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Abstract

We investigate the effect of having a child on parents' criminal behavior using rich administrative data from Brazil. Fathers' criminal activity sharply increases by up to 10% during the pregnancy period, and by up to 30% two years after birth, while mothers experience only a transitory decline in criminal activity around childbirth. The effect on fathers lasts for at least six years and can explain at least 5% of the overall male crime rate. Domestic violence within the family also increases after childbirth, reflecting both increases in actual violence and women's propensity to report. The generalized increase in fathers' crime stands in sharp contrast with previous evidence from developed countries, where childbirth is associated with significant and enduring declines in criminal behavior by both parents. Our findings can be explained by the costs of parenthood and the pervasiveness of poverty among newly formed Brazilian families. Consistent with this explanation, we provide novel evidence that access to maternity benefits largely offsets the increase in crime by fathers after childbirth.

JEL-Codes: D100, J130, K420, H550.

Keywords: crime, parenthood, maternity benefits.

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1 Introduction

Parenthood is a critical life juncture that may profoundly influence many dimensions of individual behavior, including crime. Social control theories of deviance predict that parenthood is a "turning point" in criminal trajectories, lowering criminal engagement due to increased social bonds and pressure for social conformity (see, e.g., Sampson and Laub, 1990, 1992). This prediction is in line with evidence from earlier empirical studies based on survey data as well as with more recent papers leveraging administrative data and state of the art causal inference methods (Monsbakken et al., 2013; Massenkoff and Rose, 2022; Eichmeyer and Kent, 2022). For instance, Massenkoff and Rose (2022) show that arrest rates decrease by up to 20% and 50% for fathers and mothers, respectively, in the three years after childbirth.

However, this body of evidence remains entirely confined to the United States and a few other developed countries. In the context of lower income countries, where more families live in poverty and there is less social protection, childbirth may have very different effects on parents' involvement in crime. Specifically, childbirth may be associated with significant financial constraints due to the costs of parenthood, which in turn may lead to higher criminal engagement by parents. However, no systematic evidence on such effects is available for low- and middle-income countries, which are also characterized by higher crime rates, fertility, and prevalence of undesired pregnancies than developed economies.

We investigate the effects of childbirth on parents' criminal behavior in Brazil – a large middle-income country characterized by widespread poverty and high crime rates. We document effects of childbirth that differ greatly from previous research in rich countries. In particular, the crime rate of Brazilian fathers sharply increases with childbirth, while the crime rate of mothers exhibits only a temporary decline around birth. Several pieces of evidence support the idea that the increase in fathers' crime is due to the financial constraints faced by new parents. Moreover, a simple estimation exercise shows that the effect on fathers can explain at least 5% of the overall male crime rate. Given the relevance of this result, the second part of our paper investigates the effectiveness of public policies in mitigating such responses. Using a regression discontinuity (RD) design, we provide novel evidence that access to income transfers by mothers strongly reduces the probability that fathers commit crime after childbirth.

Our analysis leverages unique individual-level data tracking childbirth, criminal records, family composition, and rich demographics for the entire country in the 2009-2018 period.[1] We first use these data in a stacked difference-in-difference (DID) design to compare criminal prosecution rates for first-time parents around the childbirth period with a control group who gave birth to their first child a few years later. To enhance comparability, we exactly match treatment and control parents on different characteristics, including birth year, gender, child gender, and municipality of residence.

Relative to the control group, fathers' criminal prosecution rates sharply increase by up to 10% during the pregnancy period, and by up to 30% in the second year after childbirth. Our main estimates indicate an average 18% increase in fathers' criminal prosecution in the two years after birth, while additional results indicate that these effects persist for at least six years after birth. To put these in perspective, Britto et al. (2022) show that job loss increases crime by 23% in a four-year period after layoff using similar data. Regarding mothers, we estimate a 60% reduction in criminal activity around childbirth, but this effect is transitory and disappears completely in less than a year.

We provide several pieces of evidence that support a causal interpretation of our results, focusing on the impacts on fathers. First, the fact that the effects sharply emerge in the first quarter after conception and that we find no evidence of pre-trends deviation support this interpretation. Second, although having a child is a choice, our analysis explores some randomness in the timing of conception by comparing similar parents who have their first child a few years apart.[2] We further show that our effects remain similar when building the control group based on fathers who will have a child either one, two, and three years after relative to the treatment group. Shorter time differences increase the comparability between the treatment and control groups and the plausibility of our common-trend identification assumption. Finally, we show that Brazilian fathers are less likely to be hospitalized due to accidents and assaults, which we interpret as a measure of risky behavior. This suggests that our findings cannot be

[1]Our data allow us to link 94% of children to their father, which is a high figure relative to earlier studies on the US – e.g., about 84% in Almond and Rossin-Slater (2013) using data from Michigan and Eichmeyer and Kent (2022) for Allegheny County in Pennsylvania –, and similar to Massenkoff and Rose (2022) using data from Washington State.

[2]For example, randomness in conception timing might be driven by biological factors and to uncertainty in the ability to find a partner at a given moment.

explained by sharp increases in risk preferences (e.g., due to external shocks) driving a joint decision to engage in crime and having a kid (or engaging in unprotected sex).

The strong increase in fathers' criminal behavior is largely concentrated on economic crimes such as robberies, thefts and drug trafficking, and violent crimes such as homicides and assaults, which may also be driven by economic motives (e.g., homicides driven by drug trafficking disputes or assaults committed during robberies). Instead, we find a negative effect on other crimes with no clear economic motive, such as traffic offenses, small drug possession, failure to obey, and damage to private property.

We provide additional evidence that points to the importance of economic motives and the financial constraints faced by parents after childbirth. In line with this explanation, the effect is stronger for fathers that either have no formal job or work in low-paid jobs before child conception.[3] Similarly, we find no effect on fathers' crime when mothers have a formal job, which means (among other things) that they benefit from job protection for up to five months after birth and from four months of maternity benefits. Furthermore, the increase in crime is three times stronger for younger fathers who are more likely to have unwanted pregnancies and difficulties in providing for their children, as reported in survey data. Younger parents are also more likely to move out of their parents' house to form a new household after childbirth, which imposes additional financial costs.

Beyond general crime, we separately investigate how parenthood affects domestic violence.[4] We document a remarkable increase in the probability that men are criminally prosecuted for domestic violence – a 15% and 215% increases during pregnancy and the two-year period following birth, respectively. Using third-party reports on domestic violence filled by Brazilian health units, we show that such effect is both driven by an increase in women's propensity to report and by actual increases in

[3]In line with evidence for developing and developed countries (e.g., see Kleven et al., 2023), we do not find economically significant on fathers' employment. The fact that some fathers turn to crime in response to costs of parenthood rather than formal jobs may signal that the latter is a constrained margin of adjustment – also in line with the fact that our effects are driven by economic vulnerable men who have lower access to jobs.

[4]Hence, domestic violence is not part of our main crime measure in the main analysis. We tackle these offenses separately because they are prone to reporting issues. For instance, an increase in domestic violence prosecution by fathers could be either due to increases in violence levels or mothers being more prone to report domestic offenses after childbirth. Another key reason for analyzing these in separation is that the underlying mechanisms may significantly differ from those driving variation in general crime.

domestic violence levels. Similarly to the effects on general crime, the effects on domestic violence are driven by younger men and more economically vulnerable families. The impacts on violence within the family are consistent with two mechanisms. First, domestic violence may increase because of the economic unrest due to the costs of parenthood, which may lead to stress and violence within the household. Second, the higher time spent together by partners following childbirth – e.g., due to cohabitation – may also play a role in explaining our findings.[5]

Overall, the effects on fathers' crime are sizable and persistent, and they can explain at least 5% of the overall male crime rate. Thus, it is relevant from a public policy perspective to understand whether social insurance policies targeted at parents can mitigate these effects. To answer this question, we investigate the impacts of maternity benefits transfers on fathers' criminal behavior. In Brazil, mothers employed in the formal economy receive four months of maternity benefits that fully replace their previous salary. Eligibility to these benefits extend for a "grace" period lasting roughly one year after job separation, implying that displaced mothers having a child within this period are eligible for maternity benefits.[6] This assignment rule generates an ideal Regression Discontinuity (RD) design that allows us to compare crime rates for fathers of children born to mothers that were barely eligible and ineligible for these benefits – due to the distance between the end of the grace period and childbirth. Balance tests confirm that these two groups are on average identical in all dimensions but eligibility for maternity benefits.

Access to maternity benefits by mothers reduces fathers' criminal prosecution rates by almost a third. This strong effect is robust to different specifications of the polynomial regression in the running variable and different bandwidths (including the bandwidth selected according to the criterion of Calonico et al., 2014), and to permutation tests comparing our main estimates with the distribution of estimates at placebo cutoffs. These results bolster our interpretation that the effect of parenthood on fathers' criminal activity is explained by economic needs and stringent financial constraints following childbirth. These findings also have immediate policy implications: transfers targeted at poor families in the first months after childbirth

[5] Both mechanisms are consistent with earlier evidence from Brazil showing that job loss leads to higher domestic violence both due to the economic struggle and increased time spent by partners after layoff (Bhalotra et al., 2021), and with evidence explaining the surge in domestic violence during the Covid-19 period (Arenas-Arroyo et al., 2021; Bhalotra et al., 2023).

[6] We explain eligibility rules in detail in Section 5.

may greatly reduce crime risks.

This paper contributes to the literature on the effects of parenthood on crime. Earlier studies in sociology and criminology mainly studied this topic through interviews or small-N quantitative analyses (see, e.g., Sampson and Laub, 1992; Edin and Kefalas, 2011; Edin and Nelson, 2013; Mitchell et al., 2018).[7] More recently, using administrative data from the State of Washington and a similar empirical strategy to ours, Massenkoff and Rose (2022) document strong reductions in crime by first-time fathers and mothers; Eichmeyer and Kent (2022) show similar patterns for low-income mothers using data from Allegheny County, while focusing on a broader set of outcomes. Dustmann et al. (2021) show that having a boy rather than a girl reduces criminal behavior by fathers in Denmark, but they do not estimate the impact of childbirth per se, only its differential impact depending on the gender of the child. This differential effect does not emerge in our context, as our main findings hold regardless of child gender.

This previous research has overwhelmingly focused on a few developed countries. To our knowledge, our paper provides the first large-scale analysis of the effects of childbirth on criminal activity in low and middle-income countries. We show that, in this context, parenthood leads to sizable increases in crime by fathers – contrary to the "turning points" documented in the US and in other developed economies. Compared to these other countries, Brazil is characterized by widespread poverty, with many families being severely liquidity constrained, and a less developed social safety net: we show, indeed, that these factors explain the observed increase in fathers' crime after childbirth.

Importantly, our work also provides novel evidence on the impacts of welfare policies targeted at parents on crime, showing that access to maternity benefits can mitigate the increase in fathers' crime. Since crime generates relevant negative externalities on society, these results might play a role in the design and welfare evaluation of similar transfer policies (e.g., see Jørgensen and Søgaard, 2021; Zurla, 2022). More broadly, they contribute to a literature studying the effects of social security policies on crime.[8]

[7] See Massenkoff and Rose (2022) for a complete description of papers' methods, sample size and results.

[8] For example, Deshpande and Mueller-Smith (2022) shows that in the US, youths removed from Supplemental Security Income have a 20% increase in their criminal charges, while Carr and Packham (2019) shows that the timing of SNAP benefits payments significantly affects crime. In Brazil, Britto et al. (2022) shows that unemployment benefits decrease criminal activity by recently displaced

Finally, our work contributes to the rapidly growing literature on the determinants of domestic violence (e.g., see Dugan et al., 2003; Card and Dahl, 2011; Aizer, 2010; Perova et al., 2021). We estimate strong increases in violence against women around childbirth. Massenkoff and Rose (2022) also document higher arrest rates for domestic violence in the US, but our data allow us, in addition, to distinguish between increases in actual violence from changes in reporting rates. Using criminal prosecution data along with third party reports from the health system, we find that the surge in domestic violence is driven by both an increase in reporting and by increases in violence levels against women. Therefore, policies aimed at reducing domestic violence in families with very young children may be desirable.

The paper proceeds as follows. Section 2 provides a description of the Brazilian context, while Section 3 describes the data. Section 4 describes the impacts of parenthood on crime and domestic violence. Section 5 investigates the impacts of maternity benefits, followed by Section 6 which concludes.

2 Institutional background

Brazil is a large middle-income country with 203 million individuals, ranking 5$^{\text{th}}$ and 7$^{\text{th}}$ by area and population size worldwide. Despite progress in the early 2000s, poverty remains a prevalent issue. In 2009, when we start our analysis, 27% of the population lived below the poverty line used by the World Bank for middle-income countries. Furthermore, Brazil remains one of the most unequal and violent countries in the world. In 2009, the Gini coefficient stood at 53.7, while the homicide rate reached 27 incidents per 100,000 people. These figures placed Brazil fourth in terms of inequality and thirteenth in violence on a global scale.

2.1 Social Programs and Support for Children

Although government expenditure is high relative to GDP (about 43%), social spending in Brazil is unevenly distributed. The main poverty aid program is *Bolsa Família*, a large conditional cash transfer covering about one fourth of the Brazilian population. The program is targeted at very low-income families with *per capita* monthly income below 140 Brazilian Reais (BRL), roughly equivalent to 20% of the minimum wage. The average monthly transfer per family is 150 BRL and increases by 32 BRL for each additional child in the family.[9] Overall, the program's total expenditure

workers.

[9]Our program description is based on 2014, around the center of our analysis period (2009-2018).

remains below .5% of GDP.[10]

By contrast, spending on social security amounts to 8.5% of GDP but has been largely tied to formal employment participation. It supports programs such as unemployment and disability insurance, and maternity benefits. However, almost one in two workers is employed in the informal sector, which provides little access to social security. Another important feature of the labor market is the high job turnover rate. Roughly 45 and 80% of formal jobs last less than one and three years, respectively, and workers constantly turnover across the formal and informal sector (Ulyssea, 2018). As a result, they can count on much weaker social protection during periods of informal employment.

Similar to other social security programs, maternity benefits mainly cover women who are formally employed, offering 120 days of paid leave.[11] However, only 35% of women in ages 18-40 are in formal employment and thus eligible for this benefit. The remaining 65% can only count on the modest additional monthly support of 35 BRL from "Bolsa Família" during the leave period following childbirth.

