit function to estimate the causal effects of the benefit amount using a Regression Kink Design (RKD).

The RKD will test for a change at the kink in the slope of the relationship between my outcomes of interest and the assignment variable (i.e. the pre-leave earnings). If one assumes that in the absence of the kink in the benefit function, there would be a smooth relationship between the outcomes and the assignment variable, evidence of a change in the slope would imply a causal effect of the benefit amount on the outcome. I explain more in detail the "smoothness" assumption in Sub-section 3.1 and provide tests that support the validity of the RKD in my context.

Mathematically, I want to estimate the marginal effect of maternity leave allowance (A) on the outcome (Y) at the kink point. The allowance is a function of the pre-leave earnings W, which have been normalized relative to the threshold set by the social security and therefore take the value W_0 at the kink point:

$$E\left[\frac{\partial Y}{\partial A}|W=W_0\right] = \frac{\lim_{W\to W_0^+}\frac{\partial E[Y|W=W_0]}{\partial W} - \lim_{W\to W_0^-}\frac{\partial E[Y|W=W_0]}{\partial W}}{\lim_{W\to W_0^+}\frac{\partial A(W)}{\partial W} - \lim_{W\to W_0^-}\frac{\partial A(W)]}{\partial W}} \tag{2}$$

From Equation (2), one can see that the RKD estimator is a ratio of two terms. The numerator is the change at the kink point in the slope of the relationship between the outcome Y and the pre-leave earnings W. The denominator is the change at the kink point in the slope of the benefit function. The resulting estimate can be interpreted as a local treatment-on-the treated (TT) parameter.

In theory, one could infer the denominator directly from the benefit formula. However, because of measurement errors, there may be small deviations between the theoretical and observed values. This may stem from errors in the observed values of the assignment variable or the benefit amount. In addition, not all women max out their maternity leave entitlement and the average daily allowance will vary with the total duration since the cap applies only from the 31st day. For all those reasons, I follow Card *et al.* (2015b) in using a "fuzzy" RKD and estimate also the slope change in the denominator of Equation (2).

I apply local nonparametric regressions on either side of the kink to estimate the slope changes in both the numerator and denominator.[21] The use of local nonparametric methods has been advocated in order to reduce the bias that may result from using data farther away from the kink (Lee & Lemieux, 2010). Among the key parameters, one needs to define when implementing the RKD estimator in practice, are the kernel, the order of the polynomial, and the bandwidth.

I follow the literature, notably Card *et al.* (2015b), by using a uniform kernel (i.e. no weighting).[22] As for the polynomial order, I provide results for both local linear and local quadratic specifications.[23] The tests reported in Sub-section 4.1 show that the linear specification out-performs the quadratic one in my particular context. It is therefore my preferred specification to study the impact of the maternity leave allowance.

There is an active econometrics literature on optimal bandwidth choice in the regression discontinuity design literature (see e.g. Imbens & Lemieux, 2008; Imbens & Kalyanaraman, 2012), but only a handful of papers have explored the question in the case of the RKD (Calonico et al., 2014; Card et al., 2015b). I use the "data-driven" procedure of Calonico *et al.* (2014), which is the only bandwidth selector explicitly designed for the fuzzy RKD, to explore the optimal bandwidth choice for each of my outcomes. The bandwidths picked by this procedure are reported in Table A3 in Appendix. One can observe that they range from 14 to 30 euros around the kink. For comparison purposes, it is, however, desirable to have a common bandwidth, and therefore similar sample sizes, for the analysis of the different outcomes considered. Therefore, my baseline estimates will use a common bandwidth of 22 euros, that is the median of the suggested bandwidths of Calonico *et al.* (2014)'s selector. As a robustness check, I will also report results for each individual outcome using its own optimal bandwidth, as well as other bandwidths on a 10 to 35 euros interval.

When it comes to inference, I follow Card *et al.* (2015a) in using heteroskedasticity robust standard errors. I also compute bias-corrected confidence intervals (CI), based on the procedure proposed by Calonico *et al.* (2014). Intuitively, the authors suggest to estimate the bias of the estimator by using higher order polynomials on a larger bandwidth. For my linear specification, I will therefore add a quadratic term in the assignment variable on a bandwidth that is four times the one used for the conventional estimates.[24]

[21] I implement the local nonparametric regression using the package "rdrobust" developed by Calonico, Cattaneo and Titiunik (2014) for the software Stata.

[22] Card *et al.* (2015b) explain that while a triangular kernel is boundary optimal, the efficiency losses from using a uniform kernel are small both in actual applications and in Monte Carlo simulations.

[23] Card *et al.* (2015b) explain that it is commonly assumed that a local quadratic approach is preferred to a local linear fit to estimate derivatives in the RKD because the former is expected to lead to an asymptotically smaller bias compared to the latter. However, Card *et al.* (2015b) also warm against making the quadratic model a universal choice and argue that one should also take into account the characteristics of the data set of interest, including the sample size.

[24] In my case, the preferred bandwidth is symmetric and equals to 22 euros. The bandwidth used for

This bias will then be used to correct the CIs, which in the vocabulary of the authors are therefore "robust" to large bandwidth choices.

2.3 Tests of Identifying Assumptions

The identification of treatment effects in the framework of the RKD relies on two main assumptions: (1) the density of the assignment variable, in my case the pre-leave earnings, should be smooth (i.e. continuously differentiable) at the kink (sometimes referred to as the "no sorting" assumption); (2) in the vicinity of the kink, there should be no change in the slope of the underlying direct relationship between the assignment variable and the outcomes of interest (sometimes referred to as the "smoothness" assumption).

These assumptions imply that individuals have not sorted around the kink by manipulating their earnings. This local random assignment condition seems credible in the context of maternity leave benefits as it is unlikely that first-time mothers have a perfect knowledge of the benefit schedule. First of all, because the exact location of the kink changes over time reflecting government's decisions, as well as automatic adjustment to inflation (see Figure A3 in Appendix). Thus, it seems arguably difficult for individuals to predict what would be the location of the kink at the time of their maternity leave. In addition, the threshold for maternity leave benefits is distinct from other social programs, such as unemployment insurance or public pension. Nevertheless, I follow other authors using RKD and provide standard tests for these identifying assumptions (Landais, 2015; Card et al., 2015b; Gelber, Moore, & Strand, 2017; Bana et al., 2020).

I begin by providing graphical evidence that mothers did not engage in sorting around the kink. Figure 2 (Panel A) shows that the density of the pre-leave earnings around the kink point seems smooth. To confirm this graphical diagnosis, I perform a McCrary test as is standard in the regression discontinuity design literature (McCrary, 2008). The test checks for a "jump" in the probability density function (p.d.f.) of the assignment variable at the kink. I report on Figure 2 (Panel A) the estimate for the log difference in height of the p.d.f. at the kink, as well as the standard error in parentheses. Following Card *et al.* (2015b), I extend the spirit of the McCrary test to check that the first derivative of the p.d.f. is also continuous at the kink. I therefore regress the number of individuals in each bin[25] on polynomials of the assignment variable interacted with a dummy for being above the kink. I report on the graph the coefficient on the interaction term for the first order polynomial (i.e. testing for a change in slope of the p.d.f.) and the corresponding standard error. The estimates for both tests are insignificant, which confirms that one

bias correction is therefore 88 euros.

[25] I use 50 euro cents bins and a 30 euros bandwidth.

cannot detect a lack of continuity at the kink.

Furthermore, I complement the standards tests of the RKD literature and use a novel estimation technique proposed by Cattaneo, Jansson and Ma (2020) to check for the absence of manipulation. Their approach, based on local-polynomial density estimators, does not require the data to be averaged into bins, and therefore makes no assumption about their size. In addition, the choice of the bandwidth is entirely data-driven.[26] Figure 2 (Panel B) displays the density of the assignment variable on both sides of the kink point. The graphical evidence, as well as the formal test, both suggest that one cannot detect manipulation in the neighborhood of the kink.

The second assumption of the RKD cannot be tested directly since my sample is composed of mothers who all received maternity leave benefits. I can, nevertheless, check that the "smoothness assumption" holds using pre-dermined covariates, before the women in my sample went on maternity leave. Figures 3 and 4 plot the mean values of those pre-determined covariates in each bin of the normalized pre-leave earnings, for the mother and her partner respectively. All the figures seem to suggest that covariates evolve smoothly at the kink. Formal tests can also be performed by running local nonparametric regressions on either side of the kink to estimate the slope changes, mimicking the strategy used to compute the numerator in Equation (2). Table 2 shows the estimated change in slope in the relationship between the pre-determined outcomes and the assignment variable at the kink point in the linear case. The coefficients for the covariates of both parents are all statistically insignificant, except for mother's full-time work equivalent. The coefficient for the latter variable is, however, very small in magnitude. In addition, it very likely reflects the fact that the variable is right-censored at 1, since individuals in my sample cannot work more than one full-time job. The small negative coefficient therefore reflects the fact that most women on the right of the kink have reached this maximum value, as suggested by Panel D in Figure 3.

Taken together, the previous figures and formal tests show that there is no evidence of sorting or underlying non-linearities around the kink, therefore providing support for the validity of the RKD in my particular context. I can now turn to examining the impact of the maternity leave allowance on my outcomes of interest.

[26]The Stata command rddensity (Cattaneo, Jansson, & Ma, 2018) implements manipulation testing procedures using the local polynomial density estimators proposed in Cattaneo, Jansson and Ma (2020).

3 Results

In this section, I present the main results of the impact of maternity leave allowance on mothers' subsequent fertility and labor force participation. I also discuss the timing of the effects. Finally, I conduct heterogeneity analysis based on the wage differential of parents, as well as the sector of employment of the mother, all before the first childbirth.

3.1 Impacts of Maternity Leave Allowance

First-stage estimates. I begin by exploring the effect of the kink on the amount of maternity leave benefits that women in my sample received. Figure 5 (Panel A) plots the empirical relationship between the average daily allowance and the normalized pre-leave earnings. I use the daily allowance and not the total amount of benefits received to account for the fact that women below/above the kink could have different maternity leave duration, beyond the compulsory 60 days. One can see that the empirical relationship is very similar to the theoretical prediction in Figure 1 (Panel B), with clear evidence of a kink at the threshold set by the social security administration. In the previous section, I showed that according to the benefit formula the change in slope at the kink could reach 0.5 if the mother maxes out her leave entitlement of 90 days. For all my estimations, I report the so-called "first stage" estimate, which corresponds to the denominator of my fuzzy RKD estimator in Equation (2). One can see from Table 3 that the estimated change in slope for the marginal benefits at the kink is about 0.45 in the different sub-samples, really close to the theoretical prediction.[27] Another way to represent the change at the kink is to plot instead the replacement rate, that is the share of the pre-leave income replaced by the allowance. Figure 5 (Panel B) plots this empirical replacement rate against the level of pre-leave earnings. One can see that it is flat, around 74% below the kink, which implies that for each additional euro in pre-leave income the allowance increases by 0.74 euro.[28] From the kink forward, the replacement rate then declines linearly with the income level. Taken together, the graphs and the formal estimates prove that my empirical strategy can adequately capture the kink in the benefit formula, which I can use to infer the effects of the benefit amount on my outcomes of interest.

For all the outcomes, I start by showing a graph, which plots their mean values in

[27] One possible reason for the estimated coefficients to be slightly smaller than the theoretical predication is that not all women max out their leave entitlement of 90 days. In fact, the average leave duration reported in Table 1 is 85.8 days. Since the cap on benefits applies only from the 31st day, a shorter duration would imply a smaller change in slope at the kink. This also provides another argument for using a fuzzy RKD to precisely estimate the denominator in Equation (2).

[28] Again, this is really close to the theoretical prediction of an elasticity of maternity leave allowance to the pre-leave income of 0.77 below the kink.

50 euro cents bins in the assignment variable. The graphs also display a linear trend on each side of the kink, suggesting possible changes in the slope of the relationship. Then, I report in Table 3 estimates of the treatment effect computed using local polynomial non-parametric regressions of order 1 (i.e. linear), heteroskedasticity-robust standard errors in parentheses, as well as bias-corrected confidence intervals proposed by Calonico *et al.* (2014).

Impact on maternity leave duration. First, I find weak evidence that higher allowance increases maternity leave duration among high-earning women. Figure 6 shows a slightly increasing relationship which seems to flatten after the kink. In Table 3, I report the effect on the duration measured in days, as well as taking its natural logarithm.[29] The estimated elasticity is equal to 0.126.[30] However, the bias-corrected confidence intervals include 0, which might suggest that the results are not robust to the inclusion of higher order polynomials and larger bandwidth definitions. The difficulty in getting a precise estimate of the elasticity might stem from the fact that the Belgian system for maternity leave is not particularly generous in terms of duration, just slightly above international standards, as mentioned before. So new mothers might need all the time available to recover from childbirth and create bonds with their newborn, as suggested by the fact that 75% of mothers in my sample take between 84 and 90 days (the maximum) of maternity leave. The distribution of total leave duration for women near the kink is indeed highly skewed (see Figure A5 in Appendix), suggesting that most women tend to max out their leave.[31]

Impact on fertility. I now turn to the main outcome of interest and examine the impact of maternity leave allowance generosity on subsequent fertility. The argument is that the first maternity leave acts as an information shock on the opportunity cost of childbearing. Since the wage replacement is only partial in Belgium, like in most OECD countries, mothers suffer a net income loss for each child they bear. Having a first child will provide new mothers with information on the extent of this income loss, which might affect their preference for additional children in the future. Furthermore, one should bear in mind that women in Belgium must stop working for a compulsory period of 60 days, so that this "maternity leave penalty" can only be reduced to some extent.

In Figure 7, I show how the generosity of the maternity leave allowance affects subsequent fertility decisions. Panel A plots the probability of having a second child within

[29] For the latter, I also use the log of benefits for the first stage.

[30] In comparison with other social insurance programs, this estimate is relatively small. For example, in the case of unemployment insurance, the elasticities estimated in Western Europe range from 0.3 to 2 (Card et al., 2015a).

[31] In the Swedish context, where parents can take up to 16 months of parental leave (jointly), Moberg (2019) finds that the elasticity of the mother's time on leave with respect to the benefit level is equal to 1.

the five years following the first childbirth. One can see that the probability of having a second birth tends to increase with the amount of benefits received during the first leave, up to the kink where the trend reverses. This is also true when I use the number of children as outcome (Panel B). One should note that both outcomes are based on the number of children in the household where the mother lives. As such, it would also account for new children from subsequent adoption or family recomposition. To be certain that the changes we observe reflect fertility decisions, I also provide a measure of new maternity leaves taken by the same mother (Panel C). This additional outcome will, however, underestimate the number of children from the same mother if she has exited the labor force after her first child and is therefore no more eligible to take paid maternity leave.

To confirm this graphical exploration, I estimate treatment effects using those outcomes and report the results in Table 3. One can see that the level of maternity leave allowance positively affects subsequent fertility. The estimated coefficient suggests that for each additional euro in daily allowance the probability of having a second child increases by 0.6 percentage point. If one considers instead the total number of children after five years, an increase of 10 euros in daily allowance (i.e. 900 euros for a mother who uses her complete leave period) increases the number of children in the household by 0.09. As expected, the effect on subsequent maternity leave claims is also positive, but the coefficient is slightly lower (0.08). Furthermore, I can rule out that the effect on the number of children in the household is driven by family recomposition, since I do not find any effect on the probability of remaining married (Figure 7, Panel D).[32]

One might want to compare my results to those of Raute (2019) for Germany, who also focuses on high-earning women, although with a different estimation strategy using a difference-in-differences design around a reform introduced in 2007. She estimates that a 1000 euros increase in total benefits raises the probability that a woman will give birth in each of the five post-reform years by 0.783 births per 1000 women, that is a 2.1% increase per year (10.5% after five years) compared to the pre-reform situation (Raute, 2019). In comparison, I find that an increase in maternity leave allowance of 10 euros per day (i.e. 900 euros in total) raises the probability of having a second child within five years by 6 percentage points, that is a 7.6% increase compared to the mean reported in Table 3 (79%). My estimates in the Belgian context are therefore perfectly in line with those of Raute (2019) for Germany.

Impact on labour force participation. I turn next to examining the implications of maternity leave allowance for the career of first-time mothers. I create two outcomes,

[32]I have also tested for an effect on subsequent adoptions, since I have data on parental leave taken for adopted children. I do not find any effect on the probability of taking a leave for an adopted child over the following five years (results available upon request).

which track over a period of five years the probability of being employed (dummy) and the quarterly earnings (euros), in both salaried and self-employment. I begin by showing the long-term implications of maternity leave allowance and focus therefore on values of those outcomes after five years. I will explore the dynamics in the next sub-section.

Table 3 displays the effects measured for all those maternal outcomes. One may first notice that the generosity of maternity leave allowance does not affect the probability of being employed five years after the first childbirth. The coefficient for the outcome "employed" is not statistically significant and the robust CI include zero. However, the results suggest changes in career path. Indeed, Figure 8 (Panel A) reveals that as the amount of maternity leave benefits increases, the probability of being in salaried employment after five years tends to decrease, up to the kink where the trend reverses. Treatment effects estimates confirm that an increase of 1 euro per day of maternity leave benefits decreases the probability of being a salaried employee after five years by 0.7 percentage point. At the same time, the probability of being self-employed increases by 0.6 percentage point.