2.2 Unwanted Pregnancies and Providing for Children

Unwanted pregnancies are prevalent in economically disadvantaged contexts, particularly in Brazil where abortion is a criminal offence except under very severe circumstances.[12] We document the prevalence of this phenomenon using data from the *Pesquisa Nacional Sobre Demografia e Saúde* (PNDS), a representative survey of women aged 15 to 49 providing detailed information about prenancy histories and childcare experiences.[13] Unwanted pregnancies represent almost half of the childbirths from young mothers aged 22 or less, and an even larger share among first-time young mothers (56.5%); see Table 1. Even for mothers older than 22, unwanted pregnancies represent one fourth of any childbirth and 40% of first-time childbirths. The survey also reveals that economic struggle is common among mothers. More than

[10] The country also offers free universal access to health care, for which the total expenditure represents 9.5% of gdp.

[11] An extended coverage is offered for women giving birth within about one year after leaving a formal job. Despite being out of a job, these mothers are entitled to receive maternity benefits. In Section 5, we will leverage variation in access to this extension to study the effects of these transfers on crime.

[12] For instance, only 1,613 legal abortions were legally authorized in 2014.

[13] PNDS is the Brazilian arm of USAID's *Demographic and Health Survey*, and it was conducted by the Brazilian Institute of Geography and Statistics (IBGE). Our data refer to year 2006, which was the last wave of the survey.

a third of all mothers struggled to earn money and more than a fourth experienced food shortage. Not surprisingly, these measures of financial hardship are even more prevalent among younger mothers and those experiencing unwanted childbirths.

Table 1: PNDS - Survey Data on Mothers and Pregnant Women

	All Mothers					Pregnant Women (First Child)				
	All Mothers	Age at Birth		Wanted Child		All Pregnant	Age		Wanted Pregnancy	
		≤ 22	> 22	No	Yes		≤ 22	> 22	No	Yes
Wanted Child at that Moment	0.600	0.510	0.747			0.530	0.435	0.597		
Had Food Shortage	0.251	0.281	0.185	0.252	0.203	0.224	0.298	0.172	0.282	0.173
Struggled to Earn Money	0.349	0.391	0.255	0.354	0.291	0.309	0.344	0.285	0.369	0.256
Struggled to Find Food	0.258	0.291	0.184	0.272	0.205	0.170	0.176	0.167	0.215	0.131
Reported Hunger Last Month	0.0973	0.112	0.0644	0.0892	0.0625	0.0978	0.130	0.0753	0.107	0.0893
Observations	10374	7161	3213	930	1393	317	131	186	149	168

Notes: This table provides summary statistics from the *Pesquisa Nacional de Demografia e Saúde*. The question *"Did you want the child at that moment?"* (first item of the table) is asked only to mothers that gave birth to their first child in the five years before the survey was collected. The other questions refer to the month of the interview.

3 Data

In this section, we describe the three main data sources used in this paper. The first source is the Brazilian welfare registry, *Cadastro Único* (Cadunico), for the period 2011-2020. This registry is maintained for the purpose of administering Federal social programs, including *Bolsa Família* cash transfers. It contains rich individual-level demographic information such as date of birth, place of residence and education, a unique person code, the individual and her parents' full names, along with the composition of the household. The registry covers 70% of individuals born in the country in our main analysis period.[14] Although Cadunico is mainly targeted at low and middle-income families, it also covers some relatively high-income individuals, which will turn useful for conducting heterogeneity analyses.

Our second main data source is the universe of criminal cases filed in first-degree courts in Brazil for the period 2009-2020. These data are based on case-level information that is publicly available on tribunals' websites and courts' daily diaries, recorded and supplied by a leading private company providing information services

[14] Coverage is computed by comparing the number of children in Cadunico born in the period 2012-2014 to the number of births recorded by the *Sistema de Informação sobre Nascidos Vivos* (SINASC) during the same period.

to law firms in Brazil. For each case, we observe its starting date, the court location, and the type of crime. Furthermore, these records identify the defendant(s) and the plaintiff(s) by their full names.[15]

Our third main data source is the *Relaçao Anual de Informaçoes Sociais* (RAIS), a linked employer-employee registry covering the universe of formal jobs in Brazil supplied by the Brazilian Ministry of Labor. It provides rich individual-level information such as the worker's date of birth, education, occupation, and earnings, and the contract's start and termination date. Workers are identified by the their full names and a unique person code.

3.1 Combining Family, Crime and Employment Records

We start by identifying individuals' parents in Cadunico with their unique person codes (*CPF*). For each individual in Cadunico, we link the parents' person codes based on the parents' (full) names.[16] We restrict attention to parents who can be uniquely identified by their names – i.e., who have no homonyms in the country – and associate their person code via exact matching. To identify which names are unique, we have built a person registry comprising all individuals ever observed in the employment data in the period 2002-19 and in Cadunico 2011-2020 (both datasets contain individuals' person codes and names). The resulting registry covers 96% of the adult population in the period of our analysis. We repeat the same procedure to identify individuals in the criminal court data with their unique person codes. Following this procedure, we are able to link children in Cadunico to their parents' criminal behavior around birth. We also add parents' labor market outcomes to these data using individuals' person codes available in the employment data.

Our linkage procedure implies that our main analyses are based on parents' with unique names. Thanks to the fact that Brazilian have multiple surnames, these individuals represents about 50% of the population. More importantly, uniquely named individuals are fairly similar to the general population along several characteristics such as income, education and race (Britto et al., 2022). In the robustness Section 4.3, we will show that our main findings are robust to an alternative linkage procedure

[15] These data were first used for research purposes in Britto et al. (2022).

[16] Although individual person codes are available in Cadunico, information on family links is not. An alternative way for identifying parents would be linking parents' person codes using information on household composition. However, this approach would make our analysis conditional on (endogenous) cohabitation status. Importantly, information on names is highly accurate in all datasets used.

which increases the population coverage of our data to 70%.

4 Criminal Behavior of First-Time Parents

In this section, we explain our empirical strategy and identification assumptions for studying the effect of childbirth on crime, and present our main results along with several robustness exercises.

4.1 Empirical Strategy

To recover the effect of having the first child on the parents' criminal behavior, we use a stacked difference in differences strategy that compares first-time parents who had children a few years apart.

We define a treatment sample comprising parents who had their first child between 2011 and 2013. Then, for each treated parent, we assign one control parent who had her/his first child between 2016 and 2018. In addition, we focus on treat-control pairs with a minimum distance of 11 quarters in birth timing, so that we can estimate effects for the pregnancy period (3 quarters) and two years after birth (8 quarters). Treated and control parents are exactly matched on year of birth, gender, gender of the child, municipality of residence, and two dummies indicating whether they have ever held a formal job and whether they have been registered in Cadunico. When multiple controls are matched to the same treated unit, we randomly pick one.[17] This procedure successful finds a match for 78% of our initial sample, yielding 1.48 million treated parents – 699 thousand mothers, and 779 thousand fathers –, each of them paired with a control parent.

Each treatment-control pair defines a single difference in differences comparison. Time is defined by quarters relative to childbirth, and control units are assigned a placebo childbirth date equal to their treated pair. We then stack each of these single treated-control pairs and build a balanced panel tracking parent outcomes for eight quarters before and after childbirth. As a result, our estimator is defined by the simple average over single difference-in-differences comparisons for each treatment-control pair, ensuring that no unit receives a negative weight (as confirmed by the diagnostic proposed by De Chaisemartin and D'Haultfœuille, 2020). Importantly, the control group is always composed of not-yet-treated units in our analysis period,

[17] In turn, one control unit may appear multiple times in the data as a control for different treated units.

ensuring that treated units are not used to absorb time effects.[18]

In practice, we estimate the following dynamic difference in differences equation:

$$Y_{it} = \sum_{t=-8, t\neq -4}^{7} \beta_t \cdot Treat_i \cdot Time_t + \sum_{t=-8, t\neq -4}^{7} \lambda_t \cdot Time_t + \gamma_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is a dummy indicating that the parent has been criminally prosecuted in a given period, $Treat_i$ is a dummy indicating the treatment group, $Time_t$ are time dummies, and γ_i are individual fixed effects.[19] The data is organized in quarters, with $t = 0$ covering the calendar month of childbirth and the two subsequent months.[20] Therefore, $t = -4$ defines the period immediately before child conception in our analysis (ten to twelve months before childbirth), and the coefficients $\{\beta_{-3}, \beta_{-2}, ..., \beta_7\}$ estimate the dynamic treatment effects starting from the child conception period. The main identifying assumption required to attach a causal interpretation to such coefficients is that treated and control units would have followed parallel trends in the absence of the treatment. This assumption seems plausible given that we are comparing individuals who had their first child only a few years apart and, in addition, we match them on several characteristics. Most importantly, the estimated coefficients $\{\beta_{-8}, \beta_{-7}, ..., \beta_{-5}\}$ in equation (1) will capture deviations from the parallel trends between the treated and control group during the pre-treatment period (i.e., before child conception). In the robustness section, we will discuss and address additional concerns related to our identification assumption.

To summarize the effects during pregnancy and after childbirth, we also estimate the following model:

$$Y_{it} = \beta_1 \cdot Treat_i \cdot \text{Pregnancy}_{it} + \beta_2 \cdot Treat_i \cdot \text{Post Childbirth}_{it} + \gamma_i + Time_t + \varepsilon_{it} \tag{2}$$

where Pregnancy_{it} is an indicator variable that takes value one during the pregnancy period (i.e., $t = \{-3, -2, -1\}$) while $\text{Post Childbirth}_{it}$ takes value one after childbirth

[18]This setting is in line with the recent methodological work by Dube et al. (2023) and addresses the concerns raised by the recent literature on difference in differences estimation in staggered settings (Athey and Imbens, 2018; De Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Imai and Kim, 2019; Goodman-Bacon, 2021a; Sun and Abraham, 2021a). Indeed, we will show that our results remain remarkably similar when using an alternative estimator proposed by De Chaisemartin and D'Haultfœuille (2020).

[19]When a control unit serve as a control for multiple treated units, we assign the control a different fixed-effect identifier in each of these cases.

[20]For example, $t = 0$ for someone having a child in May 2014 will cover the period May-July 2014.

(i.e., $t = \{0, 1, 2, 3, 4, 5, 6, 7\}$). Therefore, coefficients β_1 and β_2 estimate the effect on crime during pregnancy and after childbirth, respectively.

In Appendix Table A1, we provide summary statistics for parents in our final sample, including their criminal behavior in the pre-conception period. The same table shows that the standardized difference between the two groups remains below the threshold of 0.20, indicating that any differences in the underlying distributions are small (Cohen, 2013).

4.2 Main Results

We estimate equations (1) and (2) to analyze the effects of having the first child on crime for fathers and mothers. Since crime outcomes tend to be underreported, we follow the crime literature and focus on relative effects – specifically, we normalize all coefficients by the average prosecution rate for the treatment group in the baseline period ($t = -4$).

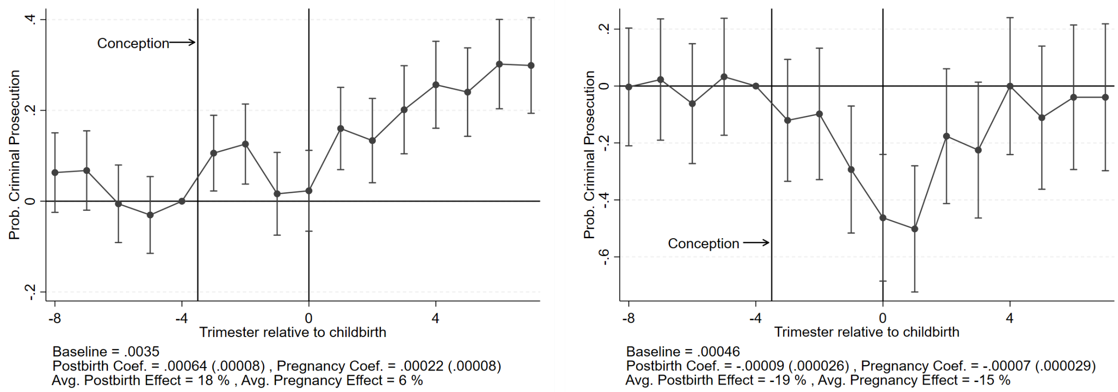
The dynamic treatment effects for fathers, based on equation (1), are presented in Figure 1a along with 95% confidence intervals; standard errors are clustered at the individual level. The graph conveys three main results. First, we find no trend differences in prosecution rates between the treatment and control groups before child conception, which supports the common-trend assumption. Second, criminal prosecution rates sharply increase by over 10% relative to the control group in the first two quarters of the pregnancy period, and decrease around birth. Third, the effect is increasing in the post childbirth period, reaching +30% two years after birth. On average, prosecution rates increases by 6% during the pregnancy period, and by 18% in the two years after birth.

Figure 1b shows the effect of childbirth on crime for first-time mothers, who display baseline prosecution rates that are an order of magnitude smaller relative to fathers. As for fathers, we find no significant evidence of differential trends before conception, supporting the common-trend assumption. On the other hand, the estimated effects after conception and childbirth are remarkably different relative to fathers. The probability that mothers commit crime sharply declines during pregnancy and the first quarters after childbirth, to return to pre-pregnancy levels one year after childbirth. On average, first-time mothers decrease their criminal behavior by 15% during pregnancy, and by 19% when pooling all periods after childbirth. These declines in crime could reflect physical and time constraints related to preg-

Figure 1: Effect of childbirth on parents' crime

(a) Fathers

(b) Mothers



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that fathers (left graph) and mothers (right graph) are prosecuted for a crime. The treatment group comprises parents who had their first child in the period 2011-2013, who are matched to control parents who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of each graph.

nancy and child care. After childbirth, mothers gradually return to their initial level of criminal activity, unlike the results of Massenkoff and Rose (2022) and Eichmeyer and Kent (2022) that document permanent reductions in criminal activity in the US.

4.3 Robustness

Endogeneity concerns. Our difference in differences design relies on the assumption that treated parents would have followed similar trends as control parents in the absence of childbirth. To make the two groups as similar as possible, we compare parents who had their first child just a few years apart and match treated and control units on an array of characteristics. Although our results show no pre-trends deviation before child conception, a key identification concern is the endogenous timing of child conception. Specifically, both crime and child conception could be outcomes driven by a common process.