We observe similar effects for quarterly earnings. Maternity leave allowance generosity has no effects on total earnings, but the streams of income do change (Figure 8, Panels C and D). In fact, I measure that for each additional euro in daily allowance, quarterly salaried income decreases by 38 euros five years after the first childbirth, while self-employed income increases by 33 euros (Table 3).[33] Taken together, these results suggest that more generous maternity leave allowance increases the transition from salaried to self-employment, while not affecting labor force participation and earnings overall.

3.2 Timing of Effects

In this sub-section, I explore the dynamics of the effects found on subsequent fertility and transition to self-employment. To do so, I plot in Figure 9 the coefficients for the treatment effects from separate regressions in each quarter after childbirth and up to five years.

Figure 9 (Panel A) reveals that the effect on the probability of having a second child is only statistically different from zero in quarter 8 after the first childbirth[34] and continues to increase up to quarter 12. Interestingly, the effects are remarkably stable from the third year onwards and never converge back to zero, which suggests that it is not due to increased birth spacing. This is also confirmed by the fact that total fertility measured

[33]The effects on earnings are estimated after trimming of the top 1% of the distribution to reduce the influence of outliers.

[34]It makes perfect sense that the effect is not immediate since the return of postpartum fertility takes several weeks or even months if the mother is breastfeeding

with the number of children (Panel B) remains positive.

I now turn to the analysis of how maternity leave allowance affects post-leave employment trajectories. From Figure 9 (Panel C), one can see that the probability of being a salaried employee becomes negative already around quarter 3 after childbirth and continues to decline until quarter 7. At the same time, the probability of becoming self-employed (Panel D) increases sharply. Thus, it appears that most of the women who transition from salaried to self-employment do so during the two years that follow their first childbirth.

Taken together, these results indicate that the effects on salaried and self-employment precede the effects found on fertility. This provides suggestive evidence that women transition to self-employment in anticipation of a second child. As such, I believe that these analyses reveal how, by switching to self-employment, women who received higher benefits during their first maternity leave conjugate their desire for more children and the pursuit of their career.

3.3 Heterogeneous Effects by Wage Gap between Parents

In this sub-section, I explore how the effects found on fertility and transition to self-employment vary according to pre-birth characteristics of the parents. I am particularly interested in the wage differential between the parents prior to having a first child. Following Bertrand, Kamenica and Pan (2015), I compute the relative income within the household, that is the mother's income divided by the total household's income. I then distinguish between two cases: (1) when the relative income is lower than 0.5, which implies that the mother contributes less than her partner to the household's income, and (2) when the relative income is equal or higher than 0.5, which means that the mother contributes equally or more compared to her partner. The two groups represent respectively 45% and 55% of my sample of mothers with earnings in a 22 euros bandwidth around the kink.[35]

Table 4 reports the treatments effects estimated on both sub-samples. The last two columns also present z-tests to check whether the difference in the estimated coefficients appears to be statistically significant. When first looking at the fertility outcomes, especially the number of children, one can see that the effects are fairly stable across the different sub-groups considered. In fact, the z-tests formally reject that the coefficients are different in the two sub-populations. However, when considering the consequences on labor force participation, one notices that women who used to earn less than their

[35]Results reported in Table 2 suggest that there is no discontinuity around the kink in the share of household income earned by the mother, measured 4 quarters prior to having a first child.

partner before entering motherhood are two times more likely to leave salaried employment for self-employment. The z-tests confirm that the difference between the two groups is statistically significant for both outcomes, although only at a 10% level for salaried employment.

I believe that the marked differences observed between the two sub-samples could stem from at least two self-reinforcing mechanisms. First, some women might find it less risky to leave salaried employment for self-employment when their partner is the main breadwinner in the household. Second, mothers who contribute less to the household's income are often found to assume a larger share of child-related activities than fathers (Bittmann, 2015; Pailhé & Solaz, 2008). Switching to self-employment might provide a way for those mothers to conjugate increased family responsibilities and the pursuit of their career. In fact the literature in management and sociology demonstrates that the balance between work and family demands are among the main motivational factors cited by women who become self-employed (Budig, 2006; Gangl & Ziefle, 2009; Kirkwood, 2009). Self-employment is indeed reported as providing greater time flexibility for young mothers (Boden, 1999; Georgellis & Wall, 2005).

I further explore the possibility of within-household specialization by looking for potential spillover effects on the career of the co-parent. The argument is that the effects found on subsequent fertility could also affect the father's career. Similar to what I have previously done, Table 5 reports RKD estimates for the impact of maternity leave allowance on the co-parent's outcomes five years after the birth of the couple's first child. I find weak evidence that higher maternity leave allowance slightly decreases the probability that the co-parent takes a paternity leave. The effect is only significant at the 10% level using heteroskedasticity-robust standard errors, but the 95% bias-corrected confidence intervals do not include zero. However, I do not find any effect on the co-parent's career in the long run. In fact their earnings are largely unaffected by the amount of maternity leave allowance received by their partner. This finding is not entirely surprising given that previous studies have highlighted the fact that fathers assume less household responsibilities than mothers even when they are financially dependent on their partner (Kühhirt, 2011). There might be several reasons for that, including compliance with social norms (Bertrand et al., 2015; Kühhirt, 2011) or imperfect substitution between mother's and father's time (Bittmann, 2015; Pailhé & Solaz, 2008).

3.4 Heterogeneous Effects by Sector of Employment

In the previous sub-section, I demonstrated that the probability of women who receive higher maternity leave allowance to become self-employed varies according to their household's characteristics. Now, I want to test whether the workplace's characteristics also imply different impacts. More precisely, I want to investigate whether working in a particular industry prior to having children changes the probability to transition to self-employment for young mothers.

While it is well documented that motherhood creates incentives for women to move to sectors that are more family-friendly (Hotz, Johansson, & Karimi, 2018; Kleven, Landais, Posch, Steinhauer, & Zweimüller, 2019; Pertold-Gebicka, Pertold, & Datta Gupta, 2016), intersectoral mobility might be more constrained for some. One reason could be that their human capital is specific to their sector of employment and moving to a different sector would suppose a large wage penalty (Parent, 2000; Sullivan, 2010; Zangelidis, 2008). As such, pre-motherhood choices might entail long run consequences.

I take advantage of my matched employer-employee data to observe the sector of the firm where the mother was working one year before giving birth for the first time. I distinguish 8 sectors[36] and estimate how the transition to self-employment differs across them.[37] The estimated coefficients are reported in Figure 10. One may observe that two sectors stand out: "Health and social work" and "Retail trade and hospitality industry." In those two sectors, the coefficient for the transition to self-employment five years after the first childbirth is positive and highly significant.

Interestingly, when interviewed for the European Working Conditions Survey (EWCS), workers in those two sectors are more likely to report poor match between working hours and family commitments, notably because they are often asked to work atypical hours[38] (Eurofound, 2014). Goldin (2014) explains that this translates into "time pressure" on workers, which might be difficult to conjugate with household responsibilities. As discussed above, becoming self-employed might be a way for young mothers in those sectors to gain greater time flexibility.

I conclude from the two previous heterogeneity analyses that women who receive higher maternity leave allowance are more likely to transition to self-employment when they used to earn less than their partner and when they worked in sectors offering poor work-family balance. As such, it appears that both the households' and workplaces' characteristics play a role in the decision to become self-employed. I believe this gives credit to my argument that the change in career path reflects non pecuniary preferences, but rather a need to conjugate family demands and the pursuit of a career.

[36]I create 8 sectors from the NACE classification Rev. 1.1 for mothers of children born until 2008 and from the NACE classification Rev.2 for those born after.

[37]The results for all the outcomes are available in Table A1 in Appendix

[38]The European Working Conditions Survey asks respondents how many times per months they are required to work on weekends, evenings or nights.

4 Robustness Checks

In the following section, I provide various tests for the robustness of the RKD estimates presented above. I explore the sensitivity of the results to the choice of the polynomial order and bandwidth. Then, I discuss the issue of functional dependence between the assignment variable and the outcomes, before providing tests that corroborate the strength of my findings.

4.1 Sensitivity Analysis

Functional form. I begin by analyzing the sensitivity of the results to the choice of the functional form. I start with a graphical exploration and provide in Appendix plots for the main outcomes of interest using both linear and quadratic functions of the assignment variable. One can observe that for both fertility (Figure A6) and employment outcomes (Figure A7), the trends estimated with the different polynomial orders suggest similar discontinuities at the kink, and many times the lines are almost perfectly aligned (the dashed line is for the linear specification, while the solid line is for the quadratic one). To confirm this, I also provide estimates for the treatment effects using both linear and quadratic specifications in Table A2 in Appendix.[39] First of all, one may notice that both specifications report comparable first stage estimates (first columns of "linear" and "quadratic" panels), even though the Aikake Information Criterion (AIC) suggests that the linear specification almost always dominates the quadratic one (last panel titled "polynomial minimizing AIC"). This is not surprising given that the benefit schedule is indeed a linear function. When it comes to the treatment effects (third column of "linear" and "quadratic" panels), in most cases the sign is the same in both specifications and the coefficients are qualitatively similar.[40] One may note, however, that when controlling for a quadratic polynomial, the standards errors increase drastically. In fact, the AIC advises on using a linear specification also for the second stage estimates. Taken together, these results confirm the claim of Gelman and Imbens (2019) that controlling for high-order polynomials in regression discontinuity analysis might lead to poor coverage of confidence intervals. For all these reasons, my preferred specification is the linear case, as in most

[39] Contrary to the previous specifications using local nonparametric methods for estimation, here I use parametric regressions in order to report conventional goodness of fit measures. In particular, I show the Aikake Information Criterion (AIC) in square brackets. The last columns of Table A2 in Appendix show which specification (linear or quadratic) minimizes this information criterion. The columns "first stage" and "second stage" are reduced form estimates for the change in slope of the maternity leave benefit amount and the outcomes, respectively. The column "treatment effect" reports coefficients from two-stage least squares estimations, where the benefit amount is instrumented with the interaction between a dummy for being above the kink and the polynomial in the assignment variable.

[40] With the exception of the maternity leave duration, which does not appear to be robust across functional forms.

studies using the RKD and surveyed in Ganong and Jäger (2018).

Choice of bandwidth. I now turn to testing the sensitivity of my results to the choice of bandwidth. As mentioned in Sub-section 2.2, only a few papers offer guidance on optimal bandwidth choice in the RKD case (Calonico et al., 2014; Card et al., 2015b). The main similarity with the standard regression discontinuity design is the tradeoff between bias and variance. Larger bandwidths will likely be more biased, but at the same time the RKD has been reported to do pretty poorly with small samples (Landais, 2015). In sub-section 2.2, I explain that I use the data-driven bandwidth selector developed by Calonico *et al.* (2014) - CCT selector from now on - as a primary guide. The CCT selector is the only bandwidth selector explicitly designed for the fuzzy RKD and builds on earlier work by Imbens and Kalyanaraman (2012), who proposed an algorithm to compute the MSE-optimal bandwidth. In particular, their procedure involves a regularization term, which reflects the variance in the bias estimation and guards against the selection of large bandwidths.

Table A3 in Appendix reports treatment effects for my outcomes of interest using their optimal bandwidth picked by the CCT selector, as well as four different bandwidths in the 15 to 30 euros range. When compared with my baseline estimates using a 22 euros bandwidth (Table 3), one immediately notices that these new results are highly similar. The effects on subsequent fertility are always positive across the different bandwidth choices. The coefficient on the probability of having a second child ranges from 0.003 to 0.006. Most importantly, the estimate using the data-driven CCT bandwidth is 0.005, really close in magnitude to my baseline estimate of 0.006. The coefficients for the total number of children and maternity leaves are also all positive and highly significant. When it comes to the labor market outcomes, the effects are also very similar across bandwidths. The coefficient on salaried employment is always negative and ranges from - 0.005 to -0.007, very much in line with my baseline estimate of -0.007. The coefficient on self-employment is always positive and ranges from 0.004 to 0.006, again highly similar to my baseline result of 0.006. Finally, the estimates on earnings also appear relatively stable across the different bandwidth specifications, with as expected standard errors that get larger as the sample size decreases.

In order to visualize the relationship between my estimates and the bandwidth choice, I also plot the coefficients for the linear case against all possible bandwidths in 1 euro increments of normalized pre-leave daily earnings from 10 to 35 euros. Two vertical lines materialize the 22 euros bandwidth (dashed line) used for the baseline estimates and the data-driven CCT bandwidth (dotted line). One can observe that the effects are relatively stable beyond the 15 euros bandwidth for both fertility and employment outcomes (Figures A8 and A9, respectively). Taken together, these tests confirm that the results are consistent across bandwidth choices, but also that the common 22 euros bandwidth offers highly similar results to the ones based on the CCT selector.

4.2 Functional Dependence

In Section 2, I explained that the RKD relies on the assumption that the underlying relationship between the assignment variable and the outcomes (in the absence of a kink) should be smooth. A legitimate concern could be that the effects captured by the RKD result from non-linearities in this relationship. The graphical evidence that I provided before seems to exclude this possibility. Indeed, subsequent fertility increases with the benefit amount up to the kink. It is unlikely that this captures a functional dependence with the assignment variable since most studies find instead an inverse relationship between income and fertility (see e.g. Anderson et al., 2002; Bertrand et al., 2010; Hotchkiss et al., 2017; Raute, 2019). Nevertheless, to address this concern I provide several tests that have become standard in the RKD literature.

I begin by including controls in my regressions that would account for possible non-linearities. Ando (2017) suggests that controlling for relevant pre-determined covariates should reinforce the credibility of the RKD. I control for the mother's age and region of living,[41] as well as her partner's income, all at the moment of the birth of the first child. I have chosen those covariates in particular because they are likely to be correlated with both the assignment variable and the outcomes of interest. They should therefore help capturing potential non-linearities. Table A4 in Appendix shows that when controlling separately and then adding all covariates the results remain highly similar to the baseline estimates (Table 3).

Finally, in order to assess the sensitivity of my results to non-linearities in the relationship between the assignment variable and my outcomes of interest, I perform a series of permutation tests, as proposed by Ganong and Jäger (2018). The idea is to estimate RKD models using placebo kinks at various points along the distribution of the assignment variable. I estimate 300 placebo RKD models around the true kink point, using a 22 euros bandwidth surrounding each placebo kink point. The placebo kinks are situated at a distance of -100 to 50 euros from the true kink point, which covers about 95% of the earnings distribution. I report results for fertility and employment outcomes, all five years after the first childbirth. One should note that the permutation tests are estimated as reduced form models, which correspond to the slope change measured in the numerator of Equation (2). As such, the placebo kink coefficients are of the opposite sign from those reported so far, which were scaled by the negative coefficients of the denominator.

[41] I create an indicator variable that takes on the value 1 if the mother was living in Flanders.

The figures plot RKD estimates along placebo kink values, specified in terms of distance from the true kink point (Figures A10 and A11 in Appendix). One can see that for all the outcomes, the coefficients estimated at the true kink point (i.e. 0 on the horizontal axis) are much larger than those at placebo kinks. Taken together, the results from these multiple robustness checks strongly support the validity of the RKD in my context.

4.3 Placebo Groups

In a last exercise, I use two new samples of individuals who face similar fertility and career decisions than my sample of salaried mothers, but were not affected by the kink in the maternity leave benefit schedule. The first group is composed of self-employed mothers who by law receive a flat amount of benefits. The second group is composed of fathers who did not take any leave after the birth of their child[42] and therefore did not receive any benefits. Intuitively, because these two groups are unaffected by the kink in the benefit schedule, I can use them to test for the absence of underlying relationship between pre-parenthood earnings and fertility and career decisions in the vicinity of the threshold set by the social security.

Starting with the sample of self-employed mothers, I calculate their earnings before going on leave for the first time and normalize them to a placebo kink that corresponds to the threshold set by the social security administration for salaried mothers. One can see from Panel A of Figure A12 in the Appendix that the earnings distribution for self-employed women is highly similar to the one in Figure A4 for the sample of salaried women. The placebo kink is also located at a similar point of the earnings distribution, around the 90th percentile. As mentioned before, self-employed women receive a flat amount of benefit when they go on maternity leave. This is illustrated by Panel B of Figure A12. Self-employed women are therefore a perfect placebo group to observe the direct relationship between pre-leave earnings and subsequent fertility in the absence of variation in financial incentives. One can see from Panels B and C that the probability to have a second child or the number of children are completely unrelated to the pre-leave earnings of self-employed women in the vicinity of the placebo kink.

Moving now to the second sample of fathers who did not go on leave, I explore their probability to be self-employed five years after the birth of their child. This group is perfectly suitable for the exercise since they did not receive any benefits from the social security administration. Therefore, they would help capture any underlying relationship between earnings and the probability to be self-employed. One could fear, for instance,

[42]Fathers in Belgium were entitled to take two weeks of paternity leave from July 2002 until the end of the period covered by my sample.

that there are tax incentives to become self-employed when earnings are above a certain level. To rule out that it is what is driving the results for salaried mothers, I use fathers with similar earnings and compare their probability to be self-employed in the vicinity of a placebo kink similar to the one used in my main estimates. Figure A13 in the Appendix shows that the probability to be self-employed is almost perfectly flat around 10 percent for all fathers who did not go on leave and have earnings in the vicinity of the placebo kink.

Altogether, these results reinforce the credibility of my main findings that the fertility and career of salaried women are affected by the kink in the maternity leave allowance schedule and that the effects do not stem from underlying relationships around the kink.

5 Conclusion

The level of compensation during maternity leave varies significantly across countries. Some like Austria, France or Mexico offer complete wage replacement, while others like Canada only cover 55% of the lost income. In addition, many of the OECD countries have caps on the benefit amount, which results in a much lower replacement rate for high-earning women.

In this paper, I examine how the generosity of maternity leave allowance affects first-time mothers' subsequent fertility decisions and career trajectory. I develop the argument that the first maternity leave acts as an information shock on the opportunity cost of childbearing. Indeed, having a first child will provide new mothers with information on how much income they lose while being away from work, which might affect their preference for additional children in the future.

My empirical strategy relies on a Regression Kink Design. I exploit a discontinuity in the maternity leave benefit schedule to estimate the causal effects of the allowance generosity on women's outcomes up to five years. Because of the kink in the benefit formula, women with pre-leave earnings above the maximum threshold set by the social security administration face a lower replacement rate than those below.

Comparing first-time mothers within a small bandwidth around the kink, I find that higher benefits increase subsequent fertility: for each additional euro in daily allowance the probability of having a second child increases by 0.6 percentage point. Subsequently, I explore the consequences for their career and show that those who received higher benefits are more likely to leave salaried employment for self-employment. The heterogeneity analyses reveal that the transition to self-employment is higher among women who used to earn less than their partner and those who worked in sectors offering poor work-family balance. I believe that these results offer suggestive evidence that by switching to self-employment, those women have found a way to conjugate their desire for higher fertility and the pursuit of their career. I think this is supported by the fact that their earnings are not affected in the long run, so that the career changes might in fact reflect non pecuniary preferences.

These findings should be of broad interest outside of Belgium. First, because the features of the Belgian maternity leave system are similar to the standards set by the International Labor Organization, offering plausibly good external validity. Second, because the majority of OECD countries have placed caps on their maternity leave benefits, paving the way for similar studies using a Regression Kink Design in other countries.

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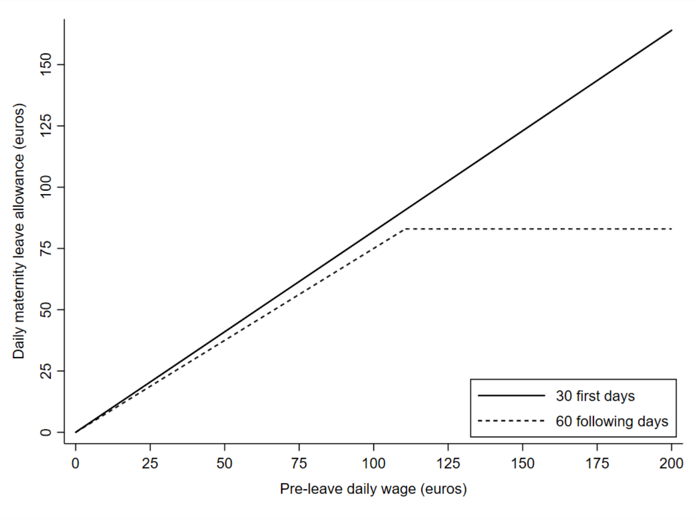
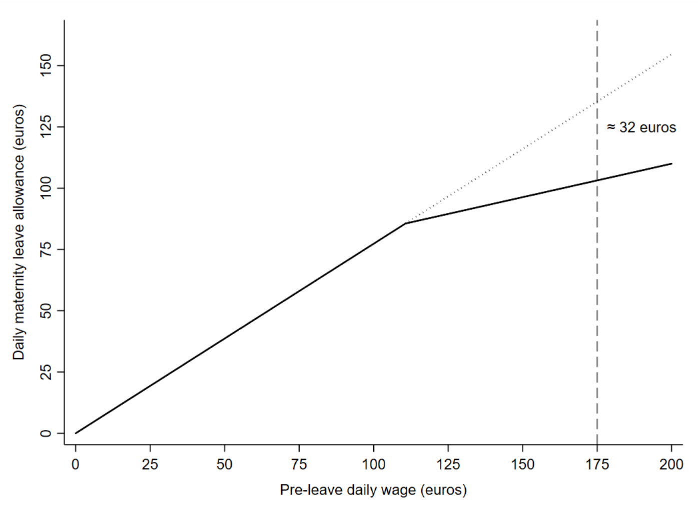
Figure 1: Maternity leave allowance as a function of pre-leave earnings (simulation)

Panel A: Daily allowance first 30 days / remaining 60 days



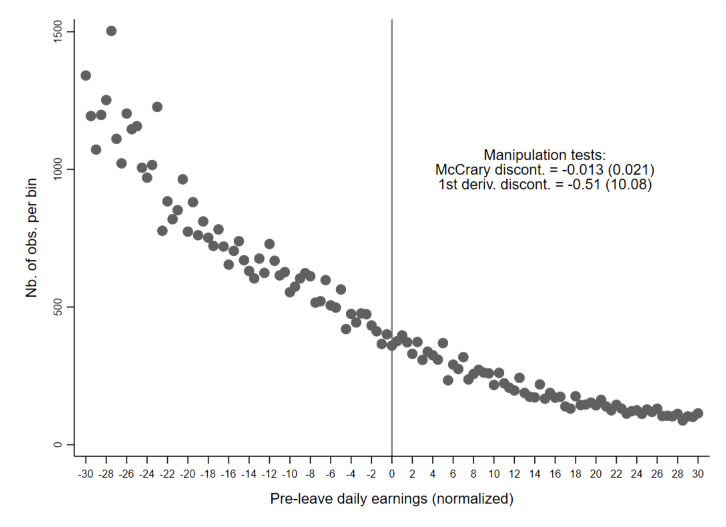
Panel B: Average daily allowance for 90 days



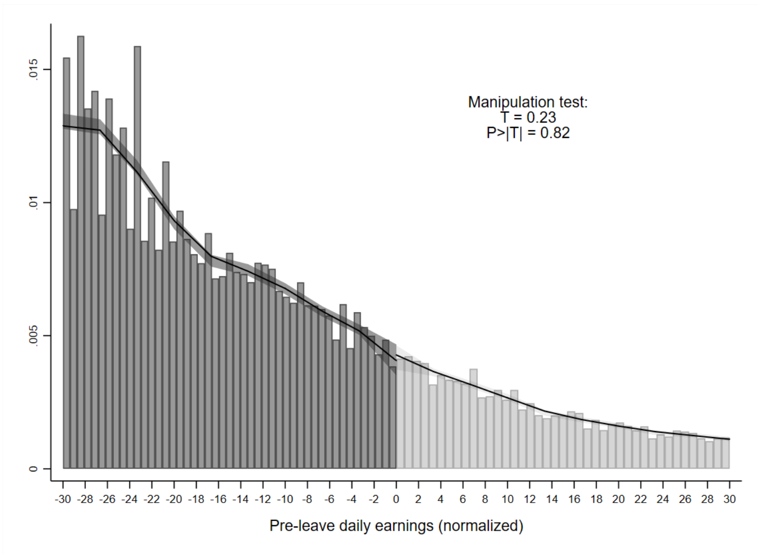
Notes: Both panels simulate the benefit schedule based on the rules set by the social security administration, that is a replacement rate of 82% of pre-leave earnings during the "30 first days" and 75% for the "60 following days" of the maternity leave. Panel A plots the daily allowance paid during the first 30 days (solid line), which is a linear function of pre-leave earning. Panel A also shows the daily allowance paid during the remaining 60 days (dashed line), which is capped. The earnings threshold on both panels is set at 110.655 euros, which corresponds to the one in place on January 1st 2007 in the middle of my sample window. Panel B illustrates the kinked function for a total leave duration of 90 days (i.e. when a mother maxes out her maternity leave entitlement). The average daily allowance is based on Equation (1). The dashed line on Panel B illustrates the situation of a mother with pre-leave earnings of 175 euros, who receives an average daily allowance of about 103 euros. In the absence of the kink (i.e. if the benefit schedule was linear), she would receive a daily allowance of about 135 euros, that is 32 euros more per day.

Figure 2: Manipulation tests

Panel A: Frequency distribution of assignment variable



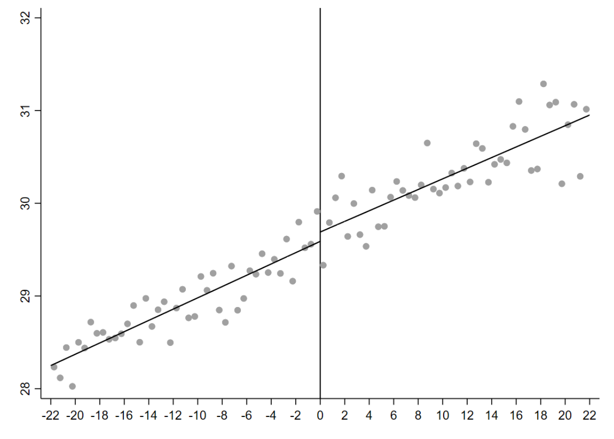
Panel B: Manipulation testing using local-polynomial density estimation



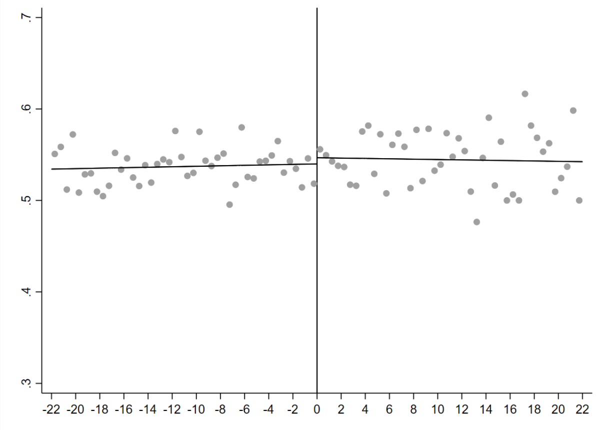
Notes: The graphs assess the validity of the RDK assumption that mothers did not engage in sorting around the kink point. Panel A shows the frequency distribution of pre-leave earnings in 50 euro cents bins, over a 30 euros bandwidth. The graph also displays two manipulation tests: the standard McCrary (McCrary, 2008) test that checks for a "jump" in the p.d.f. of the assignment variable, and the extension proposed by Card et al. (2015b) to test that the first derivative of the p.d.f. is also continuous at the kink. I report the coefficients for both tests, as well as the corresponding standard errors in parentheses. Panel B displays the probability density function of the assignment variable around the kink, but this time estimated using local-polynomials, as proposed by Cattaneo et al., (2020). They also suggest a novel manipulation test, which is reported on the graph with the corresponding p-value. The graphical evidences from both panels, as well as the formal tests, all suggest that the density of the pre-leave earnings around the kink point seems smooth and therefore that one cannot detect manipulation.

Figure 3: Mother's outcomes 4 quarters before the birth of her first child

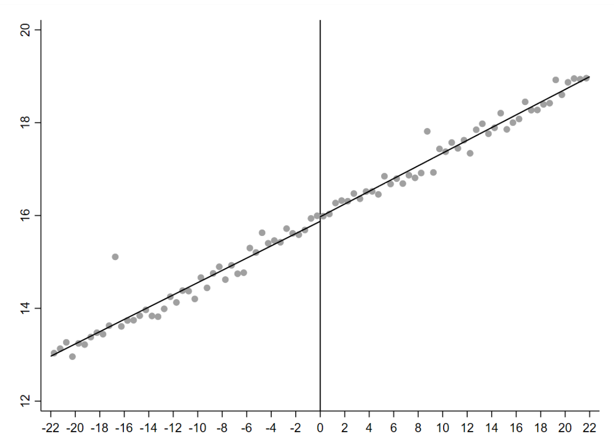
Panel A: Age of mother (years)



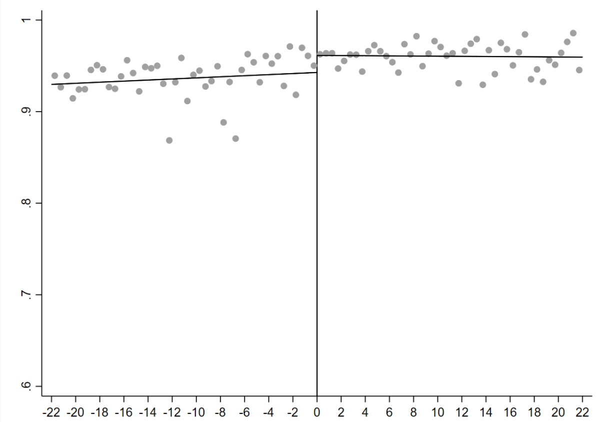
Panel B: Married (0/1)



Panel C: Hourly wage (euros)



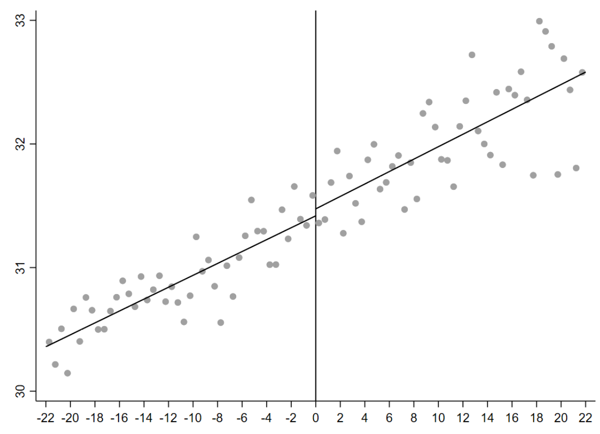
Panel D: Full-time equivalent [0,1]



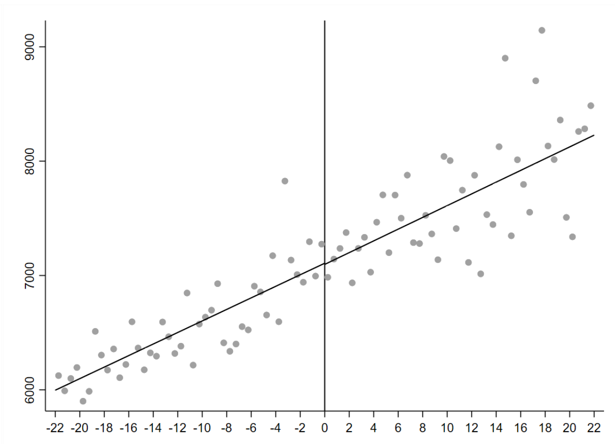
Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

Figure 4: Co-parent's outcomes 4 quarters before the birth of the child

Panel A: Age of co-parent (years)



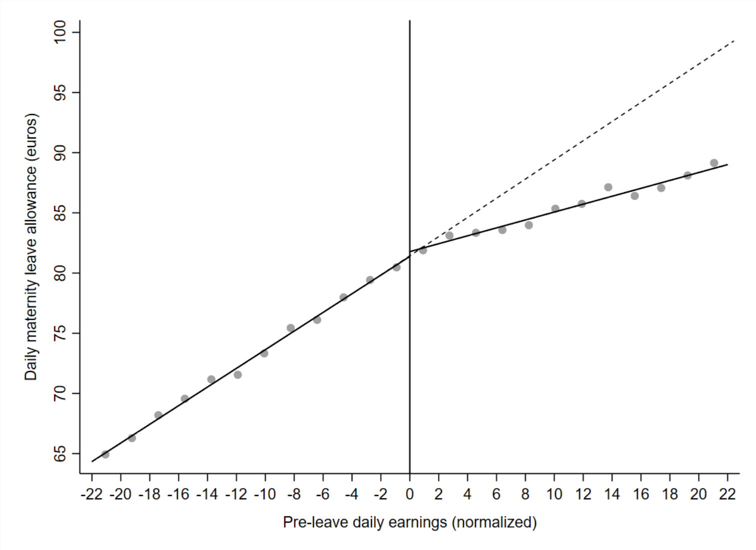
Panel B: Quarterly earnings of co-parent (euros)