We provide several pieces of evidence that support the causal interpretation of our results. First, although having a child is a choice, there is some randomness in the timing of conception, due both to biological factors and to uncertainty in the ability to find a partner in a given moment. This implies that child conception should take some time, at least for some individuals. If our findings were driven by a joint decision to have a child and engage in crime, we would likely observe an increase in criminal behavior before child conception, contrary to the patterns displayed in Figure 1a. Consistently with the interpretation that child conception causes higher crime by fathers, the effects sharply emerge in the quarters following conception, while no anticipation effects are observed prior to conception.

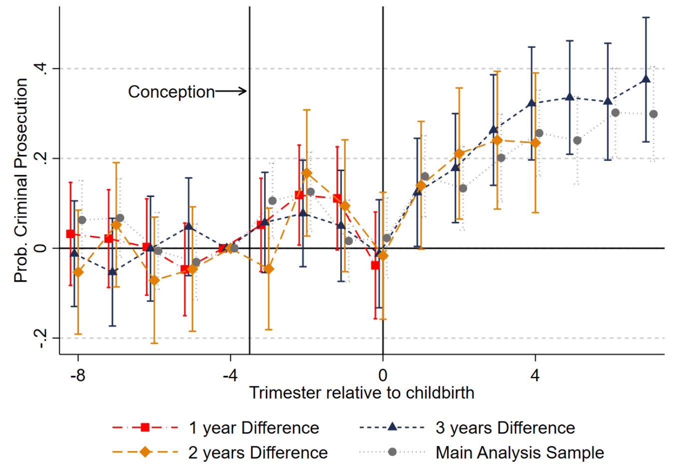
We provide an additional test leveraging the partial randomness in the timing of childbirth. We replicate our main strategy while matching our treatment group to control parents who had their first child one, two, and three years apart. Using smaller differences makes the treatment and control groups more comparable. It also makes it more plausible that conception timing is as good as random across the two groups. In line with this idea, survey evidence indicates that about 50% of first-time mothers do not have their first child in the moment they want to (see Section 2.2).[21] The drawback of restricting the difference in childbirth dates between treated and control groups is that we can only estimate impacts over shorter periods of time, because the analysis can only last up to the point when control parents conceive their child. Figure 2 shows that using parents who had a child one, two, or three years after as controls lead to very similar patterns relative to our baseline analysis, strongly supporting our main results.

Can sharp change in risk preferences explain the results? We next address the concern that a joint increase in crime and parenthood could reflect sharp increases in preferences for risk-taking, which in turn could be driven by third factors (e.g., an adverse life event). To this purpose, we examine how hospitalizations due to accidents and assaults, which we interpret as a proxy for risky behavior, change around childbirth.[22] We leverage hospitalization data provided by the Ministry of Health (SIH/Datasus) tracking all hospitalization covered by the universal public health system in Brazil. Since individual identifiers are not provided, we consider that parents in our data have been hospitalized when we observe hospital entries by someone living in the same postal code, date of birth, and gender – all these variables can be observed both in our main sample and the hospitalization data. Within the

[21]This strategy is similar to the one used by Fadlon and Nielsen (2021) to study the impact of health shocks.

[22]Specifically, we consider hospitalizations for externals causes within ICD-10 categories S,V,T,X,Y, mainly covering accidents and interpersonal violence (within these categories we only exclude a small share of events related to medical care complications, poisoning and legal interventions).

Figure 2: Effect of childbirth on father's crime, different control groups



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for a crime. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child one, two, and three years later, and, as in our main analysis, at least 11 quarters later during the period 2016-2018. The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

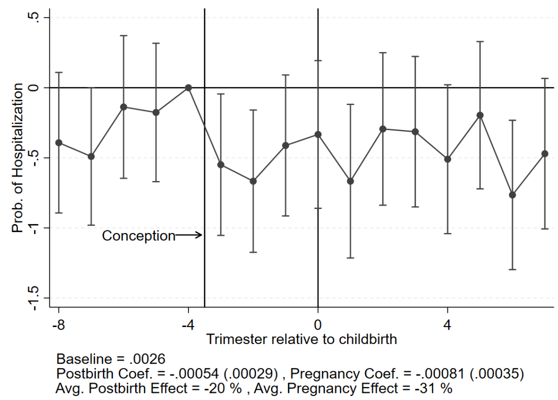
population covered by Cadunico, representing two-thirds of the Brazilian population, 99% of individuals can be uniquely identified by these characteristics.[23]

Figure 3 shows a sharp and persistent reduction in hospitalizations for fathers after childbirth, decreasing by 31% and 20% during the pregnancy and post-birth period, respectively. This finding runs contrary to the hypothesis that higher crime around childbirth reflects positive shifts in attitudes towards risk. To some extent, these results also reconcile our findings with the evidence of strong reductions in crime around childbirth in the US (e.g., see Eichmeyer and Kent, 2022; Massenkoff and Rose, 2022). One interpretation for the latter result is that parenthood represents a turning point after which parents become more risk averse and less prone to deviant behavior. In line with this interpretation, fathers in Brazil also engage in less risky behavior following child conception; at the same time, they are also more likely to be financially constrained compared to fathers in the US and other developed countries. We will present additional evidence consistent with this idea in Section 4.4.

Additional robustness. Finally, in Appendix A.2 we report additional robustness

[23]The fact that postal codes usually refer to a single street in large Brazilian cities significantly increases the precision of this imperfect matching procedure.

Figure 3: Effect of childbirth on father's probability of hospitalization due to accidents or assaults



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is hospitalized due to accidents or assaults. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline hospitalization rate of the treatment group during the last quarter before conception ($t = -4$). The baseline hospitalization rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

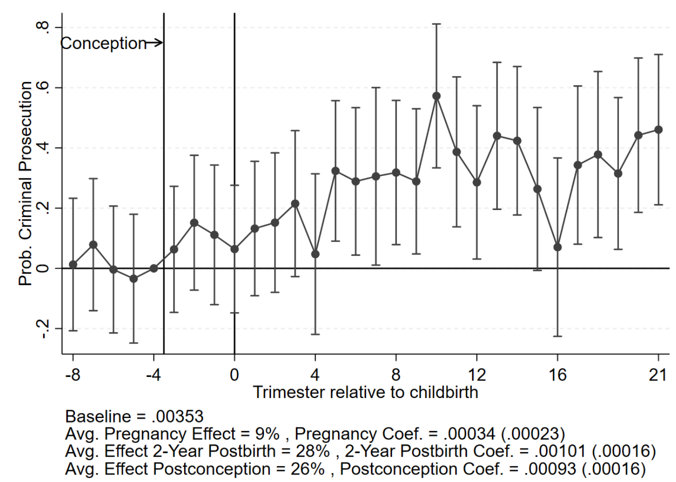
exercises. First, we address sample selection issues related to the fact that our main analysis is based on parents with unique names in the country. Second, we show that negative weight issues are not present in our DID design and that the results are robust to the estimator proposed in De Chaisemartin and d'Haultfoeuille (2020).

4.3.A Effects Over Longer Periods and its Relevance for the Overall Crime Rate

We proceed by estimating the impacts of childbirth on fathers' crime over a longer time horizon and by providing an estimate for the relevance of these findings for the overall crime rate. We replicate our main analysis using control fathers who have their first child with a six-year difference relative to the control group, allowing us to estimate impacts for up to 24 quarters after child conception, as presented in Figure 4. The effects during pregnancy and the two-year period after birth are fairly similar to our main analysis, indicating a +9% and +28% increase in criminal prosecution by fathers. More importantly, this analysis shows that the effect of childbirth on fathers' crime remains positive and sizable for up to six years after the conception period. On average, criminal prosecution rates increase by 26% in the six-year period after child conception.

We perform a simple exercise for estimating the relevance of these results for the overall male crime rate. We consider the Brazilian adult male population and the probability that they are criminally prosecution in 2012, the center of our treatment period. Then, we calculate the counterfactual crime probability for men who conceived their first child in a six-year window before 2012, considering that their prosecution rate is 26% higher due to the birth of their first child.[24] Based on this calculation, we find that the overall male criminal prosecution rate would be 5% lower absent the birth of their first child.[25] Hence, this calculation suggests that our main finding might explain a non-negligible portion of the overall crime rate in the economy. The key reasons behind this result are that most men in the population have children at some point in their lives and that the effect of (first) childbirth on fathers is sizable and persistent.

Figure 4: Effect of childbirth on father's crime up to six years after child conception



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for a crime. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child six years later during the period 2017-2020. The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average and relative effects during the Pregnancy, Two-year Postbirth and the entire Postconception periods are reported at the bottom of the graph.

[24] We use the person registry indicated in Section 3.1 to identify the male adult population in 2012. To identify fathers conceiving their first child, we use Cadunico data as in our main analysis.

[25] This is likely a lower bound estimate for two reasons. First, the effects may extend beyond the six-year period used in the analysis. Second, our data covers only 70% of all childbirths, hence our calculation underestimate the share of treated men in the population.

4.4 Explaining fathers' increase in criminal behavior around childbirth

We next provide several pieces of evidence that contribute to explain the increase in crime observed for fathers, and we also discuss the temporary decrease in crime observed for mothers.

4.4.A Types of Crime

We distinguish the impacts of childbirth on three different categories of crime: economically motivated crimes (drug trafficking, thefts, robberies, trade of stolen goods, fraud, corruption, tax evasion, and extortion); violent crimes (assaults, homicides, kidnappings, and threats); and other non-violent crimes without a clear economic motivation (traffic offenses, slandering, illegal gun possession, small drug possession, failure to obey, damages to private property, environmental crime, conspiracy, lynching, racial offenses, and prejudice).[26]

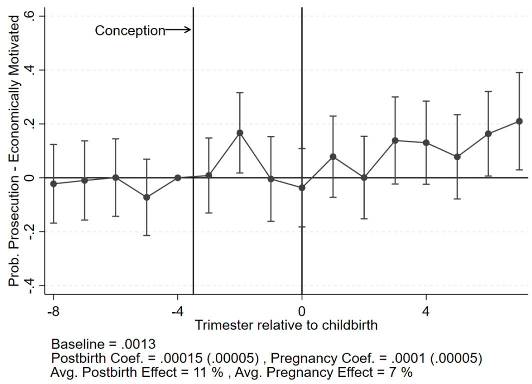
In Figure 5a, we show that economically motivated crimes by fathers increase during the pregnancy period, and even more so after childbirth. Similar patterns emerge in Figure 5b for violent crimes, which may often be committed for economic motives – for instance, assaults committed during robberies or related to drug trafficking. The link between economic and violent crimes may be particularly strong in the Brazilian context, where criminal activities often involve firearms and take place in areas without state presence. On average, economic and violent crimes increase by 11% and 22% after childbirth. Instead, Figure 5c shows that no clear changes emerge for other crimes with no clear economic motivation. Interestingly, the average effect on these crimes is negative and statistically significant in the two years after childbirth, decreasing by 11%, which may reflect a reduction in risk taking following child conception (in line with our previous result indicating lower hospitalization after childbirth). Overall, these results are consistent with the hypothesis that increase in fathers' crime following childbirth are mainly explained by economic needs.

For first-time mothers, we estimate a temporary decrease in all types of crimes around the period of childbirth which vanishes in about one year, in line with the overall effects on mothers' crime – see Figure A3 in the Appendix.

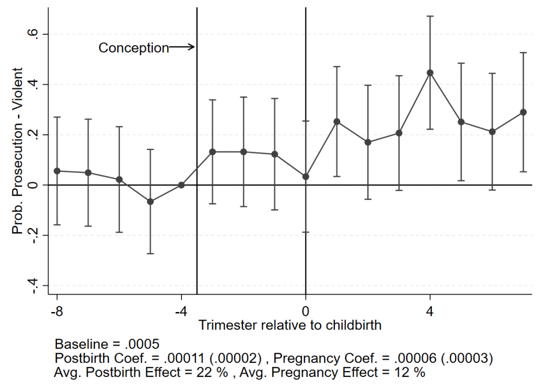
[26] These definitions follow Britto et al. (2022). None of these categories include domestic violence, which we discuss separately in Section 4.5.

Figure 5: Effects of childbirth on father's crime, by type of offense

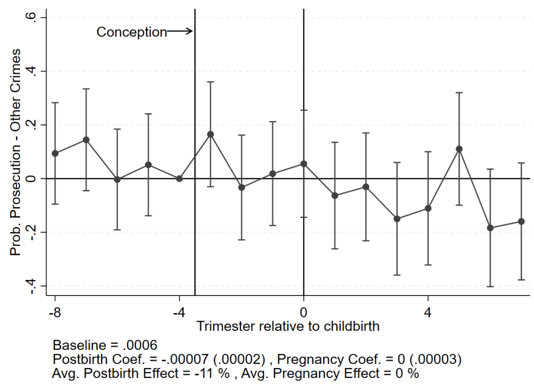
(a) Economically Motivated



(b) Violent Crimes



(c) Other Crimes without Clear Economic



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for different types of crime, indicated on top of each column. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of each graph.

4.4.B Heterogeneity Analysis

Employment. In Table 2 we study how the effects on crime for first-time fathers vary with parental income prior to conception. We split our main sample into four groups based on fathers' formal income during the five quarters before conception. The first group comprises fathers' without formal employment in the entire period, while fathers with positive income are allocated into three groups. The effect of childbirth on fathers' crime are the strongest for fathers with zero formal income before child conception and, more generally, it decreases with income.[27] We repeat the same exercise splitting the sample based on the mother's employment status prior to conception.[28] The results show that the increase in fathers' criminal activity is entirely driven by families where the mother is not formally employed in the pre-conception period – see Appendix Figure A4.

Table 2: Effects of childbirth on father's crime, by income level before conception

	(1)	(2)	(3)	(4)
	Prob. of Criminal Prosecution x 100			
		Formal Labor Income Percentiles		
	No Formal Income	[0,33)	[33,66)	[66,100]
Treated x Post-Birth	0.092***	0.081***	0.071***	0.033***
	(0.01)	(0.01)	(0.01)	(0.01)
Treated x Pregnancy	0.051***	0.013	0.021	0.026**
	(0.01)	(0.02)	(0.01)	(0.01)
Pre-Conception Dep. Var Mean x 100	.383	.423	.193	.179
Avg. Monthly Income Pre-Period	0	183.578	557.263	1393.398
Observations	8551120	4863984	4863488	5008592

Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for a crime, separately by income group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Overall, our main results on fathers' crime are driven by parents with lower income and employment prior to conception, once again in line with an economic explanation for the increase in crime following childbirth.