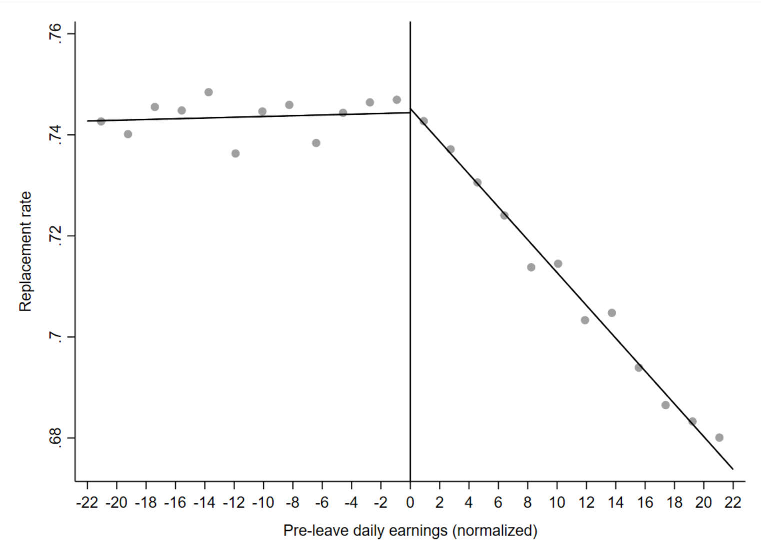
Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

Figure 5: Maternity leave allowance as a function of pre-leave earnings

Panel A: Daily allowance (first stage estimates)

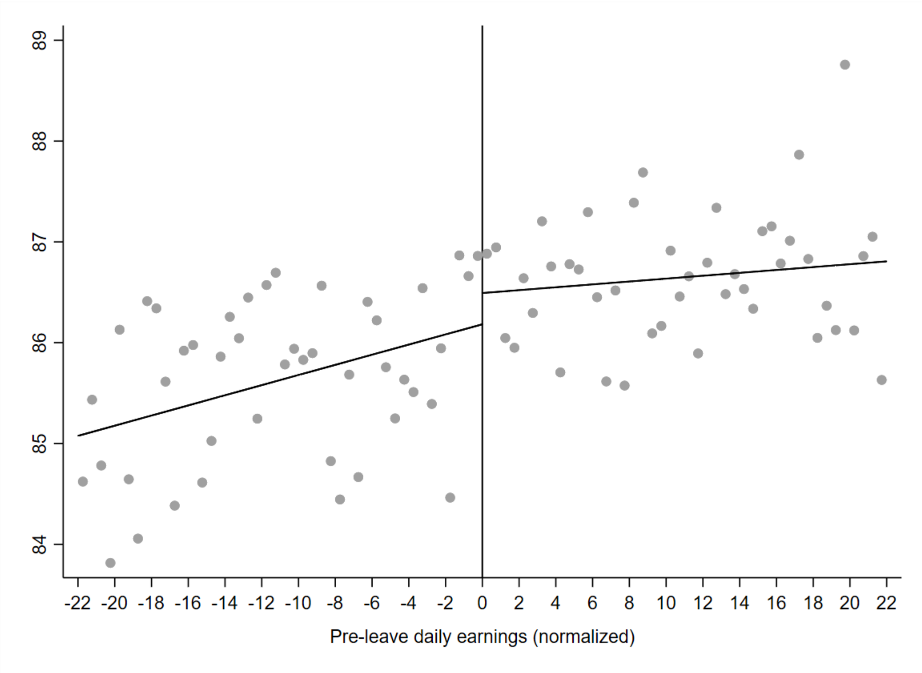


Panel B: Replacement rate



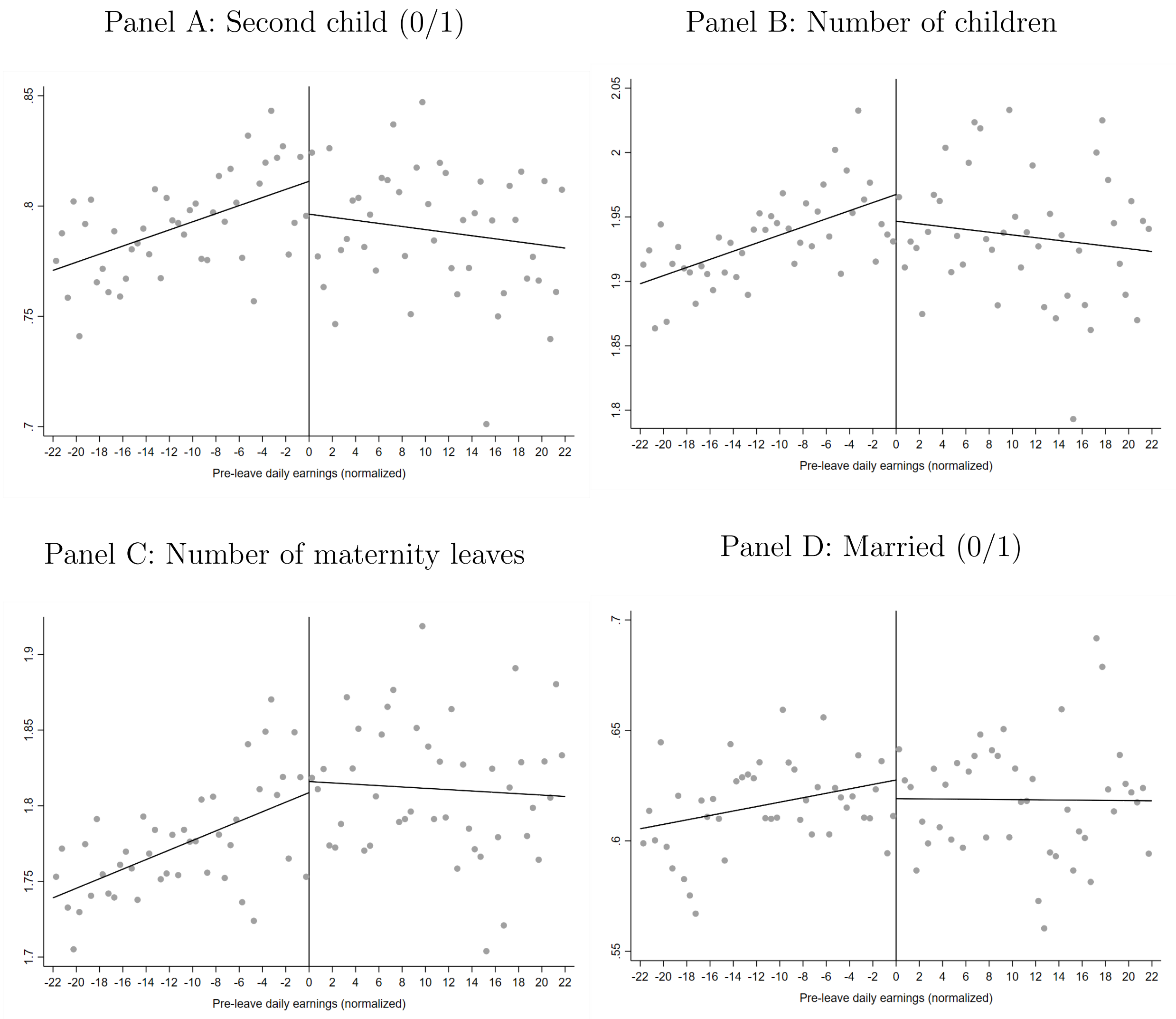
Notes: The first graph (Panel A) shows the empirical relationship between the daily maternity leave allowance and the pre-leave earnings of women within the 22 euros bandwidth around the kink. It corresponds to the "first stage" estimate, that is the change in slopes for the denominator of Equation (2). The second graph (Panel B) shows the the empirical relationship with the replacement rate, that is the percentage of pre-leave earnings replaced by the allowance. In both graphs, the horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in 12 bins.

Figure 6: Duration of maternity leave (# days)



Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

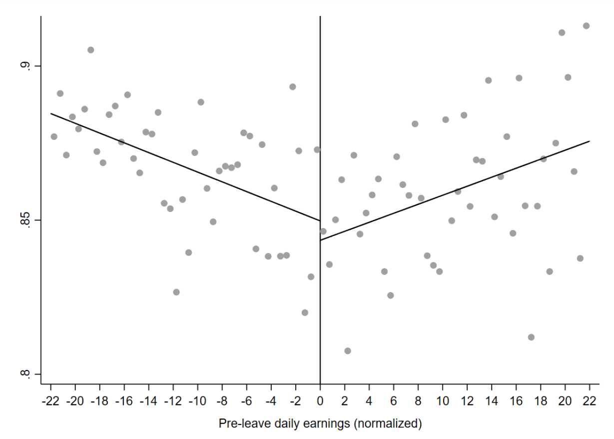
Figure 7: Mother's outcomes 5 years after the birth of her first child



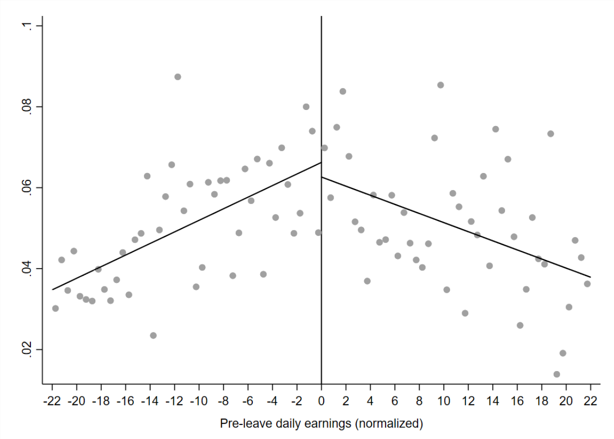
Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

Figure 8: Mother's outcomes 5 years after the birth of her first child

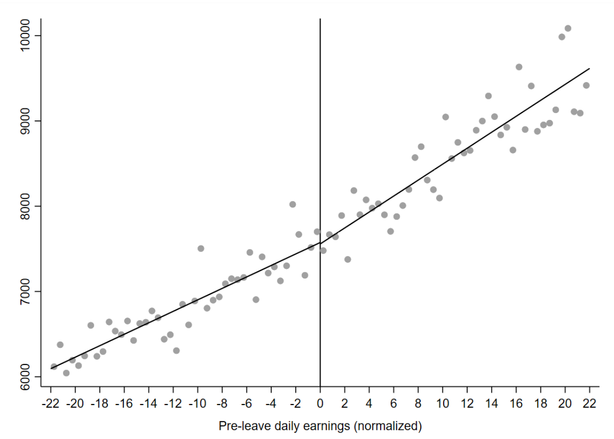
Panel A: Salaried employee (0/1)



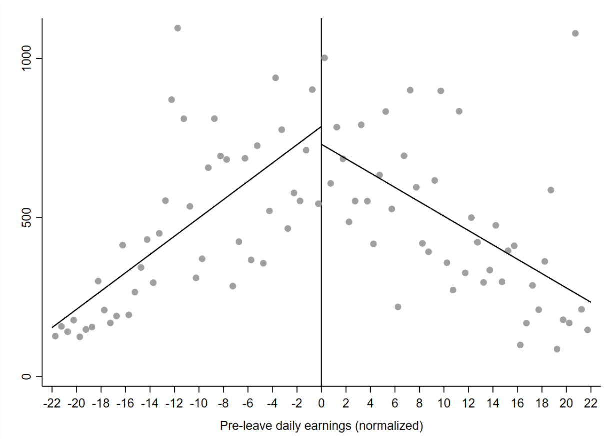
Panel B: Self-employed (0/1)



Panel C: Salaried income (euros)

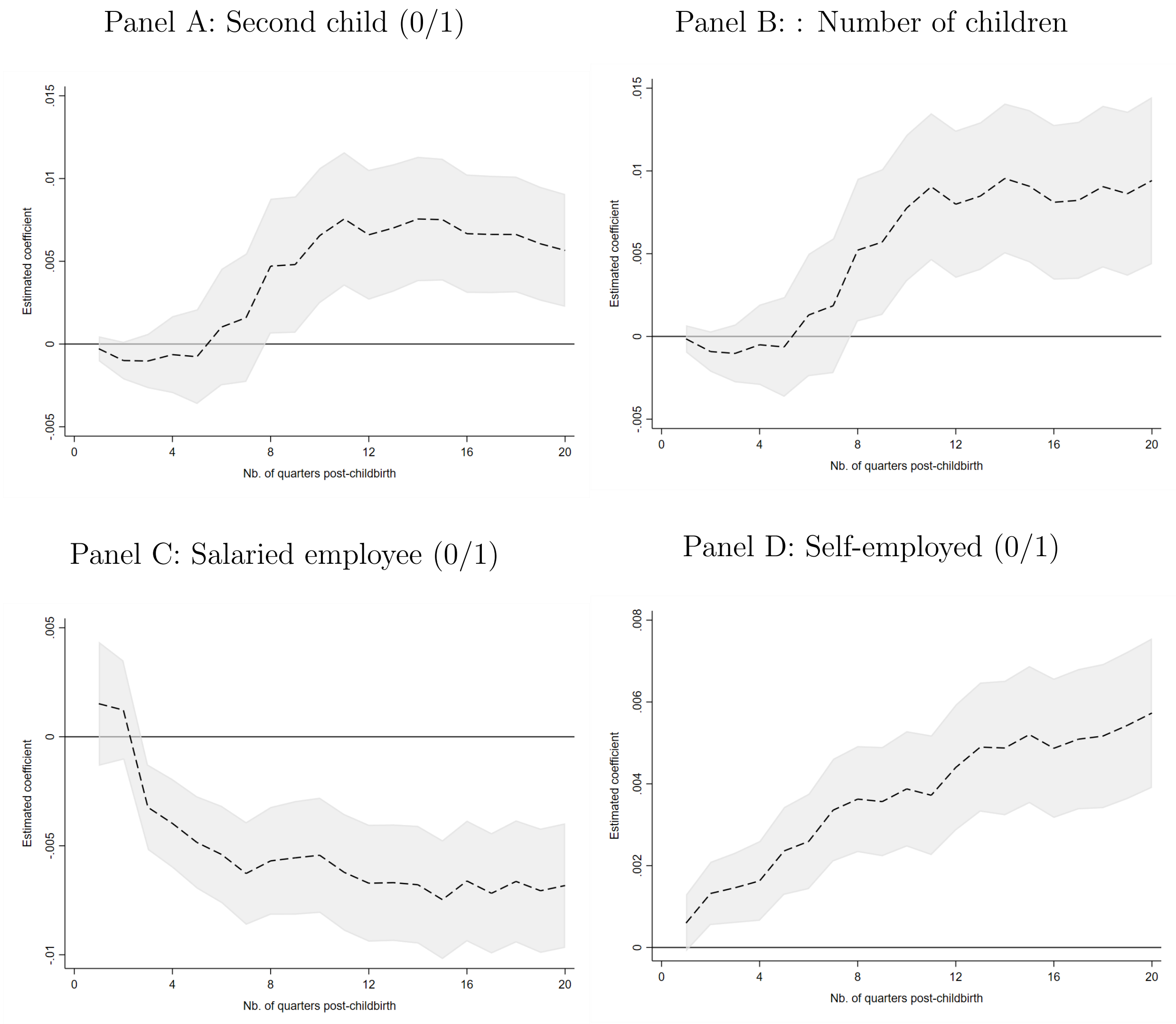


Panel D: Self-employed income (euros)



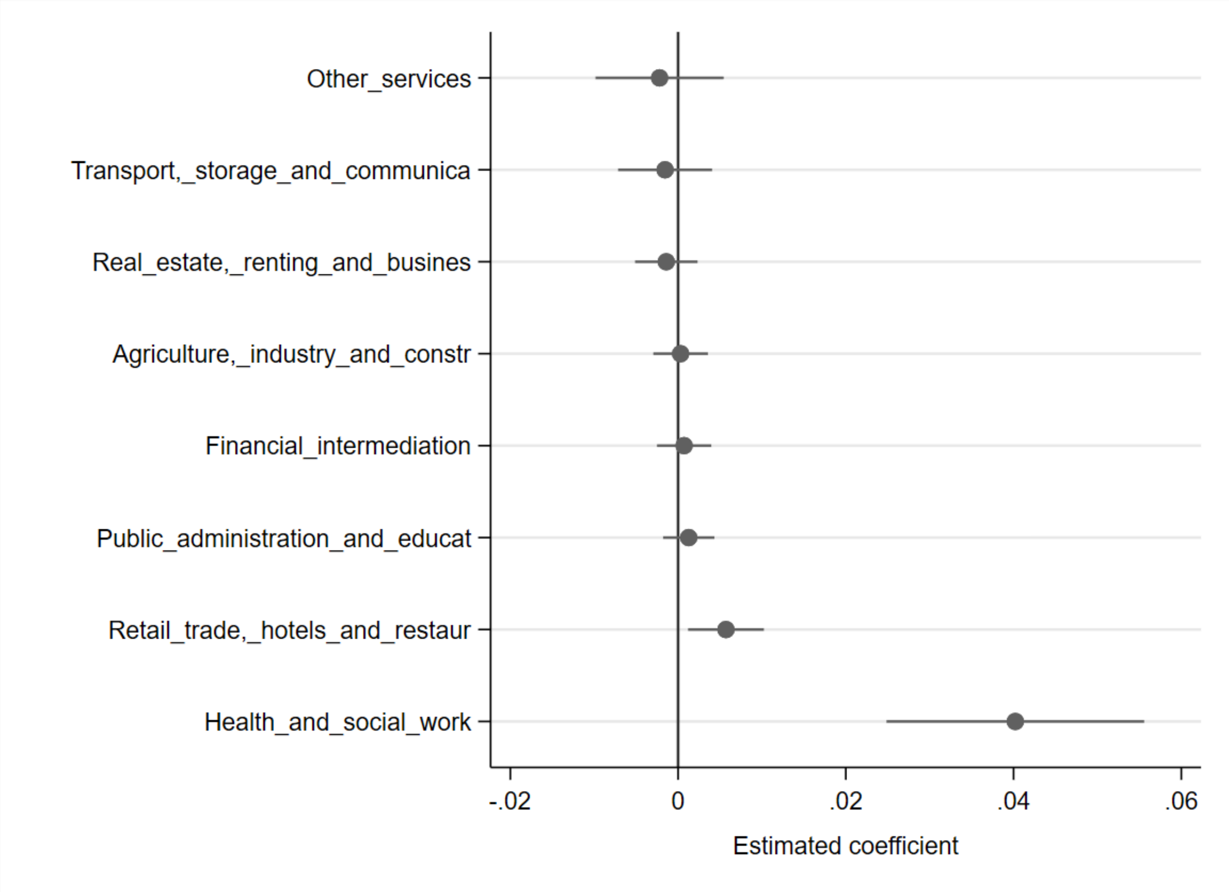
Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

Figure 9: Dynamic effects - Mother's outcomes over 5 years



Notes: These figures show treatment effects (dashed line), based on the RKD estimator of Equation (2), as well as 95% confidence intervals (shaded area). The coefficients are from separate regressions for each quarter following the birth of the mother's first child. All specifications use a common bandwidth of 22 euros around the kink.