Father's age at birth. As discussed in Section 2, younger parents are more likely to give birth to unwanted children and, in addition, they struggle more to provide for their family (see Table 1). In Table 3, we show that fathers aged 22 years old or less experience a substantial increase in the probability of being criminally prosecuted after childbirth (+44%, column 1). In turn, the effects are significantly smaller for fathers in age groups older than 22 (columns 2-4) – an average effect of +13.4% when grouping all fathers above that age (column 5). In Appendix Table A2, we

[27] Fathers in the upper tercile lie roughly in the 80^{th} percentile of the overall income distribution (based on PNAD survey for employed men aged 18-50 years old), meaning that the welfare registry Cadunico does provide some coverage for relatively high-income individuals.

[28] Because the share of formally employed mothers is significantly smaller relative to fathers, we pool together all formally employed mothers to retain a reasonable sample size and statistical power.

show that a similar gradient emerges for economic and violent crimes. Overall, the gradient over age seems consistent with the idea that the effects of fatherhood on crime are driven by economic needs. Younger parents tend to be more economically constrained – e.g., they work less and have less access to credit. In addition, they are more likely to father unplanned children, which may be associated with additional economic constraints.

Table 3: Effect of childbirth on father's crime, by age

	(1)	(2)	(3)	(4)	(5)
	Prob. of Criminal Prosecution x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	0.14***	0.043***	0.029**	0.038**	0.039***
	(0.010)	(0.01)	(0.01)	(0.02)	(0.007)
Treated x Pregnancy	0.061***	0.028**	-0.0018	0.022	0.014*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.008)
Pre-Conception Dep. Var Mean x 100	.318	.315	.273	.217	.29
Observations	9853696	7543600	5823104	2407600	15888976

Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for a crime, separately by age group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Position in the household. We complement this evidence by showing that the increases in crime are substantially stronger for fathers who have not formed their own household prior to child conception, i.e., who live with their parents' or other relatives'.[29] While prosecution rates increases by 10% and 23% during pregnancy and after childbirth for fathers who have not yet formed a household, the same effects are significantly smaller for fathers heading their own household (+0% and +14%, respectively) – see Appendix Figure A5. In the Section 4.4.C, we will show that the probability that parents form a household following childbirth strongly increases after birth. Since household formation may be a relevant component of the costs of parenthood, these results seem consistent with the idea that economic needs may explain the large increases in fathers' crime.

Child gender. Dustmann et al. (2021) have shown that young fathers who have boys in Denmark commit 19% fewer crimes than those who have girls (see also Dasgupta et

[29] We consider them to have formed their own household if they show up in Cadunico as household head or the spouse of the household head. This analysis is done for the subsample of fathers who show up in Cadunico data before child conception.

al., 2022, for Australia). They argue that fathers commit less crimes as they attempt to become role models when having boys rather than girls. In Appendix Table A3, we show that no such differences emerge in our setting, as prosecution rates increase in a similar way for fathers having boys and girls. Given that childcare costs should not vary strongly by child gender, this finding seems in line with the idea that, in the context of Brazil, economic vulnerability is the main reason why fatherhood leads to more crime.

4.4.C Additional Outcomes

We complement the evidence on crime effects by showing impacts along other dimensions.

Household Formation. In Figure 6, we show the effects of childbirth on the probability that fathers form a household of their own.[30] First-time fathers are 17.2 percentage points more likely to form their own household after childbirth, respectively. Since household formation may be an important component of the economic costs of having the first child, this finding provides additional evidence in favor of an economic explanation for our main results. It also lines up well with the previous results showing stronger effects on crime for fathers who have not formed a household of their own before child conception.

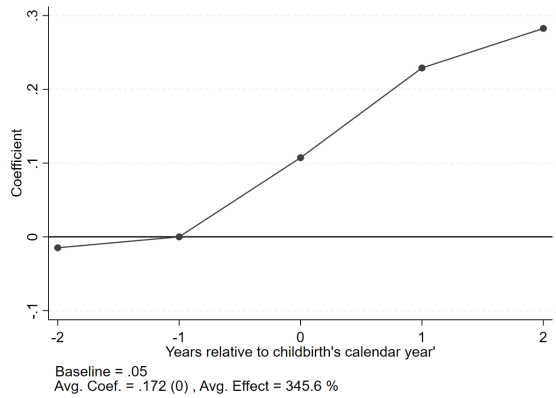
Employment. Appendix Figure A6 shows that father's employment increases only slightly around childbirth – by less than three percentage points, which is likely insufficient to accommodate the greater economic needs of the family after the arrival of the newborn.[31] One possible explanation is that formal employment might be a constrained margin of adjustment, particularly in developing countries, so that fathers may turn to crime to increase family income.[32] In turn, Appendix Figure A7 shows that mothers experience significant child penalties, in line with the evidence available for several other countries (see, e.g. Kleven et al., 2023). Formal employment and

[30] In line with the previous heterogeneity exercise in Figure A5, this outcome take value one when the father is either the head or the spouse of the household head. We focus on the subset of families where both fathers appear in Cadunico in the whole analysis period, so that it is possible to track his position in the household.

[31] The effect of childbirth on employment is similar to what is found in Massenkoff and Rose (2022) using a restricted sample of fathers who were arrested at some point.

[32] This would be in line with an *exclusion view* of formal labor markets in developing countries, whereby it may be difficult for many individuals to find formal jobs (see, e.g. Gerard and Gonzaga, 2021; Perry, 2007).

Figure 6: Effects on the probability that the father forms a household



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father forms a household. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at yearly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. The baseline outcome, the average and relative effects during the postbirth period are also reported at the bottom of the graph.

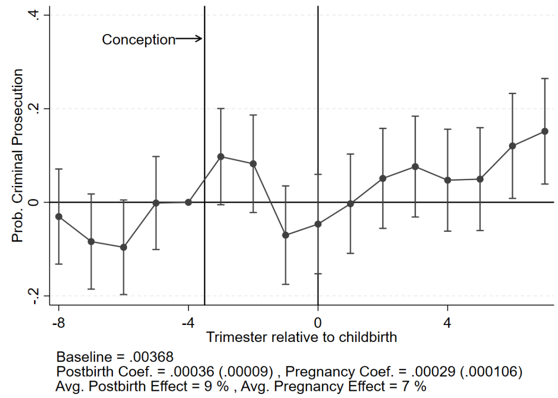
earnings start to decline at the onset of child conception, and they are about 40% and 50% lower two years after childbirth, respectively. These large penalties likely impose further economic constraints on the family, in addition to the direct monetary costs of childbearing.

4.4.D Effects of the Second Child

So far we have focused on the effects of the first child. To investigate the effects of having a second child, we match (treatment) parents that had their second child between 2011 and 2013 with (control) parents that had a second child between 2016 and 2018, and run our baseline difference in difference analysis (Section 4.1).[33] The effects in Figure 7 are qualitatively similar to those estimated for the first child, showing higher criminal prosecution rates both during pregnancy and after childbirth, but the magnitude is different. Although the effect on criminal activity during pregnancy is virtually the same (+7%), the effect during the two-year period after pregnancy is significantly smaller for the second child (+9%) than for the first child (+18%). This difference may reflect a lower economic burden of having a second child, as the cost of household formation is undertaken with the first child, and some durable goods may be transferred from one child to another.

[33] We also restrict the sample to parents who had the first and second child with at least a one-year difference.

Figure 7: Effects of the second child on father's crime



Notes. This figure plots the dynamic treatment effect of the second childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for a crime. The treatment group comprises fathers who had their second child in the period 2011-2013, who are matched to control fathers who had their second child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group in the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

4.4.E Additional Results for Mothers

In Section 4, we have shown that first-time mothers reduce their criminal behavior during pregnancy and shortly after childbirth. As for first-time fathers, we also estimate the model for different groups of mothers according to income and age groups. In Table A4, we show that reductions in crime are larger among women with no formal income, in contrast with our findings for fathers. With respect to age, Table A5 shows that reductions in prosecution rates do not vary strongly over age for mothers, also different from our results for fathers. Overall, the effects on mothers' crime cannot be consistently explained by economic vulnerability. We interpret these results as evidence that criminal activity might not be a relevant margin of income adjustment for mothers. This could be explained by the fact that crime in Brazil, like in other Latin American countries, tends to be extremely violent, which could strongly discourage women from such activities. In line with that, baseline criminal prosecution rates are an order of magnitude lower for mothers than for fathers.[34]

[34] By contrast, pre-conception arrest rates in the US are only twice as large for fathers relative to mothers (Massenkoff and Rose, 2022).

4.5 Domestic Violence

We next focus on the effects of childbirth on domestic violence. We study domestic violence separately from other crimes because the channels and motivations might be different. While the Becker-Ehrlich model, which emphasizes the balance between expected benefits and costs, provides an adequate framework for explaining most types of crime, domestic violence may depend on additional factors such as the relative bargaining power of each partner, the time spent together by the couple, and psychological stress (see, e.g., Aizer, 2010; Anderberg and Rainer, 2013; Bloch and Rao, 2002; Bhalotra et al., 2021). Moreover, the mother's propensity to report domestic violence may be endogenous to childbirth, posing additional challenges in terms of measurement and estimation.

Figure 8 shows the effect of childbirth on the probability that fathers are prosecuted for domestic violence, estimated using the same empirical strategy described in Section 4.1. The probability that fathers are prosecuted for domestic violence increases after child conception and especially after childbirth – by as much as 215% two years after birth. In Appendix Figure A8, we show that these effects are robust to using different control groups, as previously done in Section 4.3 for general crime. Importantly, these prosecutions refer to any form of violence against women by an intimate partner, independently of cohabitation or marriage status. Hence, these results cannot be mechanically explained by increased cohabitation or marriage following child conception.

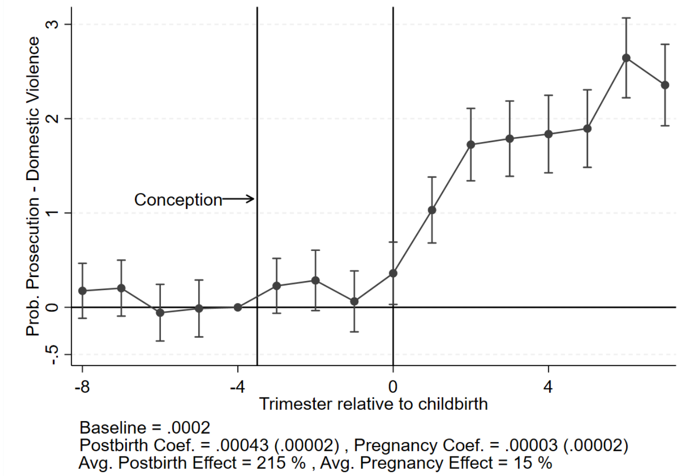
4.5.A Changes in Violence Levels vs. Reporting Behavior

We next investigate to what extent the effects on domestic violence prosecution reflect changes in violence levels and changes in women's reporting behavior, notably because women could be more prone to report such cases after childbirth. We use SINAN data, based on mandatory notifications of domestic violence (SINAN) filed by Brazilian health units whenever they know or suspect that a patient has been victim of domestic violence.[35] In addition to being reported by a third party, these notifications are not automatically disclosed to judicial authorities, further reducing under-reporting concerns due to fear of retaliation.

Since individual identifiers are not available in SINAN, we code a women as a

[35]SINAN data, maintained by the Ministry of Health, covers a broad range of domestic violence cases, which is another advantage over alternative measures that include only the most severe events such as hospitalizations and feminicide.

Figure 8: Effects of childbirth on the probability that the father is prosecuted for domestic violence



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for domestic violence. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

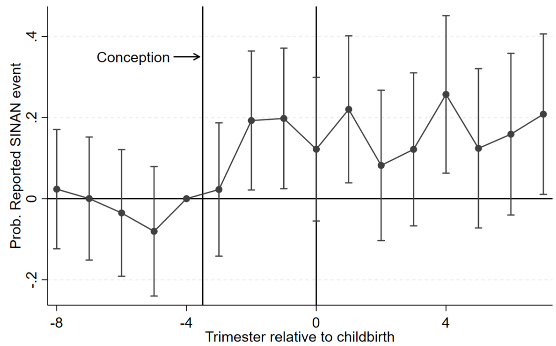
victim whenever we find a notification for a woman born in the same day and living in the same municipality. This approach necessarily entails classical measurement error in the dependent variable, which reduces the precision of our estimates. To alleviate this problem, we will restrict the analysis to municipality-birthdate cells that include at most two mothers.

Figure 9 shows that the probability of being victim of aggression in SINAN increases after conception and childbirth by 15% and 17%, respectively. At the same time that these effects are sizable, they are substantially smaller than the effects on domestic violence prosecution in the post-birth period (+215%). Together, these results indicate that the large effects on domestic violence prosecution are both explained by increases in actual violence and a higher propensity that women report any incidents to the police.

4.5.B Explaining Higher Domestic Violence following Childbirth

These large increases in domestic violence could be explained by different mechanisms. First, stress due to the economic costs of parenthood can generate violence within the family. Second, the fact that parents spend more time together due to childbirth

Figure 9: Effect of childbirth on the probability that the mother is victim of domestic violence



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the mother is recorded in the SINAN as a suspect victim of domestic violence. The treatment group comprises mothers who had their first child in the period 2011-2013, who are matched to control mothers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline victimization rate of the treatment group during the last quarter before conception ($t = -4$). The baseline victimization rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

could increase exposure to domestic violence. This mechanism has been discussed in earlier studies (e.g., see Dugan et al., 2003) and is consistent with evidence that domestic violence increases during nights, weekends, and national holidays (Vazquez et al., 2005). Furthermore, previous evidence from Brazil supports the idea that both financial distress and time spent together by partners increase the risk of domestic violence (see Bhalotra et al., 2021).

Supporting an economic explanation, we find significantly stronger effects for more economically vulnerable individuals, namely fathers with lower formal employment and income – see Appendix Table A6. In turn, the effects are also stronger for younger fathers – see Appendix Table A7. Since younger parents are more likely to start cohabiting after childbirth, they experience both larger economic costs to form a new household and larger increases in time spent together. Overall, we interpret the larger increases in DV rates for younger fathers as consistent with both economic and exposure-based explanations.

5 Maternity Benefit Access and Crime of First-time Fathers

In the previous section, we have shown that fathers are more likely to be criminally prosecuted in the two years following childbirth and that this effect can be explained by the economic costs of parenthood, which are more relevant for economically vulnerable families. We corroborate this mechanism by showing that access to government benefits targeted at parents can decrease the criminal behavior of first-time fathers. We do so by exploring a discontinuity in the provision of maternity benefits to unemployed mothers. These results bear important policy implications: transfers targeted at new parents could be an important tool for preventing the substantial increases in criminal activities by economically vulnerable fathers.

5.1 Maternity Benefit Provision to Unemployed Mothers

Access to social security in Brazil is strongly linked to formal employment. Women employed at the time when they have a child have access to four months of maternity leave fully replacing their salaries.[36] This coverage extends to a "grace" period of one year after the termination of a formal job, so women who have children within the grace period are also entitled to four months of maternity benefits. These rules generate plausibly exogenous variation in eligibility to maternity benefits, which we leverage to estimate the effect of the latter on fathers' criminal behavior around childbirth.

5.2 Empirical Strategy and Sample Definitions

We focus on parents in Cadunico who had their first child between 2011 and 2018, and that can be uniquely identified in employment and criminal records (see Section 3 for details on data linkage). In addition, we restrict the sample to mothers leaving their last job before birth due to the termination of a fixed-term contract. For these workers, the statutory duration of the grace period is 12 months, but it can be effectively extended from 45 to 75 additional days. In fact, the grace period starts on the first day of the first calendar month after the termination of the job and ends on the 15th day of the 14th calendar month after the termination of the job, which is the due date for social security contributions relative to month 13.[37]

To estimate the effect of maternity benefits on fathers' crime, we compare families

[36] These benefits are capped at the maximum level of social security benefits, which is fairly high: 6.3 minimum wages in 2012, equivalent to the 90th percentile of the distribution of women's formal wages.

[37] As an example of the effective grace period calculation, consider a worker whose contract ends on February 8, 2012. Her statutory grace period would run from March 1, 2012, through February 2013 (month 12). However, the effective grace period extends to the due date for social security contributions relative to March 2013 (month 13), which implies that the worker will be effectively covered until April 15th 2013.

whose mother's (effective) grace period ended just before and after childbirth using a regression discontinuity (RD) framework:

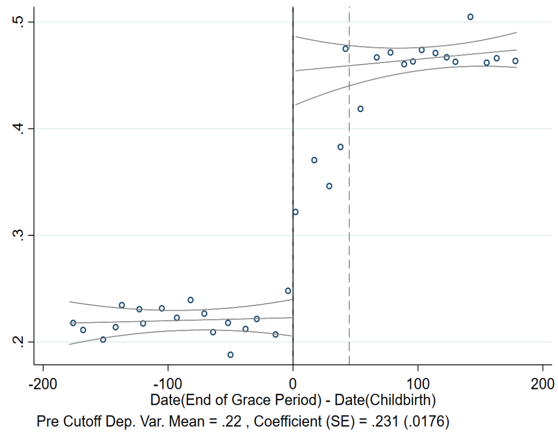
$$Y_i = \alpha + \beta \cdot D_i + f(R_i) + f(R_i) \cdot D_i + \epsilon_i \tag{3}$$

where Y_i is an indicator variable for the father of child i committing crime; R_i is the distance between the end date of the mother's grace period and her child's birth date (i.e., the running variable of the RD design), and $f(.)$ is a flexible polynomial; D_i is an indicator variable equal to value one when the grace period ends at or after childbirth ($R_i \geq 0$); and ϵ_i is a residual term. Our baseline specification of equation (3) includes a local linear polynomial and restricts the sample to mothers giving birth within a bandwidth of 180 days around the cutoff, but we will show results for different specifications of the polynomial function $f(.)$ and different bandwidths (including the optimal bandwidth by Calonico et al., 2014).

The estimated coefficient β in equation (3) can be interpreted as the causal effect of eligibility for maternity benefits, D, if the latter is as-good-as-randomly assigned across observations near the cutoff (conditional on distance from the cutoff, R). The evidence in Figures A9 and A10 is consistent with this assumption. In particular, Figure A9 shows that the density of observations is continuous around the cutoff, as confirmed by the formal tests of McCrary (2008) and Cattaneo et al. (2018). In turn, Figure A10 shows that parents' characteristics such as age, education, and income before child conception are also balanced around the cutoff. This evidence supports the assumption that eligibility for maternity benefits is as-good-as-randomly assigned near the cutoff.

Eligible mothers can only receive benefits by actively filing an application, however many of them may lack adequate knowledge about the rules for eligibility – particularly regarding the exact definition of the grace period. For this reason, a large number of eligible mothers may not actually receive benefits. We measure the actual take-up of maternity benefits (and how it varies around the cutoff) using individual-level data on maternity benefits from the National Social Security Institute (*INSS*). We match these data to our sample by the mother's exact birth date, municipality, and period of childbirth. Specifically, we assume that a mother in our sample receives maternity benefits if the INSS data include a beneficiary living in the same municipality, born on the same day, and whose maternity benefits were issued within a time window of 6 months before/after childbirth. This matching procedure necessarily generates some degree of measurement error – and thus attenuation bias in RD estimates of the effect of eligibility on the take up rate (Britto, 2022, formally shows this result).

Figure 10: Take up of maternity benefits around the eligibility cutoff



Notes. This figure plots the probability that mothers receive maternity benefits over the running variable R in the RD equation (3) defining benefit eligibility. The latter is the difference, in days, between the end of the grace period (14 months) for receiving maternity benefits after job separation and the childbirth date. Therefore, mothers to the right of the cutoff $R = 0$ are eligible for benefits, while mothers to the left of the cutoff are not. The vertical dashed line indicates the "donut" of 45 days to the right of the cutoff within which the take up of benefits is much lower due to the complexities of eligibility rules (see Section 5.2 for additional details). The graph also plots the estimated relationship between the take up of maternity benefits and the running variable R, based on a linear specification of function $f(.)$ in equation 3. The mean take up rate to the left of the cutoff and the estimated coefficient β (and standard error) are reported at the bottom of the graph.

With these caveats in mind, in Figure 10 we plot the share of actual beneficiaries against the running variable. There is significant non-compliance with eligibility rules on both sides of the cutoff. To the left of the cutoff, approximately 20% of mothers whose grace period ended before they had a child receive maternity benefits. This group may include mothers who can convincingly claim to be "involuntarily unemployed", in which case INSS can extend the grace period by one year. To the right of the cutoff, more than half of mothers who are eligible for maternity benefits do not actually receive them. Many of these workers may not actively apply for benefits because they lack adequate information about eligibility rules, particularly regarding the exact rules for calculating the grace period. This is consistent with the fact that the take-up rate is lower over a range of 45 days to the right of the cutoff, which corresponds to the difference between the "effective" and "nominal" duration of the grace period, as explained above. For this reason, we estimate a "donut" specification of equation (3) that excludes mothers who give birth within 45 days to the right of the cutoff. We will show that results are robust to different definitions of the donut.[38]

[38] Gerard and Gonzaga (2021) follow the same approach to estimate the effects of unemployment

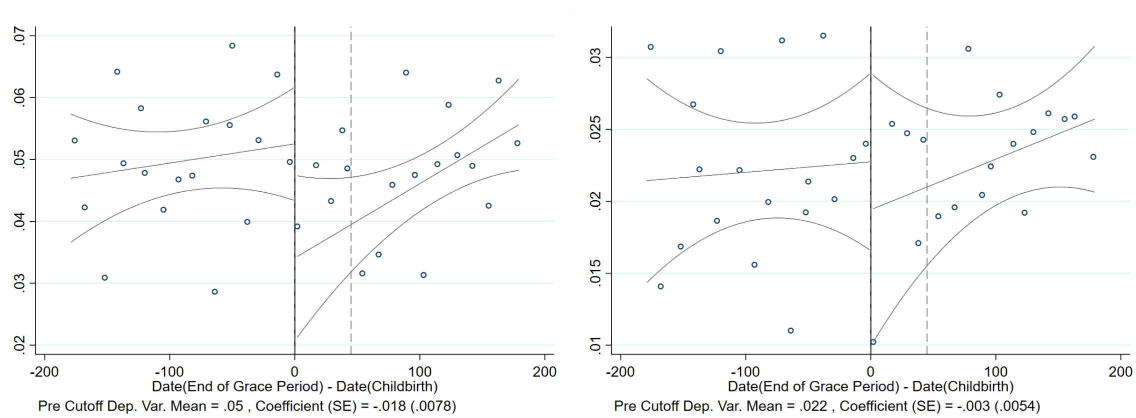
The dashed vertical line in Figure 10 shows the limit of the 45-days donut to the right of the cutoff as well as the relationship between the running variable and the take up rate estimated using this donut RD regression. According to this specification, the difference in the take up rate between eligible and ineligible mothers equals 22 percentage points.

5.3 The Effect of Maternity Benefit on Parents' Criminal Activity

Figure 11a shows that fathers in families who are marginally eligible for benefits are less likely to be criminally prosecuted in the two years following childbirth. By contrast, Figure 11b shows that prosecution rates before childbirth were balanced around the cutoff, offering strong support for the validity of our design.

Figure 11: Effect of maternity benefits on father's crime after and before childbirth

(a) After Childbirth **(b)** Before Conception



Notes. This figure plots the probability that fathers are prosecuted for a crime in the two years after childbirth (left graph) and the five quarters before conception (right graph), over the running variable R in the RD equation (3) defining eligibility for maternity benefits. The latter is the difference, in days, between the end of the grace period (14 months) for receiving maternity benefits after job separation and the childbirth date. Therefore, fathers to the right of the cutoff $R = 0$ had a child with a mother that is eligible for benefits, while fathers to the left of the cutoff do not. The vertical dashed line indicates the "donut" of 45 days to the right of the cutoff within which the take up of benefits is much lower due to the complexities of eligibility rules (see Section 5.2 for additional details). The graph also plots the estimated relationship between fathers' probability of being prosecuted for a crime and the running variable R, based on a linear specification of function $f(.)$ in equation 3 with a 180 days bandwidth. The mean prosecution rate to the left of the cutoff and the estimated coefficient β (and standard error) are reported at the bottom of each graph.

According to our main specification of equation (3), which excludes observations within a donut of 45 days to the right of the cutoff, the effect at the cutoff amounts to -1.8 percentage point, or a 37% reduction relative to the baseline prosecution rate; see Table 4, column (4). The other columns of the table show that estimates remain

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insurance in Brazil, which is characterized by a similar ambiguity in eligibility dates. For an earlier application of a donut RD regression in a different context, see Barreca et al. (2011).

sizable and statistically significant when varying the width of the donut from 0 to 45 days, though it decreases in magnitude when reducing the width of the donut. This is consistent with the much lower take up rate of benefits for individuals just to the right of the cutoff, reflecting in turn the cumbersome rules for computing the grace period (see Section 5.2).

Table 4: The effect of maternity benefits on father's crime based on different donut specifications

	(0)	(1)	(2)	(3)
Donut Size	0 Days	15 Days	30 Days	45 Days
RD Estimate	-0.0101*	-0.0113*	-0.0119*	-0.0188**
	(0.00598)	(0.00642)	(0.00708)	(0.00772)
Pre-cutoff Dep. Var Mean	.05	.05	.05	.05
Observations	22113	21227	20276	19359

Notes: This table shows the effect of maternity benefits on father's crime, as estimated by coefficient β in the RD equation (3), for different widths of the "donut" to the right of the cutoff, indicated on top of each column (see Section 5.2 for additional details on the motivation for the donut). The estimates are based on a linear specification of function $f(.)$ in equation 3 with a 180 days bandwidth. The mean of the dependent variable to the left of the cutoff is also reported in the table.

Appendix Tables A9 and A10 show that our main estimates are robust to varying bandwidth choices (including the bandwidth selected by the criterion of Calonico et al., 2014), the polynomial degree, and to the inclusion of controls to the regression. In addition, Figure A11 shows that the effect estimated at the true cutoff lies clearly outside the distribution of estimates obtained for a range of placebo cutoffs.

As an additional placebo test, we replicate the analysis for mothers displaced without a just cause. Since they are involuntarily unemployed, mothers in this group can extend the grace period for an additional 12 months (i.e., up to a total of 26 months) and, as a consequence, the 14-month cutoff should be irrelevant. In fact, there is no discontinuity in prosecution rates at the placebo cutoff, neither before nor after childbirth (Figure A12). Therefore, the drop in fathers' prosecution rates shown in Figure 11a is caused by the receipt of maternity benefits rather than by other differences between families who have children just before and after one year after job separation.

In Appendix Table A8, we estimate the effect of access to maternity benefits on different types of crime by fathers. Overall, point estimates suggest stronger reductions in economic and violent crimes relative to without a clear economic motive, in line with an economic explanation for our main results.[39] However, due to the lack of statistical power, these estimates are not statistically significant and we are not able to draw strong conclusions about the effects of maternity benefits for different types of crime.

6 Conclusion

We leverage detailed administrative records on family links, crime, and labor market outcomes to show that childbirth increases the criminal activity of first-time fathers in Brazil. Such effect can explain as much as 5% of the overall male crime rate. Our findings show that economic needs related to childbirth can explain the increase in fathers' crime, which is mainly driven by offenses with a plausible economic motivation. In addition, we also show strong and significant increases in domestic violence prosecution by fathers after childbirth. These seem to be driven both by higher levels of actual violence against women in the household and changes in reporting behavior. Both economic unrest and time spent between parents due to childcare seem to play a role in explaining the increase in violence within the household.

Our findings also have important policy implications. Increases in criminal activity are mainly driven by economically vulnerable fathers, which are often excluded from formal social security. In line with this explanation, we show that access to maternity benefits granted by the government reduces the criminal activity of first-time fathers. Attaching benefits to formal employment might be problematic in a setting with a large informal sector, as it excludes the most vulnerable fathers from the social security network.