Figure 10: Transition to self-employment by sector



Notes: The horizontal axis plots the estimated treatment effect for each sector using separate local polynomial nonparametric regressions of order 1 (i.e. linear) and a symmetric bandwidth of 22 euros around the kink. The dependent variable is a dummy for being self-employed five years after the birth of the first child. The lines on each side of the dots represent the 95% confidence intervals. Detailed results are reported in Table A1 in Appendix.

Table 1: Descriptive statistics

	Full sample Mean (SD)	Kink sample Mean (SD)
Age of mother at first childbirth	28.4	30.2
	(4.0)	(3.3)
Total leave duration (# days)	84.7	85.8
	(13.6)	(11.4)
Total leave benefits (euros)	4808	6487
	(1910)	(1509)
Pre-leave quarterly gross wage (euros)	5245	7999
	(2876)	(1056)
Pre-leave full-time equivalent [0,1]	0.80	0.99
	(0.28)	(0.05)
Pre-leave hourly wage (euros)	12.58	15.92
	(10.12)	(15.67)
Household size (#)	2.0	2.0
	(0.4)	(0.3)
Live in Flanders (0/1)	0.64	0.69
	(0.5)	(0.5)
Married (0/1)	0.50	0.57
	(0.50)	(0.50)
Age of co-parent at childbirth	30.9	32.1
	(5.0)	(4.5)
Co-parent took paternity leave (0/1)	0.57	0.58
	(0.49)	(0.49)
Co-parent employed (0/1)	0.86	0.89
	(0.35)	(0.31)
Co-parent quarterly earnings (euros)	5636	7007
	(4440)	(4667)
Number of observations	180,327	37,906

Notes: This table presents the means and standard deviations (in parentheses) of some of the key variables for women having a first child during 2003-2010. The "kink sample" includes mothers whose daily base earnings are within 22 euros of the kink and corresponds to the sample used in all baseline regressions. All outcomes are measured at the moment of the birth of the first child, except for household size, which is measured before, as well as mothers' outcomes relative to the pre-leave employment.

Table 2: Predetermined outcomes - 4 quarters before the birth of the first child

	Coef. / SE	N
Household size (#)	0.001	37858
	(0.001)	
Live in Flanders (0/1)	0.001	37859
	(0.001)	
Age of mother	-0.004	37906
	(0.006)	
Married (0/1)	0.000	37892
	(0.001)	
Full-time equivalent [0,1]	-0.001 **	37111
	(0.000)	
Hourly wage (euros)	0.005	37090
	(0.006)	
Age of co-parent	0.002	37074
	(0.008)	
Co-parent quarterly earnings (euros)†	-2.205	36994
	(7.695)	
Mother's share of household income [0,1]	-0.001	37367
	(0.000)	

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The coefficients test for a change in slope at the kink for the predetermined covariates. They provide evidence for the validity of the smoothness assumption of the RKD. The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table 3: Mother's outcomes 5 years after the birth of her first child

	First stage	Treatment effect	Robust CI	Mean	N
Duration of maternity leave (# days)	-0.45 ***	0.081 *	[-0.075 , 0.105]	85.85	37906
	(0.02)	(0.042)			
Duration of maternity leave (log)	-0.01 ***	0.126 **	[-0.042 , 0.193]	4.44	37906
	(0.00)	(0.055)			
Second child (0/1)	-0.45 ***	0.006 ***	[0.002 , 0.010]	0.79	37178
	(0.02)	(0.002)			
Number of children	-0.45 ***	0.009 ***	[0.005 , 0.016]	1.93	37178
	(0.02)	(0.003)			
Number of maternity leaves	-0.45 ***	0.008 ***	[0.001 , 0.012]	1.78	37906
	(0.02)	(0.002)			
Married (0/1)	-0.45 ***	0.002	[-0.002 , 0.006]	0.62	37858
	(0.02)	(0.002)			
Employed (0/1)	-0.45 ***	-0.001	[-0.004 , 0.001]	0.90	37906
	(0.02)	(0.001)			
Salaried employee (0/1)	-0.45 ***	-0.007 ***	[-0.011 , -0.004]	0.87	37906
	(0.02)	(0.001)			
Self-employed (0/1)	-0.45 ***	0.006 ***	[0.004 , 0.008]	0.05	37906
	(0.02)	(0.001)			
Quarterly earnings (euros)†	-0.44 ***	-5.202	[-48.416 , 28.042]	7651.30	37527
	(0.02)	(17.353)			
Salaried income (euros)†	-0.44 ***	-38.194 **	[-89.100 , -8.521]	7194.92	37527
	(0.02)	(18.261)			
Self-employed income (euros)†	-0.44 ***	32.991 ***	[24.236 , 53.011]	456.37	37527
	(0.02)	(6.485)			

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The column "first stage" reports changes in slopes for the denominator of Equation (2). It captures the change in marginal benefits at the kink. The column "treatment effect" reports estimates based on the RKD estimator of Equation (2). The coefficients show the estimated effect of a 1 euro increase in daily maternity leave benefits on the outcomes. The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. I also provide bias-corrected confidence intervals ("robust CI") proposed by Calonico et al. (Calonico et al., 2014). The column "Mean" reports the average of the dependent variable within the defined bandwidth. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table 4: Mother's outcomes 5 years after the birth of her first child (Heterogeneity analysis)

	Mother's prebirth earnings lower than father's Treatment effect	N	**Mother's prebirth earnings higher than father's** Treatment effect	N	Diff. (SE)	Z-stat (p-value)
Duration of maternity leave (# days)	0.215 ***	17165	-0.014	20741	0.229	2.585
	(0.070)		(0.054)		(0.089)	(0.010)
Duration of maternity leave (log)	0.308 ***	17165	0.006	20741	0.302	2.516
	(0.098)		(0.069)		(0.120)	(0.012)
Second child (0/1)	0.003	16809	0.008 ***	20369	-0.005	-1.376
	(0.003)		(0.002)		(0.004)	(0.169)
Number of children	0.008 *	16809	0.011 ***	20369	-0.004	-0.695
	(0.004)		(0.003)		(0.005)	(0.487)
Number of maternity leaves	0.004	17165	0.011 ***	20741	-0.007	-1.406
	(0.004)		(0.003)		(0.005)	(0.160)
Married (0/1)	0.001	17148	0.003	20710	-0.002	-0.441
	(0.003)		(0.003)		(0.004)	(0.659)
Employed (0/1)	-0.003	17165	0.000	20741	-0.003	-1.095
	(0.002)		(0.002)		(0.003)	(0.274)
Salaried employee (0/1)	-0.010 ***	17165	-0.005 ***	20741	-0.005	-1.690
	(0.002)		(0.002)		(0.003)	(0.091)
Self-employed (0/1)	0.009 ***	17165	0.004 ***	20741	0.005	2.501
	(0.002)		(0.001)		(0.002)	(0.012)
Quarterly earnings (euros)†	-30.586	16956	11.611	20571	-42.197	-(1.161)
	(29.157)		(21.683)		(36.336)	(0.246)
Salaried income (euros)†	-73.258 **	16956	-15.869	20571	-57.389	-1.491
	(30.995)		(22.805)		(38.481)	(0.136)
Self-employed income (euros)†	42.672 ***	16956	27.481 ***	20571	15.191	1.109
	(11.091)		(8.044)		(13.701)	(0.268)

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The column "treatment effect" reports estimates based on the RKD estimator of Equation (2). The coefficients show the estimated effect of a 1 euro increase in daily maternity leave benefits on the outcomes. The last two columns report results from z-tests to check whether the coefficients estimated on the two sub-samples are statisticaly different. The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table 5: Co-parent's outcomes 5 years after the birth of the first child

	First stage	Treatment effect	Robust CI	Mean	N
Paternity leave (0/1)	-0.45 ***	-0.004 *	[-0.010 , -0.001]	0.58	37367
	(0.02)	(0.002)			
Quarterly earnings (euros)†	-0.44 ***	-8.629	[-60.561 , 45.437]	9128.87	36994
	(0.02)	(24.409)			
Salaried income (euros)†	-0.44 ***	-29.867	[-84.807 , 33.946]	7549.98	36994
	(0.02)	(27.382)			
Self-employed income (euros)†	-0.44 ***	21.238	[-17.117 , 52.855]	1578.89	36994
	(0.02)	(16.121)			

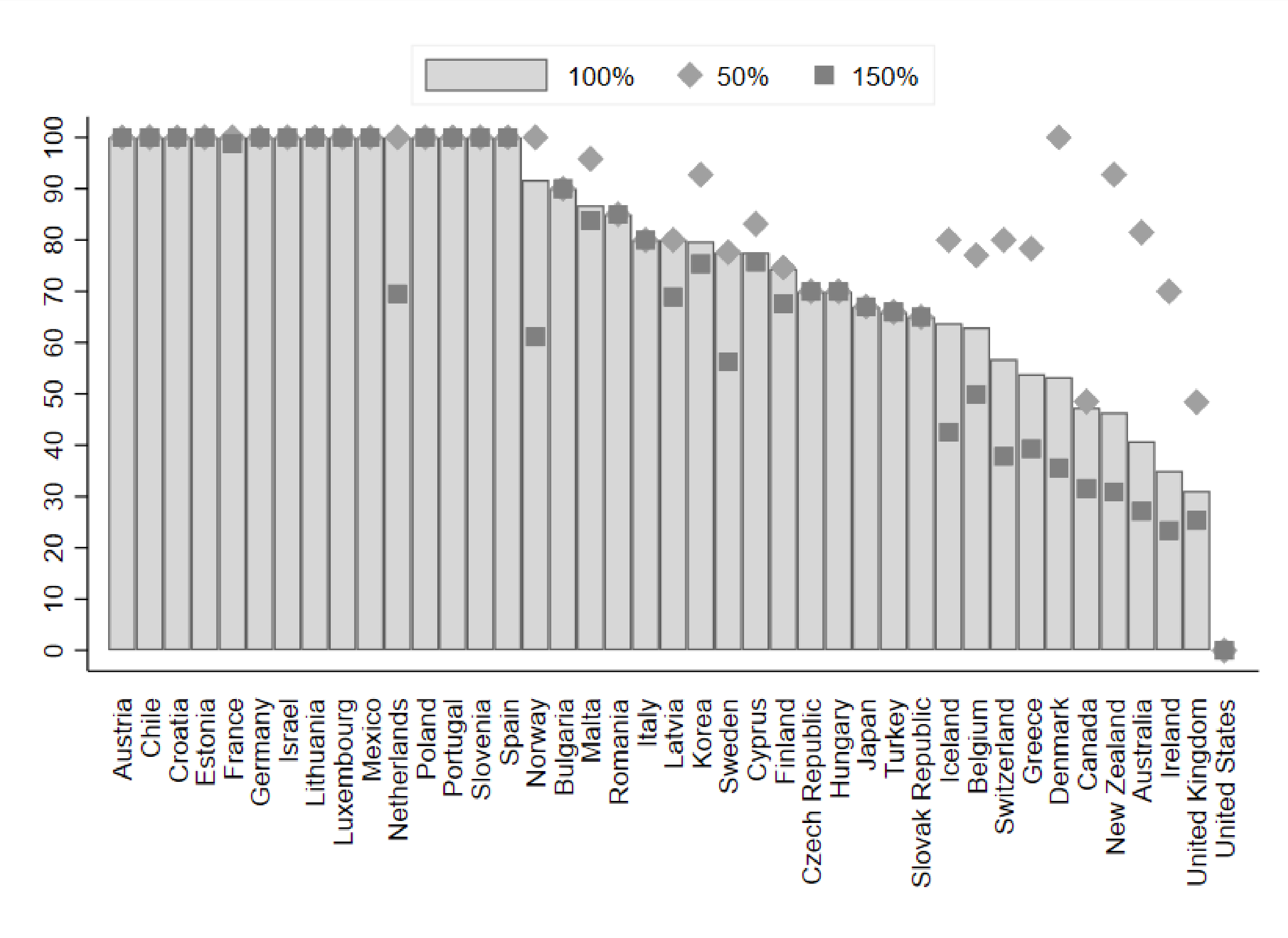
*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The column "treatment effect" reports estimates based on the RKD estimator of Equation (2). The coefficients show the estimated effect of a 1 euro increase in daily maternity leave benefits on the outcomes. The sample includes co-parents who had a first child with a mother eligible for maternity leave between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Appendix

How Does Maternity Leave Allowance Affect Fertility and Career Decisions?

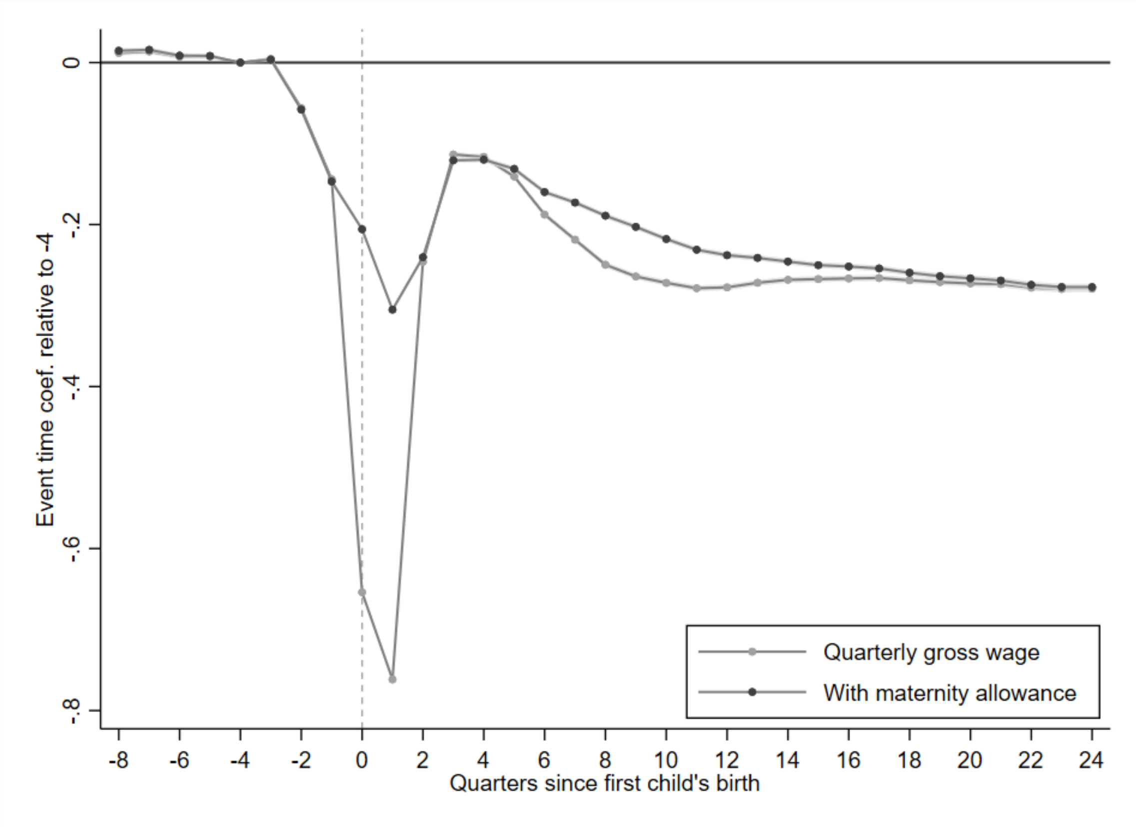
Sébastien Fontenay

Figure A1: Proportion of previous gross earnings replaced by maternity benefits (by level of earnings compared to the national average)



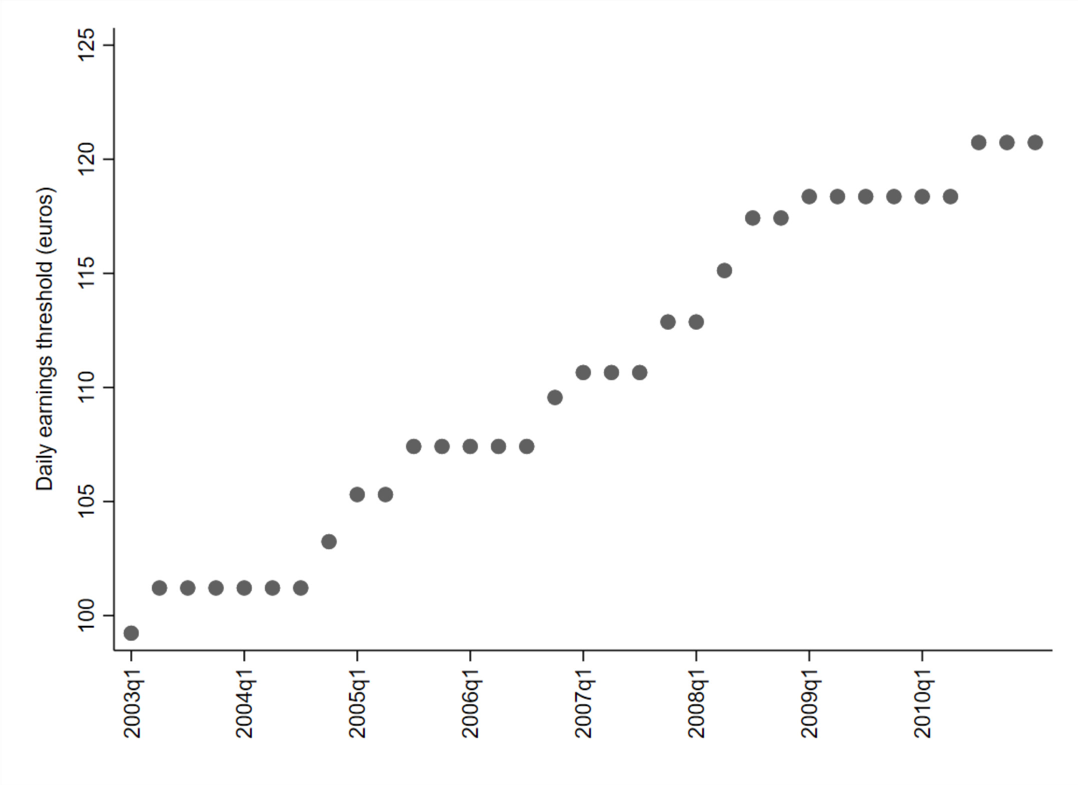
Notes: Data from the OECD Family Database, 2014. In Austria, Chile, and Germany benefits are calculated based on previous net (post income tax and social security contribution) earnings, while in France benefits are calculated based on post-social-security-contribution earnings.

Figure A2: Impact of children on mothers' quarterly gross earnings with and without maternity leave allowance



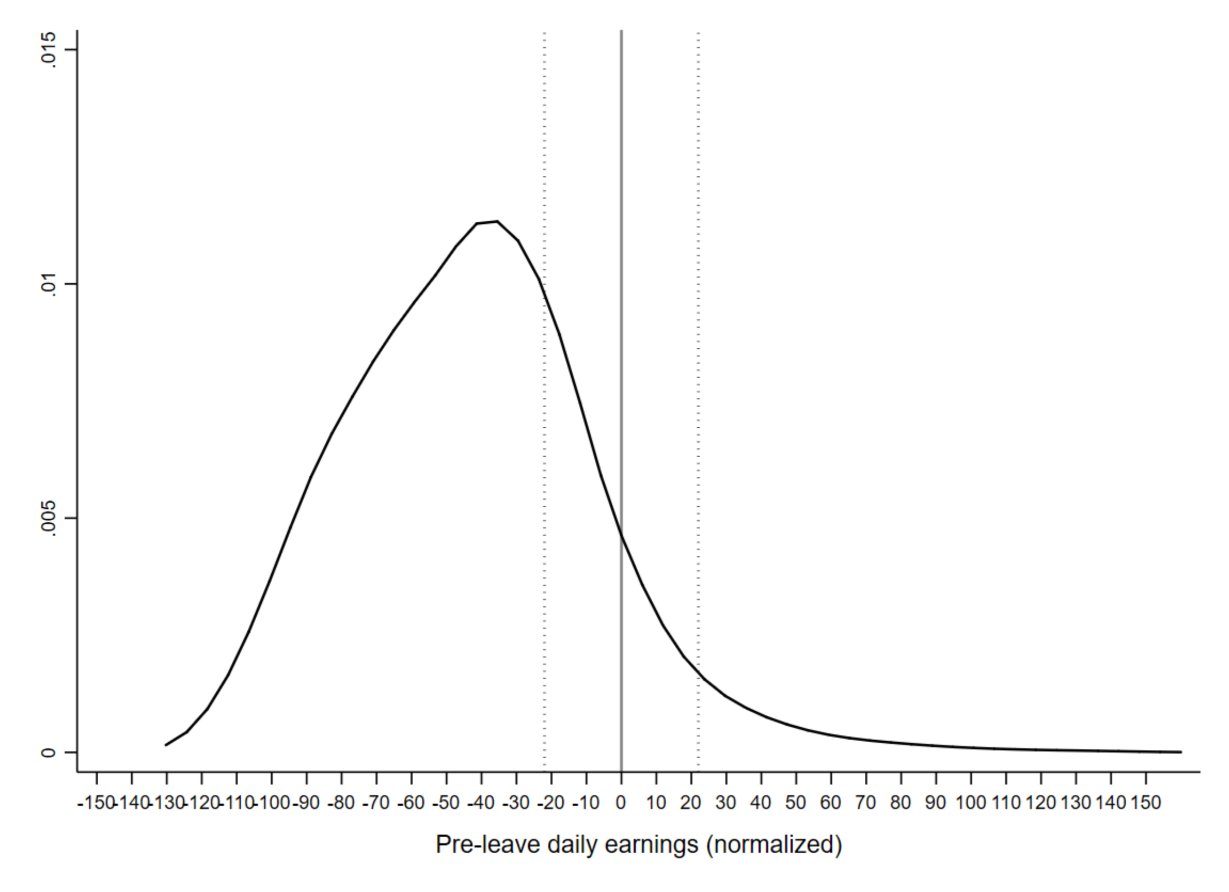
Notes: The figure shows event time coefficients (relative to the 4th quarter before the first child's birth) estimated on a sample of mothers who had their first child between 2003-2010 and were eligible for maternity leave (i.e. had sufficient work history). The coefficients are displayed as a percentage of the mean of the outcome measured at t-4. The earnings are measured conditional on labor force participation. The outcome will therefore not account for women leaving the labor market as a result of having children. The shaded 95% confidence intervals are based on robust standard errors.

Figure A3: Daily earnings threshold by quarter



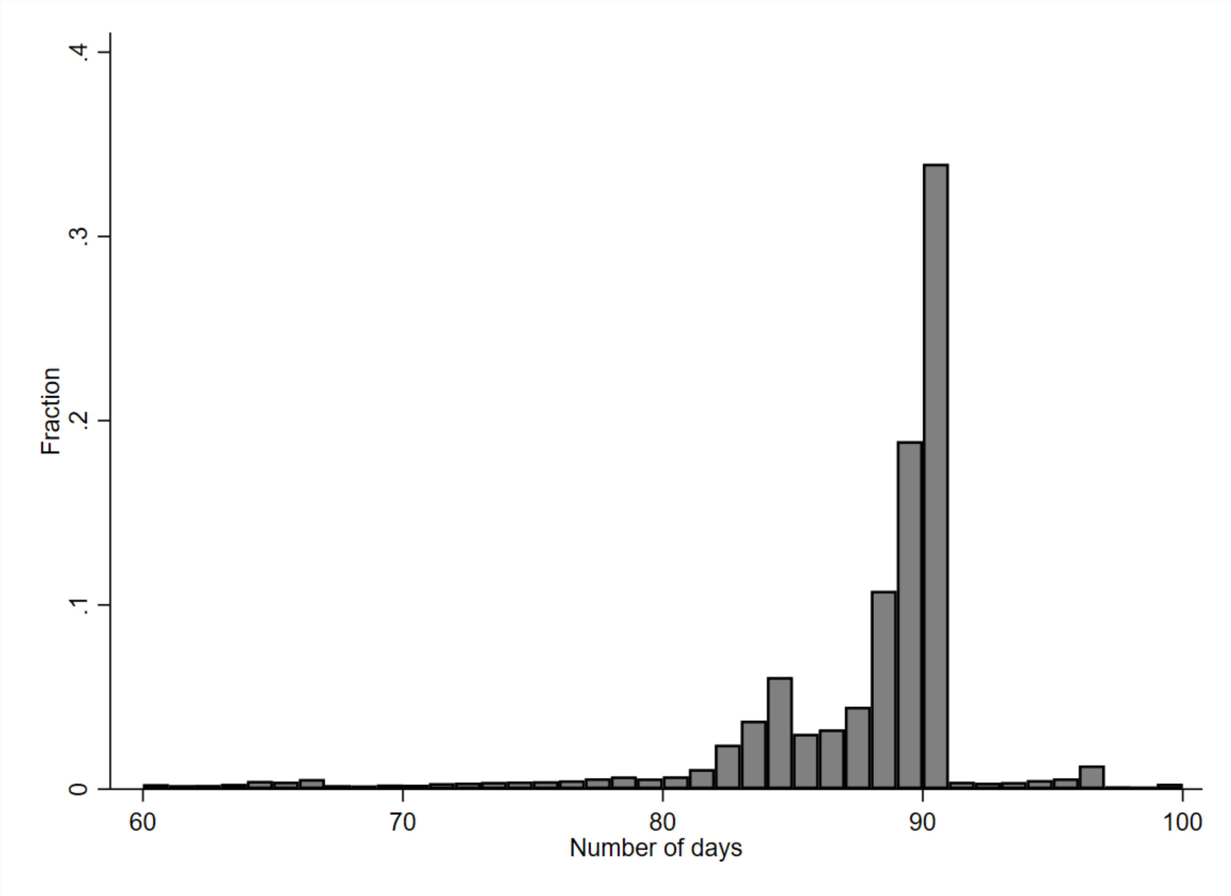
Notes: The figure shows the evolution of the earnings threshold set by the social security administration. The changes reflect government's decisions, as well as automatic adjustment to inflation. Data source: National Institute for Health and Disability Insurance.

Figure A4: Kernel density of pre-leave earnings around the kink



Notes: The graph plots the distribution of the pre-leave earnings using kernel density. The kink is located around the 90th percentile. The dashed lines represent the 22 euros bandwidth used in the baseline specifications.

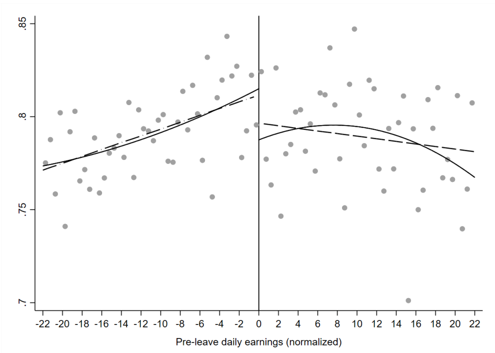
Figure A5: Distribution of total leave duration for women with earnings near the kink point



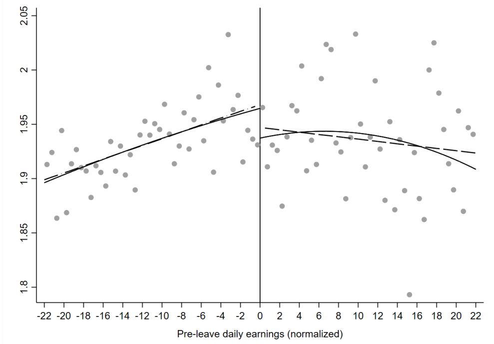
Notes: This figure plots the distribution of maternity leave duration for women with pre-claim earnings within a 22 euros bandwidth surrounding the kink point. The maximum duration of maternity leave in Belgium is 90 days, but it can be extended to 102 days for multiple births. All mothers must stop working during a compulsory period of at least 60 days.

Figure A6: Comparison between linear and quadratic functions of the assignment variable - Mother's fertility outcomes

Panel A: Second child (0/1)

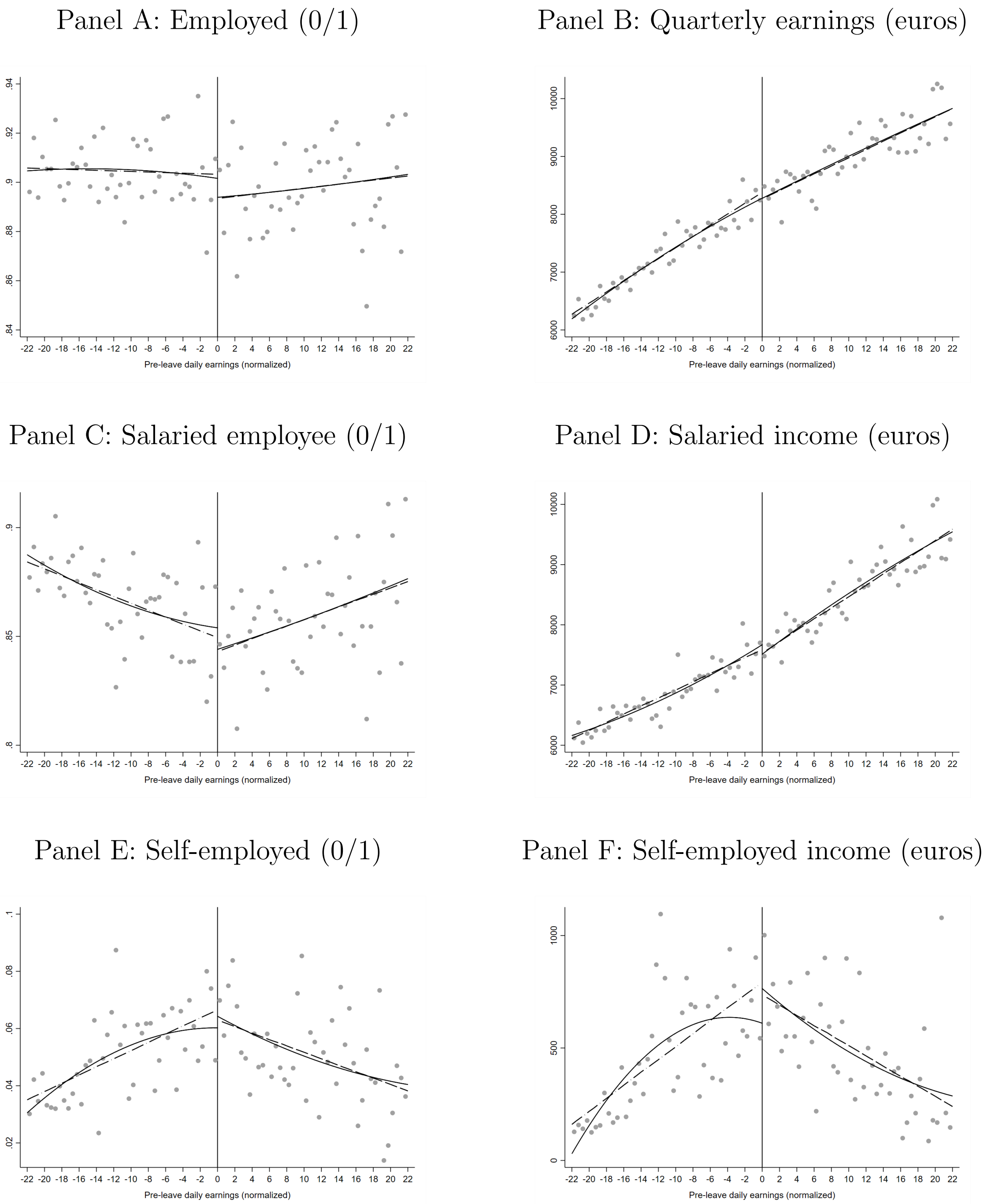


Panel B: Number of children



Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The dashed lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions of order 1. The solid lines display the underlying quadratic relationship on each side of the kink and are estimated using local nonparametric regressions of order 2.