Finally, we also find a large overlap in the characteristics of fathers that increase their criminal behavior the most and those who are more likely to father an unwanted child. This suggests large benefits for programs that reduce unwanted pregnancies targeted at younger and economically vulnerable individuals. It is also important to note that there are no legal ways to terminate a pregnancy in Brazil. This institutional setting naturally increases the scope for unwanted childbirths, which are, in turn, associated with more criminal activity.

[39] The reduction in domestic violence prosecution is also larger relative to crimes without a clear economic motive.

Bibliography

Aizer, Anna, "The gender wage gap and domestic violence," *American Economic Review*, 2010, *100* (4), 1847–59.

Almond, Douglas and Maya Rossin-Slater, "Paternity acknowledgment in 2 million birth records from Michigan," *PloS one*, 2013, *8* (7), e70042.

Anderberg, Dan and Helmut Rainer, "Economic abuse: A theory of intrahousehold sabotage," *Journal of Public Economics*, 2013, *97*, 282–295.

Arenas-Arroyo, Esther, Daniel Fernandez-Kranz, and Natalia Nollenberger, "Intimate partner violence under forced cohabitation and economic stress: Evidence from the COVID-19 pandemic," *Journal of Public Economics*, 2021, *194*, 104350.

Athey, Susan and Guido W. Imbens, "Design-based analysis in difference-in-differences settings with staggered adoption," Technical Report, National Bureau of Economic Research 2018.

Baker, Andrew C, David F Larcker, and Charles CY Wang, "How much should we trust staggered difference-in-differences estimates?," *Journal of Financial Economics*, 2022, *144* (2), 370–395.

Barreca, Alan I, Melanie Guldi, Jason M Lindo, and Glen R Waddell, "Saving babies? Revisiting the effect of very low birth weight classification," *The quarterly journal of economics*, 2011, *126* (4), 2117–2123.

Bhalotra, Sonia, Diogo GC Britto, Paolo Pinotti, and Breno Sampaio, "Job displacement, unemployment benefits and domestic violence," 2021.

_ , Emilia Brito, Damian Clarke, Pilar Larroulet, and Francisco J Pino, "Dynamic impacts of lockdown on domestic violence: Evidence from multiple policy shifts in Chile," *Review of Economics and Statistics*, 2023, *Forthcoming.*

Bloch, Francis and Vijayendra Rao, "Terror as a Bargaining Instrument: A Case Study of Dowry Violence in Rural India," *American Economic Review*, 2002, *92* (4), 1029–1043.

Britto, Diogo GC, "The employment effects of lump-sum and contingent job insurance policies: Evidence from Brazil," *Review of Economics and Statistics*, 2022, *104* (3), 465–482.

_ , Paolo Pinotti, and Breno Sampaio, "The effect of job loss and unemployment insurance on crime in Brazil," *Econometrica*, 2022, *90* (4), 1393–1423.

Callaway, Brantly and Pedro H. C. Sant'Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

_ and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Card, David and Gordon B Dahl, "Family violence and football: The effect of unexpected emotional cues on violent behavior," *Quarterly Journal of Economics*, 2011, *126* (1), 103–143.

Carr, Jillian B and Analisa Packham, "SNAP benefits and crime: Evidence from changing disbursement schedules," *Review of Economics and Statistics*, 2019, *101* (2), 310–325.

Cattaneo, Matias D, Michael Jansson, and Xinwei Ma, "Manipulation testing based on density discontinuity," *The Stata Journal*, 2018, *18* (1), 234–261.

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma, "Simple local polynomial density estimators," *Journal of the American Statistical Association*, 2019, pp. 1–7.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, "The effect of minimum wages on low-wage jobs," *The Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 2020, *110* (9), 2964–96.

Cohen, Jacob, *Statistical power analysis for the behavioral sciences*, Routledge, 2013.

Dasgupta, Kabir, André Diegmann, Tom Kirchmaier, and Alexander Plum, "The gender reveal: The effect of sons on young fathers' criminal behavior and labor market activities," *Labour Economics*, 2022, *78*, 102224.

De Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 2020, *110* (9), 2964–96.

Deshpande, Manasi and Michael Mueller-Smith, "Does Welfare Prevent Crime? the Criminal Justice Outcomes of Youth Removed from Ssi*," *The Quarterly Journal of Economics*, 06 2022. qjac017.

Dube, Arindrajit, Daniele Girardi, Oscar Jorda, and Alan M Taylor, "A local projections approach to difference-in-differences event studies," Technical Report, National Bureau of Economic Research 2023.

Dugan, Laura, Daniel S Nagin, and Richard Rosenfeld, "Exposure reduction or retaliation? The effects of domestic violence resources on intimate-partner homicide," *Law & Society Review*, 2003, *37* (1), 169–198.

Dustmann, Christian, Rasmus Landersø et al., "Child's Gender, Young Fathers' Crime, and Spillover Effects in Criminal Behavior," *Journal of Political Economy*, 2021, *129* (12).

Edin, Kathryn and Maria Kefalas, *Promises I can keep: Why poor women put motherhood before marriage*, Univ of California Press, 2011.

— **and Timothy J Nelson**, *Doing the best I can*, University of California Press, 2013.

Eichmeyer, Sarah and Christina Kent, "Parenthood in Poverty," Technical Report, Working paper. February 2 2022.

Fadlon, Itzik and Torben Heien Nielsen, "Family labor supply responses to severe health shocks: Evidence from Danish administrative records," *American Economic Journal: Applied Economics*, 2021, *13* (3), 1–30.

Gerard, François and Gustavo Gonzaga, "Informal Labor and the Efficiency Cost of Social Programs: Evidence from Unemployment Insurance in Brazil," *American Economic Journal: Economic Policy*, 2021.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

— , "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Imai, Kosuke and In Song Kim, "On the use of two-way fixed effects regression models for causal inference with panel data," Technical Report, Harvard University IQSS Working Paper 2019.

Jørgensen, Thomas Høgholm and Jakob Egholt Søgaard, "Welfare reforms and the division of parental leave," 2021.

Kleven, Henrik, Camille Landais, and Gabriel Leite-Mariante, "The child penalty atlas," Technical Report, National Bureau of Economic Research 2023.

Massenkoff, Maxim N and Evan K Rose, "Family formation and crime," Technical Report, National Bureau of Economic Research 2022.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of econometrics*, 2008, *142* (2), 698–714.

Mitchell, Ojmarrh, Monica Landers, and Melissa Morales, "The contingent effects of fatherhood on offending," *American Journal of Criminal Justice*, 2018, *43* (3), 603–626.

Monsbakken, Christian Weisæth, Torkild Hovde Lyngstad, and Torbjørn Skardhamar, "Crime and the transition to parenthood: The role of sex and relationship context," *British Journal of Criminology*, 2013, *53* (1), 129–148.

Perova, Elizaveta, Sarah Reynolds, and Ian Schmutte, "Does the Gender Wage Gap Influence Intimate Partner Violence in Brazil? Evidence from Administrative Health Data," 2021.

Perry, Guillermo, *Informality: Exit and exclusion*, World Bank Publications, 2007.

Sampson, Robert J and John H Laub, "Crime and deviance over the life course: The salience of adult social bonds," *American sociological review*, 1990, pp. 609–627.

_ **and** _ , "Crime and deviance in the life course," *Annual Review of Sociology*, 1992, *18* (1), 63–84.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

_ **and** _ , "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Ulyssea, Gabriel, "Firms, informality, and development: Theory and evidence from Brazil," *American Economic Review*, 2018, *108* (8), 2015–47.

Vazquez, Salvador P, Mary K Stohr, and Marcus Purkiss, "Intimate Partner Violence Incidence and Characteristics: Idaho NIBRS 1995 to 2001 Data," *Criminal Justice Policy Review*, 2005, *16* (1), 99–114.

Zurla, V, "How Should We Design Parental Leave Policies? Evidence from Two Reforms in Italy," Technical Report, mimeo 2022.

A Appendix to Section 4

A.1 Descriptive Statistics

Table A1: Summary statistics of the main analysis sample

		Fathers			Mothers	
	Control	Treated	Std. Diff	Control	Treated	Std. Diff
Children = Girl	0.49	0.49	0.00	0.49	0.49	0.00
	(0.50)	(0.50)		(0.50)	(0.50)	
Avg. Age	25.30	25.32	-0.00	23.51	23.52	-0.00
	(5.42)	(5.41)		(4.72)	(4.70)	
Avg. Years of Schooling	10.10	9.84	0.09	10.82	10.53	0.12
	(2.74)	(2.77)		(2.33)	(2.32)	
Avg. Formal Earnings	1320.64	1401.53	-0.03	617.86	644.56	-0.02
	(2344.54)	(2379.08)		(1403.70)	(1362.44)	
Prob. of Formally Employed	0.45	0.48	-0.06	0.27	0.29	-0.05
	(0.50)	(0.50)		(0.44)	(0.45)	
Prob. of Criminal Prosecution	0.00257	0.00304	-0.0087	0.00038	0.00044	-0.0032
	(0.0507)	(0.0550)		(0.0195)	(0.0211)	
Prob. of Economic Crime	0.0011	0.0011	-0.00030	0.0001	0.0001	-0.0001
	(0.0334)	(0.0335)		(0.0110)	(0.0111)	
Prob. of Violent Crime	0.00038	0.00050	-0.00561	0.00011	0.00013	-0.0020
	(0.0195)	(0.0223)		(0.0106)	(0.0116)	
Prob. of Other Crimes	0.00038	0.00056	-0.0083	0.00005	0.00006	-0.0026
	(0.0195)	(0.0237)		(0.0068)	(0.0081)	
Prob. of Domestic Violence	0.00019	0.00024	-0.00319	0.00001	0.00001	0.00
	(0.014)	(0.015)		(0.0033)	(0.0033)	
Observations (thousands)	779	779		699	699	

Notes: This table provides summary statistics for our main analysis sample. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Sample means and standard deviations (in parentheses) for both groups are reported, along with the standardized difference between the two groups.

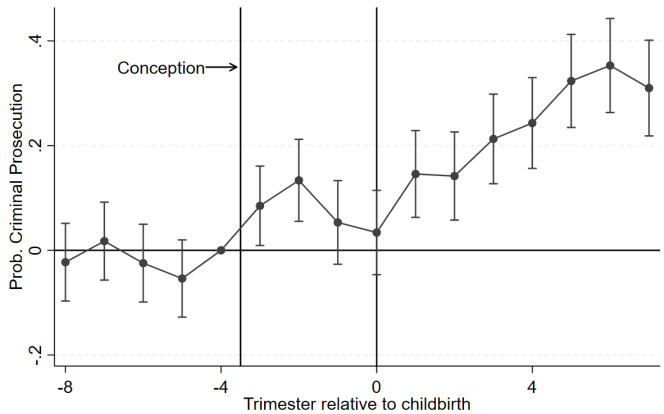
A.2 Additional robustness analyses

A.2.A Alternative Sample

Our main analysis is based on individuals with unique names in the country, so that we can identify parents in Cadunico and the criminal prosecution data solely by their names (Section 3). We rerun our main analysis by enlarging the sample to parents who have unique names in the state where they live and linking these registries based on name and state – increasing population coverage from 50% to 70%. In Figure

A1, we show that this alternative sample selection has little impact on the effects of childbirth on father's crime, supporting the external validity of our analysis.

Figure A1: Effect of childbirth on father's crime, extended sample



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for a crime. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). We extend the sample to include all individuals that have unique name within their state of residence, instead of only individuals with a unique name in the entire country as in our main sample. The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

A.2.B Discussion of the recent two-way fixed effects literature

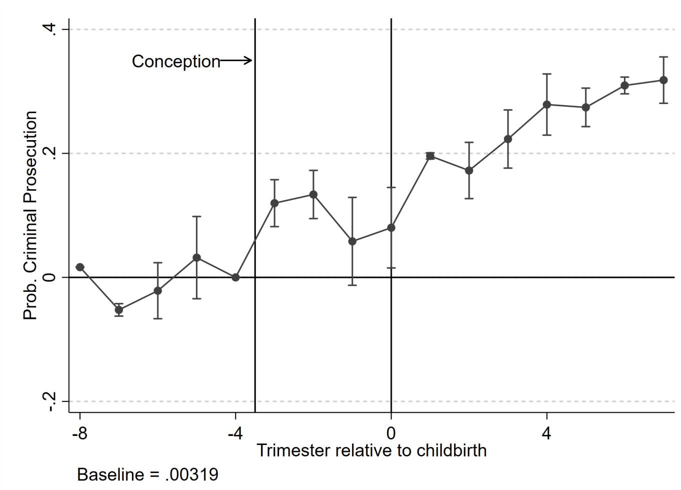
Recent methodological developments on the estimation of difference in differences models have pointed to possible concerns when there is variation in the timing of the treatment and heterogeneous treatment effects on the observation unit (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021b; Sun and Abraham, 2021b; De Chaisemartin and d'Haultfoeuille, 2020). In these cases, the estimation of treatment effects might include negative weights for some units that enter with opposite signs in different periods. This problem is particularly relevant in cases where most or all observations eventually get treated in the analysis period.

Our empirical strategy is specifically designed to avoid these problems. We select a pool of possible controls such that none of the individuals would have had their children in the analysis period, which spans from January 2009 (8 quarters before

January 2011, when the oldest child was born in our treated sample) and December 2015 (7 quarters after December 2013, when the youngest child was born in our treated). Thus, the inclusion of never treated in our analysis sample as control individuals, in addition to the *stacked* difference in differences strategy, allow us to avoid the possible issues pointed out by the recent methodological literature.[40]

Nevertheless, we estimate our dynamic treatment effects model using the methods proposed by De Chaisemartin and d'Haultfoeuille (2020) as a robustness check. We present our estimates in Figure A2. As expected given our empirical strategy, we find very similar results on the probability of being criminally prosecuted using the De Chaisemartin and d'Haultfoeuille (2020) estimator.