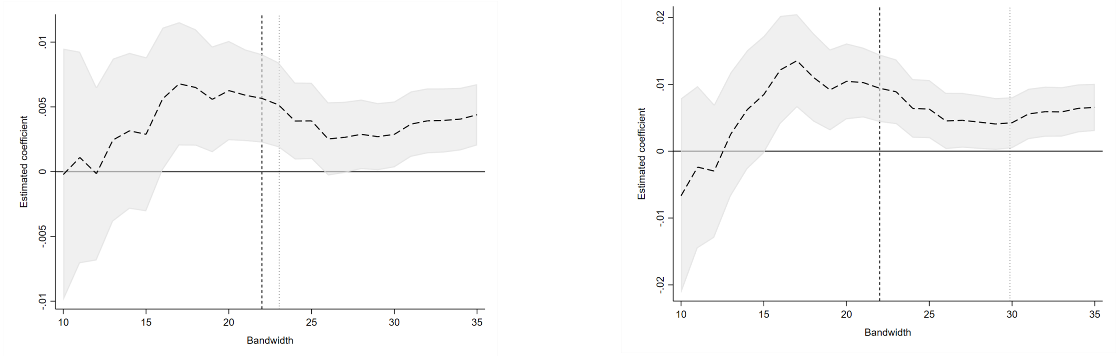
Figure A7: Comparison between linear and quadratic functions of the assignment variable - Mother's employment outcomes



Notes: The horizontal axis plots normalized pre-leave daily earnings (relative to the kink) in bins, using 50 euro cents bins. The vertical axis plots the mean of the outcome in each bin. The dashed lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions of order 1. The solid lines display the underlying quadratic relationship on each side of the kink and are estimated using local nonparametric regressions of order 2.

Figure A8: Varying bandwidth - Mother's fertility outcomes

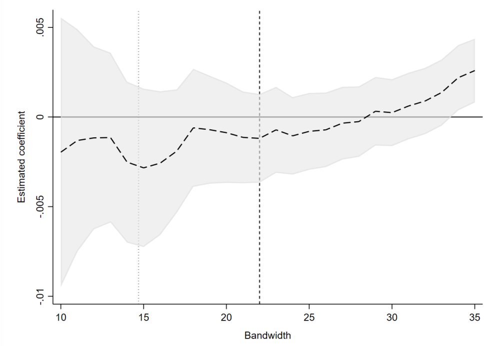
Panel A: Second child (0/1) | Panel B: Number of children



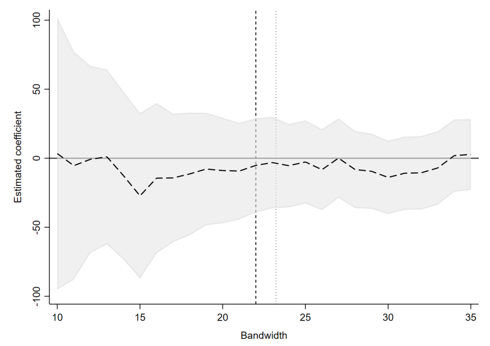
Notes: These figures show treatment effects (dashed line), estimated with local polynomial nonparametric regressions of order 1 (i.e. linear), as well as 95% confidence intervals (shaded area). The coefficients are from separate regressions using all possible bandwidths in 1 euro increments of normalized pre-leave daily earnings from 10 to 35 euros. The dotted vertical line materializes the bandwidth picked by the CCT selector of Calonico et al. (2014). The dashed vertical line materializes the common bandwidth of 22 euros used for the main estimations. All samples include mothers who had a first child between 2003 and 2010.

Figure A9: Varying bandwidth - Mother's employment outcomes

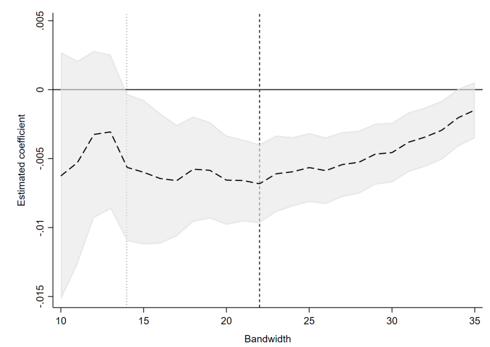
Panel A: Employed (0/1)



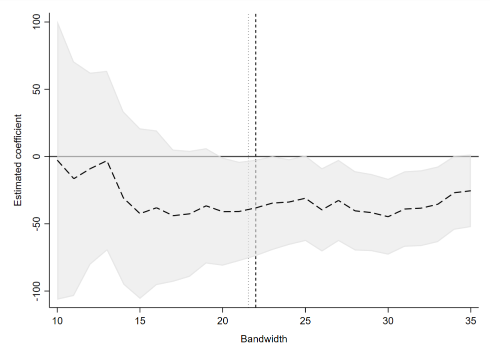
Panel B: Quarterly earnings (euros)



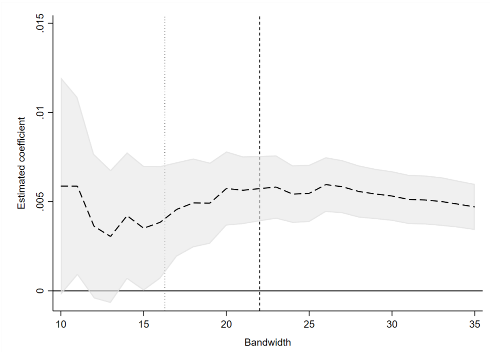
Panel C: Salaried employee (0/1)



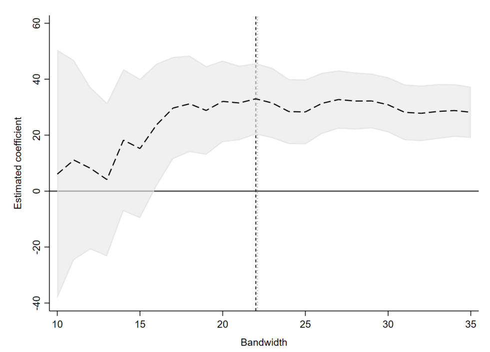
Panel D: Salaried income (euros)



Panel E: Self-employed (0/1)



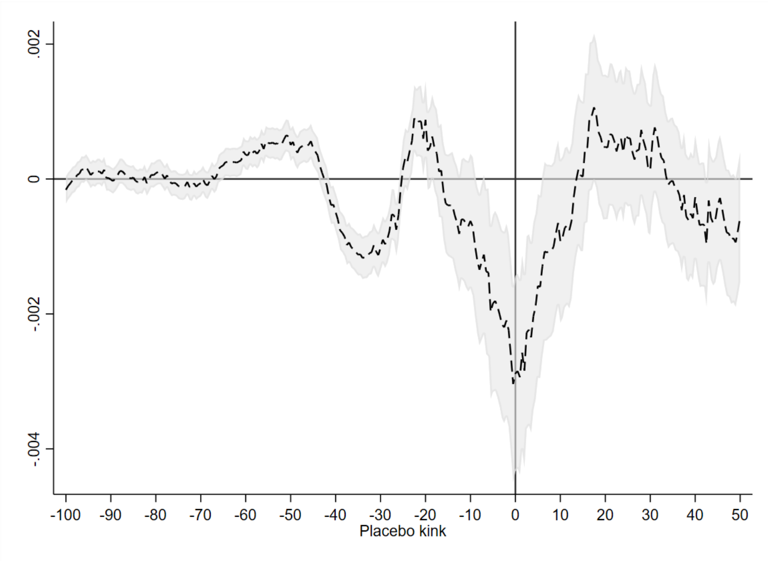
Panel F: Self-employed income (euros)



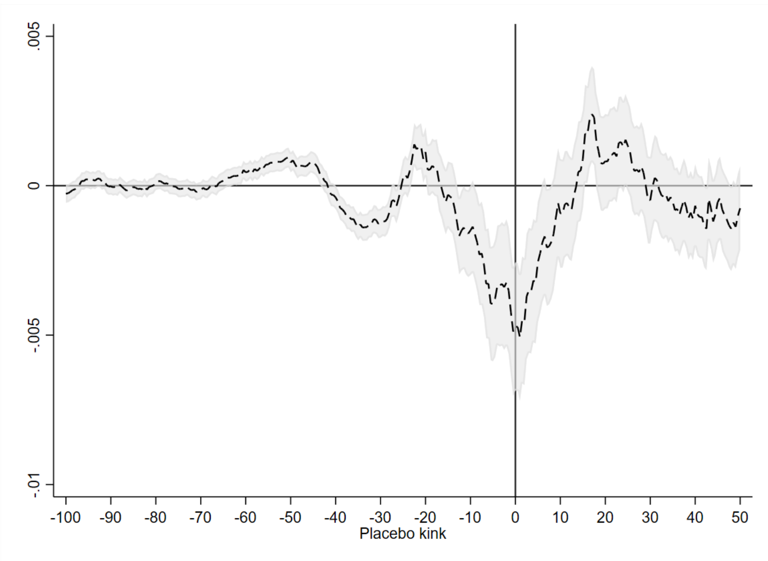
Notes: These figures show treatment effects (dashed line), estimated with local polynomial nonparametric regressions of order 1 (i.e. linear), as well as 95% confidence intervals (shaded area). The coefficients are from separate regressions using all possible bandwidths in 1 euro increments of normalized pre-leave daily earnings from 10 to 35 euros. The dotted vertical line materializes the bandwidth picked by the CCT selector of Calonico et al. (2014). The dashed vertical line materializes the common bandwidth of 22 euros used for the main estimations. All samples include mothers who had a first child between 2003 and 2010. For panels B, D and F, the outcomes are trimmed, replacing the top 1% of the distribution with missing values.

Figure A10: Permutation tests - Reduced form coefficients and 95% CI

Panel A: Probability to have a second child after 5 years



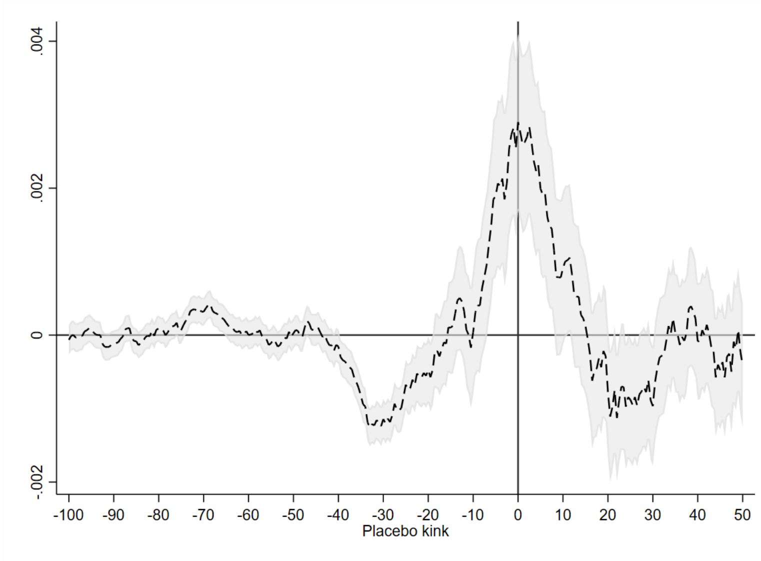
Panel B: Number of children after 5 years



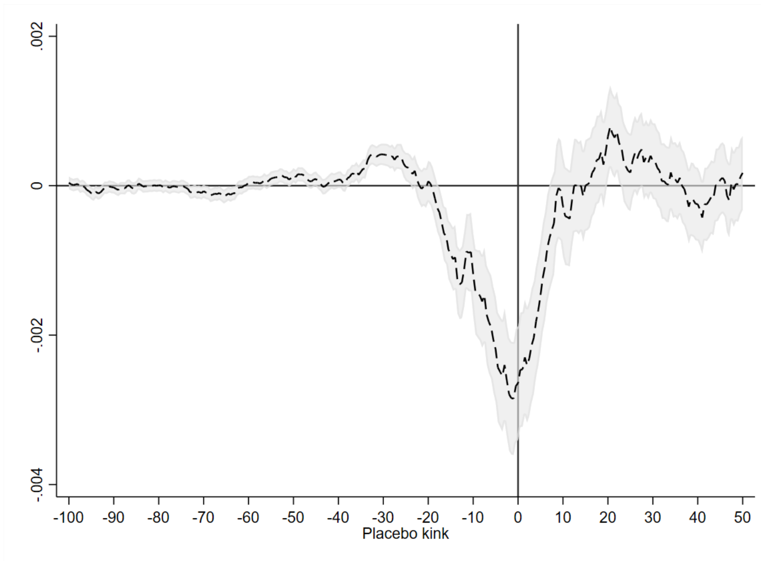
Notes: The graphs show results from permutation tests, proposed by Ganong & Jäger (2018), to assess the sensitivity of the results to non-linearities in the relationship between the assignment variable and the outcome. The figures plot the coefficients (dashed line) and 95% confidence intervals (shaded area) from 300 RKD models using placebo kinks along the distribution of the assignment variable, with a 22 euros bandwidth. The horizontal axis displays the distance from the true kink point (at 0). Note that those are reduced form estimates that correspond to the numerator of Equation (2). As such the placebo kink coefficients are of the opposite sign from those reported in the baseline specifications. One can see that the coefficient estimate at the true kink point is much larger than those at placebo kinks.

Figure A11: Permutation tests - Reduced form coefficients and 95% CI

Panel A: Salaried employee after 5 years



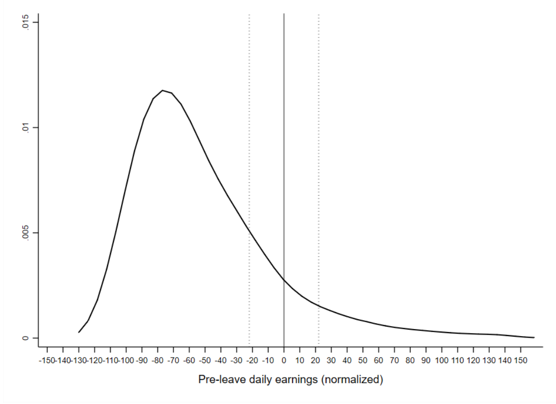
Panel B: Self-employed after 5 years



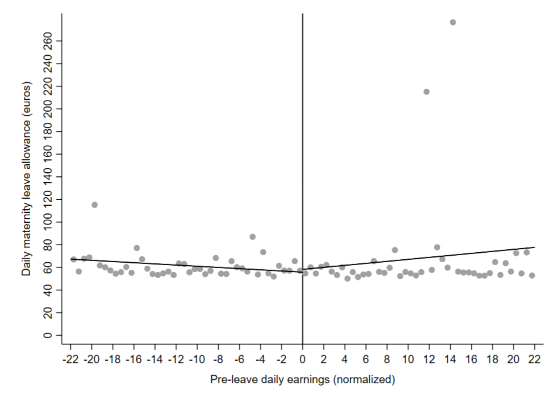
Notes: The graphs show results from permutation tests, proposed by Ganong & Jäger (2018), to assess the sensitivity of the results to non-linearities in the relationship between the assignment variable and the outcome. The figures plot the coefficients (dashed line) and 95% confidence intervals (shaded area) from 300 RKD models using placebo kinks along the distribution of the assignment variable, with a 22 euros bandwidth. The horizontal axis displays the distance from the true kink point (at 0). Note that those are reduced form estimates that correspond to the numerator of Equation (2). As such the placebo kink coefficients are of the opposite sign from those reported in the baseline specifications. One can see that the coefficient estimate at the true kink point is much larger than those at placebo kinks.

Figure A12: Placebo group - Self-employed first-time mothers

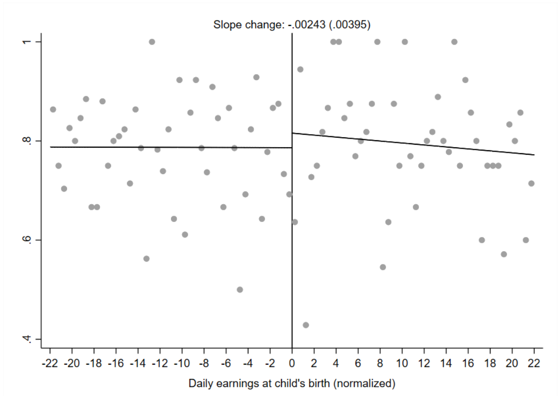
Panel A: Kernel density of pre-leave earnings around placebo kink



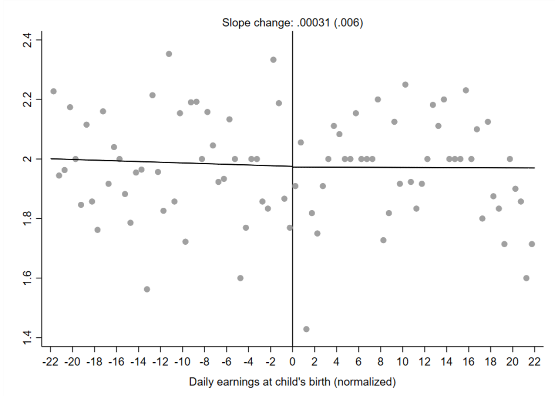
Panel B: Maternity leave allowance as a function of pre-leave earnings



Panel C: Second child after 5 years (0/1)

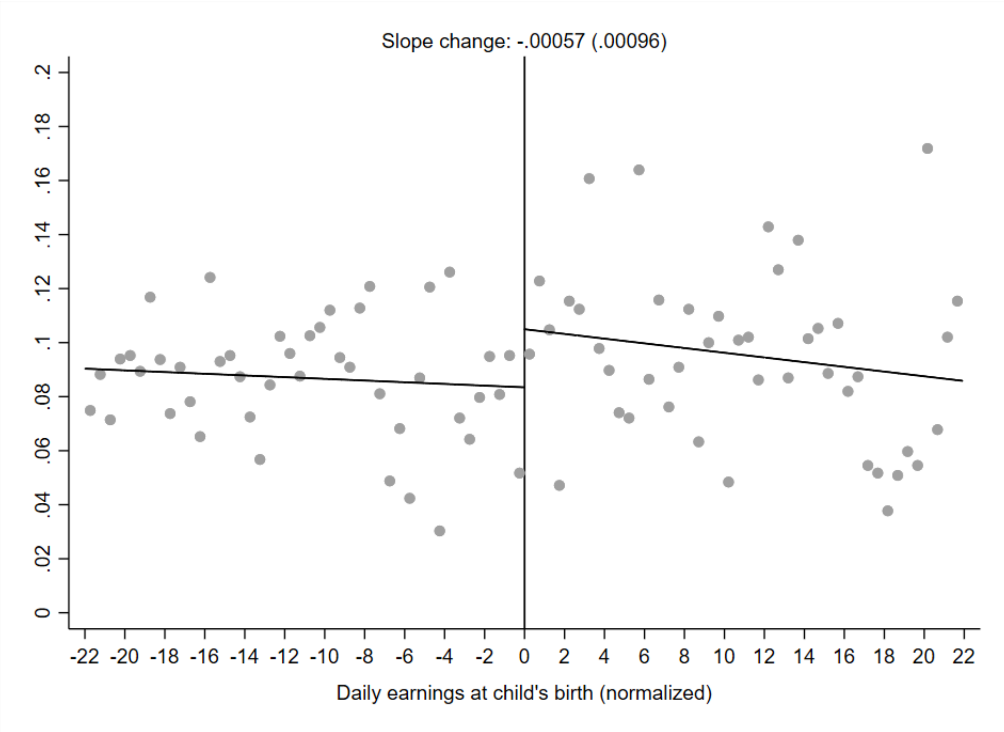


Panel D: Number of children after 5 years



Notes: The sample if composed of first-time mothers who were self-employed before the birth of their child and therefore receive a flat amount of maternity leave benefits. Panel A plots the distribution of the pre-leave earnings for self-employed women using kernel density. The placebo kink is located around the 90th percentile, similar to the main sample. The dashed lines represent the 22 euros bandwidth used in the main specifications. Panel B shows the empirical relationship between the daily maternity leave allowance and the pre-leave earnings of self-employed women within the 22 euros bandwidth around the kink. The lower panels plot normalized pre-leave daily earnings (horizontal axis) in 50 euro cents bins and the mean of the outcomes variables for self-employed women (vertical axis): dummy for having a second child (panel C) and discrete variable for the number of children (panel D). The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions. The change in slope at the kink is reported above the graph with standard errors in parentheses.

Figure A13: Placebo group - Fathers who do not go on leave
Self-employed 5 years after the birth of their child (0/1)



Notes: The sample is composed of fathers who did not go on leave after the birth of their child and therefore did not receive benefits from the social security administration. The horizontal axis plots normalized daily earnings during the quarter of birth of their child (relative to the kink) in 50 euro cents bins. The vertical axis plots the mean in each bin of the outcome variable for the probability to be self-employed after 5 years. The straight lines display the underlying linear relationship on each side of the kink and are estimated using local nonparametric regressions.

Table A1: Mother's outcomes 5 years after the birth of her first child (Heterogeneity by sector)

	Agriculture, industry and construction	Retail trade, hotels and restaurants	Transport, storage and communication	Financial intermediation	Real estate, renting and business activities	Public administration and education	Health and social work	Other services
Duration of maternity leave (# days)	0.120	-0.057	0.129	-0.117	0.002	0.408 ***	-0.011	-0.296
	(0.095)	(0.087)	(0.118)	(0.089)	(0.082)	(0.144)	(0.159)	(0.181)
Duration of maternity leave (log)	0.187	-0.073	0.106	-0.193	-0.019	0.474 ***	0.165	-0.288
	(0.171)	(0.133)	(0.107)	(0.156)	(0.110)	(0.161)	(0.221)	(0.221)
Second child (0/1)	0.004	0.010 **	0.001	-0.003	0.004	0.007 **	0.015 **	0.003
	(0.005)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)
Number of children	0.003	0.017 ***	0.008	-0.004	-0.001	0.018 ***	0.018	0.014
	(0.006)	(0.006)	(0.009)	(0.006)	(0.005)	(0.006)	(0.012)	(0.013)
Number of maternity leaves	0.010 *	0.018 ***	0.009	-0.007	0.003	0.021 ***	0.008	-0.004
	(0.006)	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)	(0.011)	(0.012)
Married (0/1)	0.000	0.013 **	0.000	-0.001	0.000	0.001	0.018 **	-0.007
	(0.005)	(0.005)	(0.007)	(0.005)	(0.004)	(0.004)	(0.009)	(0.010)
Employed (0/1)	0.004	0.004	-0.002	0.003	0.003	-0.005 *	-0.010 *	-0.030 ***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.009)
Salaried employee (0/1)	0.003	-0.001	-0.002	0.003	0.004	-0.007 **	-0.047 ***	-0.030 ***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.009)	(0.010)
Self-employed (0/1)	0.000	0.006 **	-0.002	0.001	-0.001	0.001	0.040 ***	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.008)	(0.004)
Quarterly earnings (euros)†	5.440	-9.374	59.842	83.336 **	72.075 *	-29.904	351.671 ***	-223.378 **
	(40.814)	(39.083)	(59.878)	(40.098)	(38.004)	(36.190)	(109.858)	(99.268)
Salaried income (euros)†	-0.823	-41.732	68.052	90.334 **	85.596 **	-34.448	-307.153 ***	-219.686 **
	(41.870)	(42.392)	(62.697)	(42.047)	(39.980)	(37.122)	(100.694)	(100.095)
Self-employed income (euros)†	6.262	32.359 **	-8.210	-6.999	-13.522	4.545	658.825 ***	-3.691
	(9.296)	(15.892)	(19.210)	(11.299)	(12.900)	(7.102)	(129.171)	(15.621)
Number of observations	5330	4351	2310	3927	6991	8352	4753	1816

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The column "treatment effect" reports estimates based on the RKD estimator of Equation (2). The coefficients show the estimated effect of a 1 euro increase in daily maternity leave benefits on the outcomes. The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table A2: Mother's outcomes 5 years after the birth of her first child (varying polynomial order)

	Linear			Quadratic			Polynomial minimizing AIC	
	First stage	Second stage	Treatment effect	First stage	Second stage	Treatment effect	First stage	Second stage
Duration of maternity leave (# days)	-0.437 ***	-0.029	0.066	-0.465 ***	0.101	-0.216		
	(0.020)	(0.019)	(0.044)	(0.080)	(0.072)	(0.164)		
	[296,066]	[292,005]		[296,069]	[292,006]		1	1
Duration of maternity leave (log)	-0.007 ***	-0.001 *	0.101 *	-0.004 ***	0.001	-0.291		
	(0.000)	(0.000)	(0.056)	(0.002)	(0.001)	(0.345)		
	[3,871]	-[2,817]		[3,869]	-[2,815]		2	2
Second child (0/1)	-0.439 ***	-0.003 ***	0.007 ***	-0.494 ***	-0.002	0.004		
	(0.021)	(0.001)	(0.002)	(0.081)	(0.003)	(0.006)		
	[290,471]	[38,852]		[290,474]	[38,856]		1	1
Number of children	-0.439 ***	-0.005 ***	0.011 ***	-0.494 ***	-0.002	0.004		
	(0.021)	(0.001)	(0.003)	(0.081)	(0.004)	(0.009)		
	[290,471]	[67,749]		[290,474]	[67,752]		1	1
Number of maternity leaves	-0.437 ***	-0.003 ***	0.008 ***	-0.465 ***	-0.003	0.006		
	(0.020)	(0.001)	(0.002)	(0.080)	(0.004)	(0.009)		
	[296,066]	[67,091]		[296,069]	[67,094]		1	1
Married (0/1)	-0.437 ***	-0.001	0.003	-0.468 ***	0.001	-0.003		
	(0.020)	(0.001)	(0.002)	(0.080)	(0.003)	(0.007)		
	[295,707]	[52,858]		[295,710]	[52,859]		1	1
Employed (0/1)	-0.437 ***	0.000	-0.001	-0.465 ***	0.000	-0.001		
	(0.020)	(0.001)	(0.001)	(0.080)	(0.002)	(0.004)		
	[296,066]	[15,382]		[296,069]	[15,385]		1	1
Salaried employee (0/1)	-0.437 ***	0.003 ***	-0.007 ***	-0.465 ***	0.001	-0.003		
	(0.020)	(0.001)	(0.001)	(0.080)	(0.002)	(0.005)		
	[296,066]	[25,926]		[296,069]	[25,929]		1	1
Self-employed (0/1)	-0.437 ***	-0.003 ***	0.006 ***	-0.465 ***	-0.001	0.003		
	(0.020)	(0.000)	(0.001)	(0.080)	(0.002)	(0.003)		
	[296,066]	-[8,272]		[296,069]	-[8,271]		1	2
Quarterly earnings (euros)†	-0.434 ***	2.451	-5.647	-0.468 ***	4.664	3.727		
	(0.020)	(7.214)	(16.637)	(0.081)	(27.890)	(78.527)		
	[293,275]	[722,882]		[293,278]	[722,886]		1	1
Salaried income (euros)†	-0.434 ***	17.931 **	-41.304 **	-0.468 ***	8.075	-23.418		
	(0.020)	(7.549)	(17.596)	(0.081)	(29.233)	(65.406)		
	[293,275]	[725,889]		[293,278]	[725,891]		1	1
Self-employed income (euros)†	-0.434 ***	-15.479 ***	35.657 ***	-0.468 ***	-3.411	27.145		
	(0.020)	(2.686)	(6.356)	(0.081)	(11.441)	(62.071)		
	[293,275]	[654,879]		[293,278]	[654,880]		1	1

*Notes: All coefficients are from separate regressions using a symmetric bandwidth of 22 euros around the kink. Contrary to the other specifications using local nonparametric methods for estimation, here I use parametric regressions in order to report conventional goodness of fit measures. In particular, I show the Aikake Information Criterion (AIC) in square brackets. The last columns show which specification (linear or quadratic) minimizes this information criterion. The columns "first stage" and "second stage" are reduced form estimates for the change in slope of the maternity leave benefit amount and the outcomes, respectively. The column "treatment effect" reports coefficients from two-stage least squares estimations, where the benefit amount is instrumented with the interaction between a dummy for being above the kink and the polynomial in the assignment variable (i.e. pre-leave daily earnings). The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table A3: Mother's outcomes 5 years after the birth of her first child (varying bandwidth)

	CCT			BW=15		BW=20		BW=25		BW=30	
	Bandwidth	Treatment effect	N	Treatment effect	N	Treatment effect	N	Treatment effect	N	Treatment effect	N
Duration of maternity leave (# days)	19	0.023	31755	-0.011	24734	0.014	33839	0.137 ***	44586	0.144 ***	57650
		(0.052)		(0.074)		(0.047)		(0.038)		(0.032)	
Duration of maternity leave (log)	19	0.081	31469	0.014	24734	0.084	33839	0.171 ***	44586	0.159 ***	57650
		(0.078)		(0.109)		(0.067)		(0.049)		(0.042)	
Second child (0/1)	23	0.005 ***	39506	0.003	24231	0.006 ***	33176	0.004 ***	43743	0.003 **	56569
		(0.002)		(0.003)		(0.002)		(0.002)		(0.001)	
Number of children	30	0.004 **	55996	0.008 *	24231	0.010 ***	33176	0.006 ***	43743	0.004 **	56569
		(0.002)		(0.004)		(0.003)		(0.002)		(0.002)	
Number of maternity leaves	30	0.006 ***	57010	0.008 *	24734	0.009 ***	33839	0.006 ***	44586	0.005 ***	57650
		(0.002)		(0.004)		(0.003)		(0.002)		(0.002)	
Married (0/1)	23	0.003	38864	0.000	24704	0.003	33792	0.002	44530	0.004 **	57577
		(0.002)		(0.004)		(0.002)		(0.002)		(0.002)	
Employed (0/1)	15	-0.003	24231	-0.003	24734	-0.001	33839	-0.001	44586	0.000	57650
		(0.002)		(0.002)		(0.001)		(0.001)		(0.001)	
Salaried employee (0/1)	14	-0.006 **	22955	-0.006 **	24734	-0.007 ***	33839	-0.006 ***	44586	-0.005 ***	57650
		(0.003)		(0.003)		(0.002)		(0.001)		(0.001)	
Self-employed (0/1)	16	0.004 ***	26907	0.004 **	24734	0.006 ***	33839	0.005 ***	44586	0.005 ***	57650
		(0.002)		(0.002)		(0.001)		(0.001)		(0.001)	
Quarterly earnings (euros)†	23	-2.177	40155	-27.236	24414	-8.919	33475	-2.695	44182	-13.907	57207
		(16.163)		(30.544)		(19.457)		(15.332)		(13.563)	
Salaried income (euros)†	22	-39.647 **	36657	-42.448	24414	-40.992 **	33475	-30.999 *	44182	-44.758 ***	57207
		(18.456)		(32.352)		(20.477)		(16.207)		(14.374)	
Self-employed income (euros)†	22	33.941 ***	37720	15.212	24414	32.073 ***	33475	28.304 ***	44182	30.851 ***	57207
		(6.430)		(12.697)		(7.428)		(5.907)		(5.018)	

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), based on the RKD estimator of Equation (2). The first Panel "CCT" reports treatment effects estimated using the data-driven bandwidth proposed by Calonico et al. (Calonico et al., 2014). I use their MSE-optimal bandwidth selector with a regularization parameter that guards against the selection of large bandwidths. The selected common bandwidth (used below and above the kink) is reported on the first column of the "CCT" panel. The other panels report treatments effects estimated from four samples using a bandwidth of 15, 20, 25 or 30 euros. All samples include mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Table A4: Mother's outcomes 5 years after the birth of her first child (controlling for pre-determined covariates)

	Cont. = Age		Cont. = Flanders		Cont. = Partner's income		Cont. = All	
	Treatment effect	N	Treatment effect	N	Treatment effect	N	Treatment effect	N
Duration of maternity leave (# days)	0.080 *	37906	0.081 *	37906	0.088 **	37367	0.087 **	37367
	(0.042)		(0.042)		(0.042)		(0.043)	
Duration of maternity leave (log)	0.126 **	37906	0.126 **	37906	0.132 **	37367	0.132 **	37367
	(0.055)		(0.055)		(0.055)		(0.056)	
Second child (0/1)	0.006 ***	37178	0.006 ***	37178	0.005 ***	36668	0.006 ***	36668
	(0.002)		(0.002)		(0.002)		(0.002)	
Number of children	0.010 ***	37178	0.010 ***	37178	0.009 ***	36668	0.010 ***	36668
	(0.002)		(0.003)		(0.003)		(0.002)	
Number of maternity leaves	0.008 ***	37906	0.008 ***	37906	0.008 ***	37367	0.008 ***	37367
	(0.002)		(0.002)		(0.002)		(0.002)	
Married (0/1)	0.003	37858	0.002	37858	0.002	37322	0.002	37322
	(0.002)		(0.002)		(0.002)		(0.002)	
Employed (0/1)	-0.001	37906	-0.001	37906	-0.001	37367	-0.001	37367
	(0.001)		(0.001)		(0.001)		(0.001)	
Salaried employee (0/1)	-0.007 ***	37906	-0.007 ***	37906	-0.007 ***	37367	-0.007 ***	37367
	(0.001)		(0.001)		(0.001)		(0.001)	
Self-employed (0/1)	0.006 ***	37906	0.006 ***	37906	0.006 ***	37367	0.006 ***	37367
	(0.001)		(0.001)		(0.001)		(0.001)	
Quarterly earnings (euros)†	-5.049	37527	-5.176	37527	-3.352	36991	-3.123	36991
	(17.393)		(17.352)		(17.479)		(17.532)	
Salaried income (euros)†	-38.228 **	37527	-38.159 **	37527	-36.393 **	36991	-36.377 **	36991
	(18.315)		(18.260)		(18.400)		(18.467)	
Self-employed income (euros)†	33.179 ***	37527	32.983 ***	37527	33.041 ***	36991	33.254 ***	36991
	(6.505)		(6.485)		(6.591)		(6.616)	

*Notes: All coefficients are from separate local polynomial nonparametric regressions of order 1 (i.e. linear), using a symmetric bandwidth of 22 euros around the kink. The treatment effects, based on the RKD estimator of Equation (2), are estimated controlling for the following pre-determined covariates: mother's age, mother's place of living (indicator for living in Flanders), partner's income, all at the moment of the birth of the first child. The last column controls for all the covariates. The sample includes mothers who had a first child between 2003 and 2010. Heteroskedasticity-robust standard errors are in parentheses. † trimming of the top 1% of the distribution. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*