Figure A2: Effect of childbirth on father's crime, De Chaisemartin and d'Haultfoeuille (2020) estimator



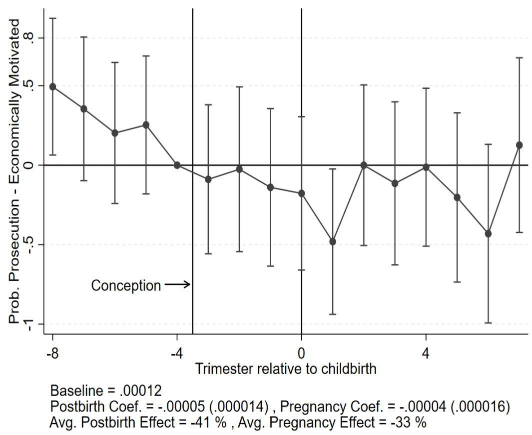
Notes. This figure plots the dynamic treatment effect of childbirth, estimated using the method of De Chaisemartin and d'Haultfoeuille (2020), on the probability that the father is prosecuted for a crime. The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate is reported at the bottom of the graph.

[40] Our empirical strategy is closely related to the one presented in Fadlon and Nielsen (2021). It is in similar spirit to the analysis of Cengiz et al. (2019) on the effects of minimum wage on employment. The main difference is that in our case, control group units were never treated in the analysis period, whereas in their case they restrict to units that were never treated in the event-window time span. In Baker et al. (2022) there is an extensive discussion of the *stacked* differences in difference model as a solution to the recent concerns raised by the recent two-way fixed effects literature and they find that the model closely approximates the other proposed estimators.

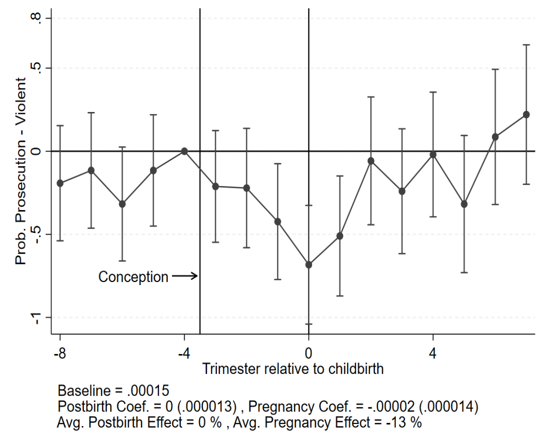
A.3 Additional results

Figure A3: Different Crime Types - Mothers

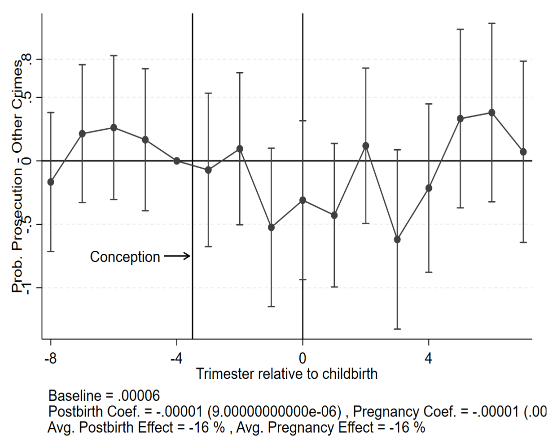
A: Economic Motivation



B: Violent Crime



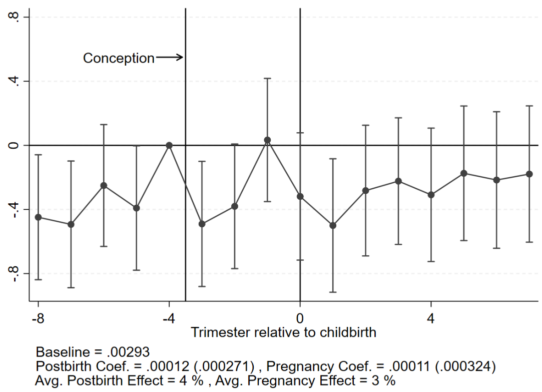
C: Other Crimes



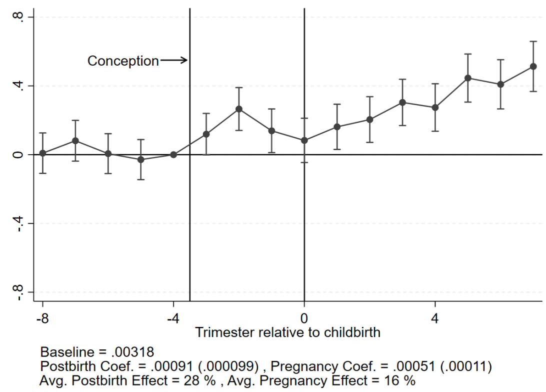
Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the mother is prosecuted for different types of crime (indicated on top of each graph). The treatment group comprises mothers who had their first child in the period 2011-2013, who are matched to control mothers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

Figure A4: Effect of childbirth on father's crime, by mother's employment status in the period before conception

(a) Mother formally employed



(b) Mother not formally employed



Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for crime, by mother's employment status in the period before conception (indicated on top of each graph). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

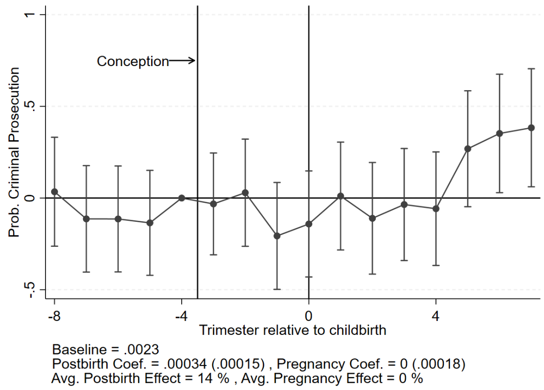
Table A2: Effect of childbirth on father's crime, by age group and type of offense

	(1)	(2)	(3)	(4)	
	Prob. of Prosecution for Economic Crimes x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	0.038***	0.011	0.0085	0.0041	0.010**
	(0.007)	(0.007)	(0.007)	(0.009)	(0.004)
Treated x Pregnancy	0.030***	0.013	-0.00045	0.011	0.0061
	(0.009)	(0.008)	(0.008)	(0.009)	(0.005)
Pre-Conception Dep. Var Mean x 100	.149	.118	.079	.043	.094
	Prob. of Prosecution for Violent Crimes x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	0.025***	0.012***	0.0070	0.0076	0.0095***
	(0.004)	(0.005)	(0.005)	(0.008)	(0.003)
Treated x Pregnancy	0.015***	0.010**	0.00096	-0.0079	0.0042
	(0.005)	(0.005)	(0.006)	(0.009)	(0.004)
Pre-Conception Dep. Var Mean x 100	.053	.05	.042	.035	.047
	Prob. of Prosecution for Other Crimes x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	0.0042	-0.010**	-0.0077	-0.0034	-0.0084***
	(0.004)	(0.005)	(0.005)	(0.008)	(0.003)
Treated x Pregnancy	0.013***	-0.0044	-0.0048	0.0053	-0.0034
	(0.005)	(0.005)	(0.006)	(0.009)	(0.004)
Pre-Conception Dep. Var Mean x 100	.062	.055	.056	.044	.055
Observations	8046608	7240624	5585360	2303952	15240576

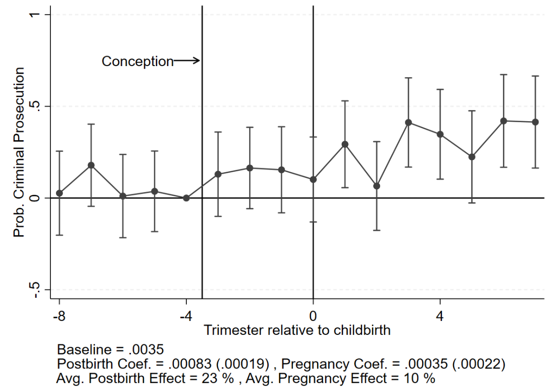
Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for different types of crime (indicated on top of each panel), by age group (top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Figure A5: Effect of childbirth on father's crime, by position in the household

(a) Father or mother head of household



(b) Not head of household



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for crime, by position in the household before child conception (indicated on top of each graph). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

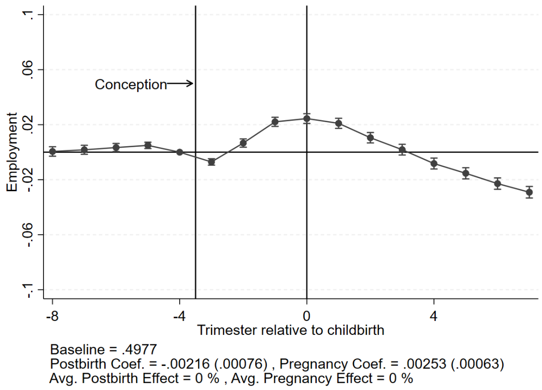
Table A3: Effect of childbirth on father's crime, by gender of the child and father's age group

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of Criminal Prosecution x 100					
	All Fathers		22 or less		More than 22	
	Child-Girl	Child-Boy	Child-Girl	Child-Boy	Child-Girl	Child-Boy
Treated x Post-Birth	0.088***	0.081***	0.16***	0.15***	0.041***	0.043***
	(0.009)	(0.009)	(0.01)	(0.01)	(0.01)	(0.01)
Treated x Pregnancy	0.031***	0.032***	0.073***	0.042***	0.026**	0.0052
	(0.009)	(0.009)	(0.01)	(0.01)	(0.01)	(0.01)
Pre-Conception Dep. Var Mean x 100	.303	.299	.318	.318	.288	.293
Observations	12517536	13225136	4810880	5042816	8182320	7706656

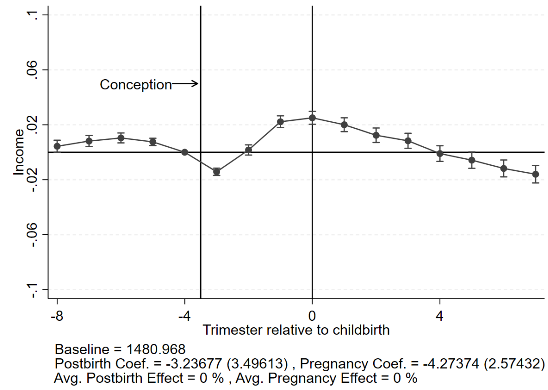
Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for a crime, by gender of the child and father's age group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Figure A6: Effect of childbirth on formal employment and earnings, fathers

(a) Formal employment



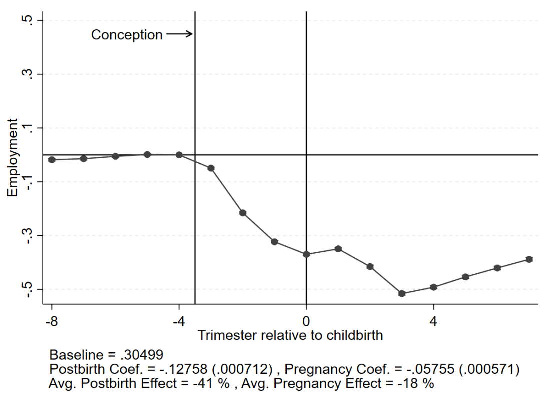
(b) Formal earnings



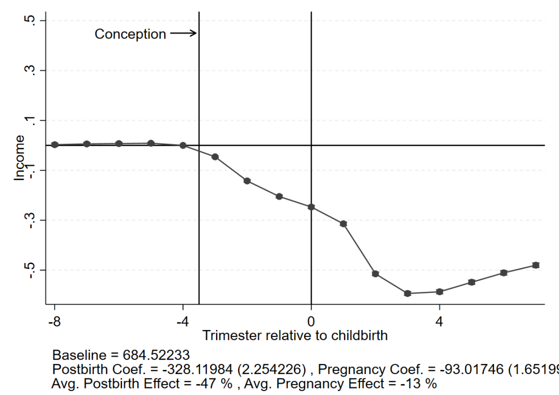
Notes. This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on father's employment (left graph) and earnings (right graph). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline outcome of the treatment group during the last quarter before conception ($t = -4$). The baseline outcome, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

Figure A7: Effect of childbirth on formal employment and earnings, mothers

(a) Formal employment



(b) Formal earnings



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on mother's employment (left graph) and earnings (right graph). The treatment group comprises mothers who had their first child in the period 2011-2013, who are matched to control mothers who had their first child after the analysis period (2016-2018). The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline outcome of the treatment group during the last quarter before conception ($t = -4$). The baseline outcome, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

Table A4: Effect of childbirth on mother's crime, by income group

	(1)	(2)	(3)	(4)
	Prob. of Criminal Prosecution x 100			
		Formal Labor Income Percentiles		
	No Formal Income	[0,33)	[33,66)	[66,100]
Treated x Post-Birth	-0.012***	-0.0025	-0.0099	-0.00096
	(0.003)	(0.007)	(0.007)	(0.006)
Treated x Pregnancy	-0.014***	-0.011	0.00077	0.012*
	(0.004)	(0.009)	(0.008)	(0.007)
Pre-Conception Dep. Var Mean x 100	.044	.064	.06	.028
Avg. Monthly Income Pre-Period	0	124.706	422.153	978.632
Unique Individuals	629469	159460	158283	157957
Observations	12580704	2758688	2758752	2842176

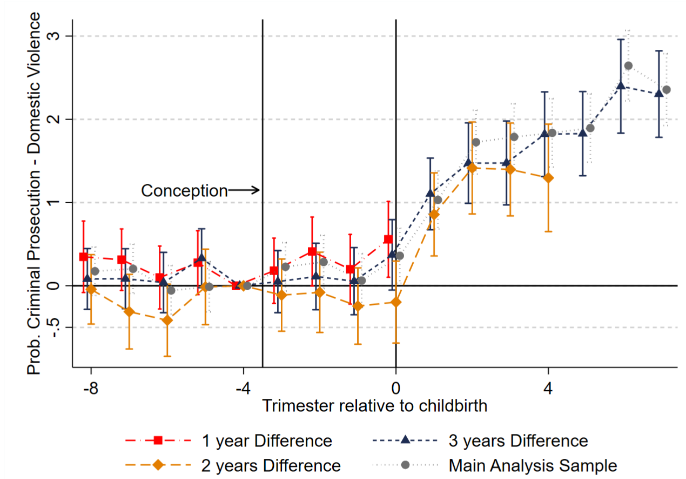
Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that mothers are prosecuted for a crime, by income group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises mothers who had their first child in the period 2011-2013, who are matched to control mothers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Table A5: Effect of childbirth on mother's crime, by age group

	(1)	(2)	(3)	(4)	(5)
	Prob. of Criminal Prosecution x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	-0.0088**	-0.0072	-0.012*	-0.011	-0.0093**
	(0.004)	(0.005)	(0.006)	(0.01)	(0.004)
Treated x Pregnancy	-0.011***	-0.0046	0.00074	-0.021*	-0.0046
	(0.004)	(0.006)	(0.007)	(0.01)	(0.004)
Pre-Conception Dep. Var Mean x 100	.044	.055	.036	.074	.05
Unique Individuals	525300	251927	175868	54723	468510
Observations	10855184	5158144	3708288	1218704	10085136

Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that mothers are prosecuted for a crime, by age group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises mothers who had their first child in the period 2011-2013, who are matched to control mothers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

Figure A8: Effect of childbirth on the the probability that the father is prosecuted for domestic violence, different control groups



Notes: This figure plots the dynamic treatment effect of childbirth, as estimated by coefficients β_t's from equation (1), on the probability that the father is prosecuted for domestic violence.The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child one, two, and three years later, and, as in our main analysis, at least 11 quarters later during the period 2016-2018. The effect is estimated at quarterly frequencies, and 95% confidence intervals based on standard errors clustered at the individual level are shown in the graph. Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The baseline prosecution rate, the average effects during the pregnancy and postbirth periods (as estimated by coefficients β_1, β_2 in equation 2), and the relative effects during such periods are also reported at the bottom of the graph.

Table A6: Effect of childbirth on the probability that fathers are prosecuted for domestic violence, by income group

	(1)	(2)	(3)	(4)	(5)
	Prob. of Prosecution for Domestic Violence x 100				
		Formal Labor Income Percentiles			
	No Formal Income	(0-25)	[25,50)	[50,75)	[75,100]
Treated x Post-Birth	0.051***	0.060***	0.037***	0.025***	0.023***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Treated x Pregnancy	0.0094***	0.0047	-0.0052	-0.00047	0.0051
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Pre-Conception Dep. Var Mean x 100	.017	.045	.03	.015	.021
Avg. Monthly Income Pre-Period	0	140.687	416.093	720.614	1595.546
Observations	8551120	3684864	3684752	3684080	3682368

Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for domestic violence, by income group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

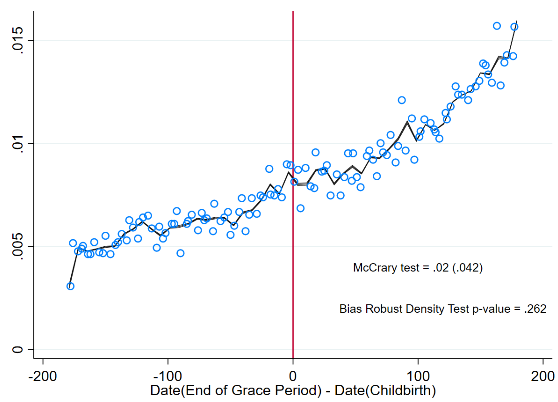
Table A7: Effect of childbirth on the probability that fathers are prosecuted for domestic violence, by age group

	Prob. of Prosecution for Domestic Violence x 100				
	Age Groups				
	$\leq$ 22 years	23-26	27-32	$\geq$32	More than 22
Treated x Post-Birth	0.061***	0.035***	0.022***	0.035***	0.031***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)
Treated x Pregnancy	0.0090***	0.0024	0.0011	-0.0021	0.0015
	(0.003)	(0.003)	(0.004)	(0.009)	(0.003)
Pre-Conception Dep. Var Mean x 100	.013	.027	.028	.039	.03
Observations	8046608	7240624	5585360	2303952	15240576

Notes: This table shows the effect of child conception and birth, as estimated by the coefficients β_1 and β_2 in equation (2), on the probability that fathers are prosecuted for domestic violence, by age group (indicated on top of each column). Coefficients are re-scaled by the baseline prosecution rate of the treatment group during the last quarter before conception ($t = -4$). The treatment group comprises fathers who had their first child in the period 2011-2013, who are matched to control fathers who had their first child after the analysis period (2016-2018). Standard errors clustered at the individual level are reported in parentheses.

B Appendix to Section 5

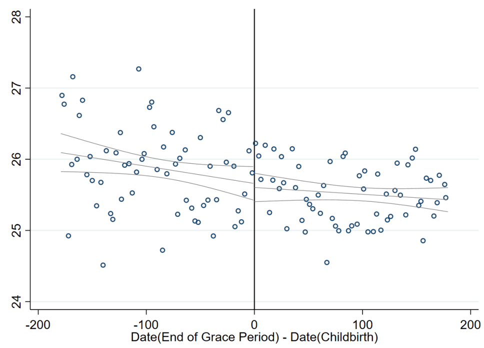
Figure A9: Density of the running variable around the RD cutoff



Notes. This figure plots the density of the difference, in days, between the end of the grace period (14 months) for receiving maternity benefits after job separation and the childbirth date, i.e. the running variable R in the RD equation (3), in our main sample. Therefore, mothers to the right of the cutoff $R = 0$ are eligible for benefits, while mothers to the left of the cutoff are not. The results of the McCrary density test and the bias robust test proposed by Cattaneo et al. (2018, 2019) are also reported.

Figure A10: Balance of covariates around the RD cutoff

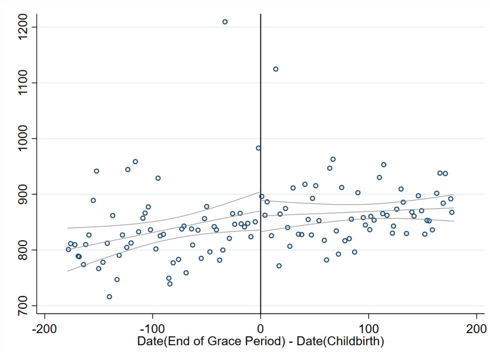
A: Father's age at childbirth



Female child

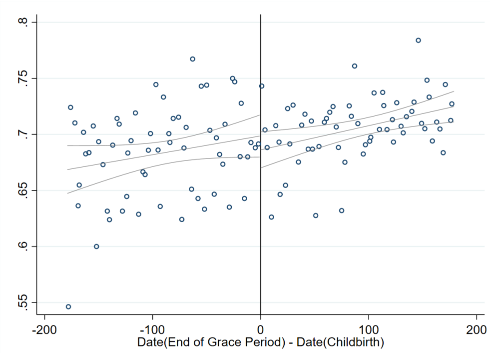
C: Father's years of schooling

D: Mother's income before conception



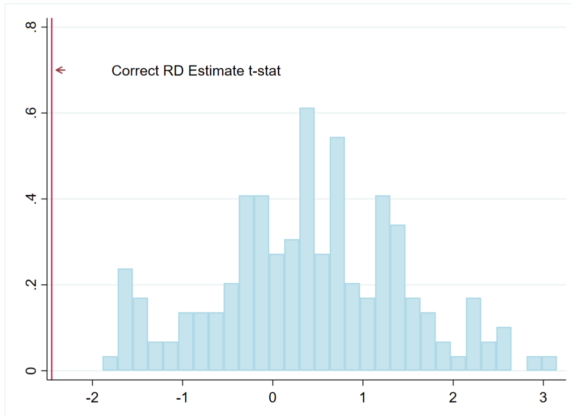
E: Father's income before conception

F: Father's employment before conception



Notes. This figure compares several covariates, indicated on top of each graph, by mother's eligibility for maternity benefits in our main sample. The variable on the horizontal axis is the difference, in days, between the end of the grace period (14 months) to receive maternity benefits after separation from work and the date of birth of the child, that is, the running variable R in the RD equation (3). Therefore, parents to the right of the cutoff $R = 0$ are in families with a mother that is eligible for benefits, while parents to the left are not. The graph also plots the estimated relationship between fathers' probability of being prosecuted for a crime and the running variable R, based on a linear specification of function $f(.)$ with a 180 days bandwidth in equation 3.

Figure A11: Effect of maternity benefits on father's probability of criminal prosecution in the two years after childbirth, permutation test at placebo cutoffs



Notes. This figure compares the t-statistic of the estimated coefficient β in the RD equation (3), indicated by the vertical line, with the distribution of t-statistics obtained at 100 placebo cutoffs between -200 and +200 days from the cutoff and excluding the 15 days before/after the cutoff. All estimates refer to a linear specification of the RD equation (3) and a bandwidth selected according to the criterion of Calonico et al. (2014).

Table A8: Regression Discontinuity Effects of Maternity Benefits on Fathers' Criminal Prosecution, By Type of Offense

	Economic	Violent	Other Crimes without Clear Economic Motive	Domestic Violence
ITT	-0.00367	-0.00333	-0.00184	-0.00370
	(0.00500)	(0.00352)	(0.00333)	(0.00255)
Pre-cutoff Dep. Var Mean	.018	.007	.007	.006
Observations	19359	19359	19359	19359

Notes: This table shows the effect of maternity benefits on father's crime, as estimated by coefficient β in the RD equation (3), for different types of offense indicated on top of each column. Following our main specification, estimates are based on a linear polynomial with a 180 days bandwidth and use a 45 days "donut" to the right of the cutoff within which the take up of benefits is much lower due to the complexities of eligibility rules (see Section 5.2 for additional details). The mean of the dependent variable to the left of the cutoff is also reported in the table.

Table A9: Regression Discontinuity Effects of Maternity Benefits on Fathers' Criminal Prosecution, Varying Bandwidths

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Dep var: Prob. of Criminal Prosecution – Two Years After Childbirth										
	Bandwidth										
	[-120,120]	[-130,130]	[-140,140]	[-150,150]	[-160,160]	[-170,170]	[-180,180]	[-190,190]	[-200,200]	[-210,210]	[-220,220]
RD Estimate	-0.0243**	-0.0268**	-0.0232**	-0.0196**	-0.0165*	-0.0197**	-0.0188**	-0.0159**	-0.0139**	-0.0152**	-0.0141**
	(0.0120)	(0.0110)	(0.00997)	(0.00925)	(0.00855)	(0.00814)	(0.00772)	(0.00734)	(0.00701)	(0.00681)	(0.00656)
Pre-cutoff Dep. Var Mean	.05	.05	.05	.051	.05	.05	.05	.05	.05	.05	.049
Observations	11250	12531	13863	15156	16527	17899	19359	20829	22308	23633	24865

Notes: This table shows the effect of maternity benefits on father's criminal prosecution, as estimated by coefficient β in the RD equation (3), for varying bandwidths to the left and right of the cutoff indicated in the table between brackets. Following our main specification, estimates are based on a linear polynomial and use a 45 days "donut" to the right of the cutoff within which the take up of benefits is much lower due to the complexities of eligibility rules (see Section 5.2 for additional details). The mean of the dependent variable to the left of the cutoff is also reported in the table.

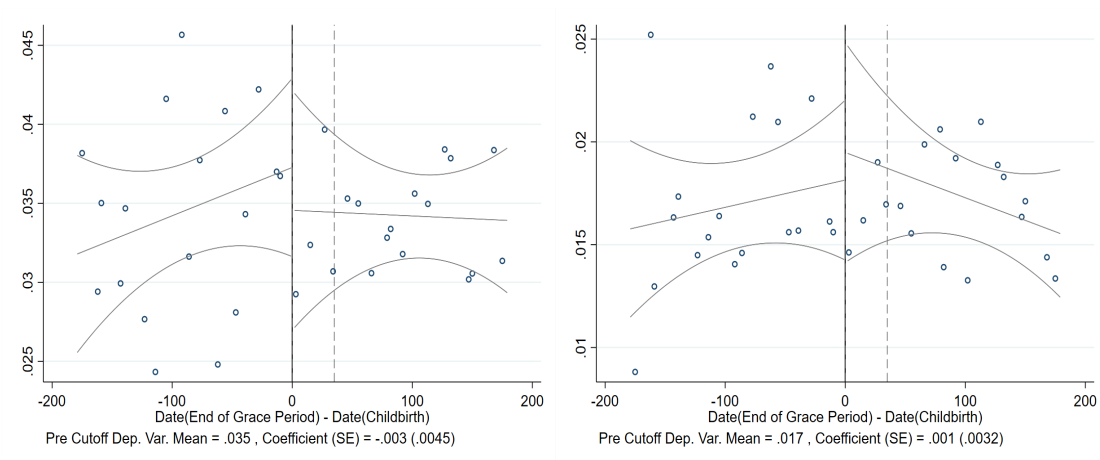
Table A10: Regression Discontinuity Effects of Maternity Benefits on Fathers' Criminal Prosecution, Endogenous Selected Bandwidths

	(1)	(2)	(3)	(4)
	Prob. of Criminal Prosecution – Two Years After Childbirth			
RD_Estimate	-0.0221**	-0.0176**	-0.0281***	-0.0189**
	(0.00904)	(0.00760)	(0.00892)	(0.00757)
Pre-cutoff Dep. Var Mean	.048	.048	.048	.048
Polynomial	Linear	Quadratic	Linear	Quadraticc
Controls	No	No	Yes	Yes
Observations	47591	47591	47278	47278

Notes: This table shows the effect of maternity benefits on father's crime, as estimated by coefficient β in the RD equation (3), for different specifications of the polynomial $f(.)$ using the bandwidth selected according to the criterion of Calonico et al. (2014). Following our main specification, estimates use a 45 days "donut" to the right of the cutoff within which the take up of benefits is much lower due to the complexities of eligibility rules (see Section 5.2 for additional details). The control variables included in columns 3-4 are fixed effects for the calendar month when the child was born, father's age at childbirth, income child before conception, and years of schooling, and the child's gender. The mean of the dependent variable to the left of the cutoff is also reported in the table.

Figure A12: Effect of maternity benefits on father's probability of criminal prosecution in the two years after childbirth, placebo sample

A: After childbirth **B: Before conception**



Notes. This figure plots the probability that fathers are prosecuted for a crime in the two years after childbirth (left graph) and the five quarters before child conception (right graph) against the running variable R in the RD equation (3) for a placebo sample of mothers for whom the standard grace period for maternity benefits eligibility is not binding. The graph also plots the estimated relationship between fathers' probability of being prosecuted for a crime and the running variable R, based on a linear specification of function $f(.)$ with a 180 days bandwidth in equation 3. The mean prosecution rate to the left of the cutoff and the estimated coefficient β (and standard error) are reported at the bottom of each graph.