Parenthood and Productivity: Evidence from Administrative Data in Brazil*

Diogo G.C. Britto† Caio de Holanda‡ Bruno Ferman§

Alexandre Fonseca¶ Breno Sampaio‖ Lucas Warwar**

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Abstract

Child penalties explain a sizable part of the gender gap in labor market outcomes. However, little is known about the drivers of this phenomenon. The challenge rests on the fact that the child penalty could come from the demand or supply side of the female labor force since mothers choose not to keep the same jobs after childbirth, and firms opt to dismiss them. While the supply effect could come from women shifting preferences after giving birth, the demand impact could be due to employers discriminating against mothers for viewing them as less productive. We provide evidence from a unique setting that allows us to overcome the crucial challenges in estimating the impacts of having a child on productivity. We study this question for a group of workers with an official and precise relevant measure of productivity whose labor demand is fixed. We find that childbirth leads only to a short-lived reduction in productivity for mothers when there is no effect on employment and earnings. We show that remote work (enabled by technology) and migration make mothers attenuate the penalty. We also find no evidence that parents adjust their work to maintain productivity.

Keywords: Child penalty, productivity, gender gap

JEL Classification: J16, J24, J31

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†Bocconi University, BAFFI-CAREFIN, CLEAN Center for the Economic Analysis of Crime, GAPPE/UFPE, IZA. Address: Via Roentgen 1, 20136, Milan, Italy. E-mail: diogo.britto@unibocconi.it.

‡Sao Paulo School of Economics, FGV. E-mail: deholandacaio@gmail.com.

§Sao Paulo School of Economics, FGV. Address: Rua Itapeva, 474, Sao Paulo, Brazil, 01332-000. E-mail: bruno.ferman@fgv.br.

¶Federal Revenue of Brazil, GAPPE/UFPE. E-mail: alexandre.fonseca@rfb.gov.br.

‖Federal University of Pernambuco, GAPPE/UFPE. Address: Rua dos Economistas, Cidade Universitária, 50740-590, Recife, Pernambuco, Brazil. E-mail: brenosampaio@ufpe.br.

**Federal University of Pernambuco, CLEAN Center for the Economic Analysis of Crime, GAPPE/UFPE. E-mail: lucas.warwar@ufpe.br.

1 Introduction

Mounting evidence shows that having a child has several consequences for parents' careers, with mothers experiencing a decline in earnings and labor force participation compared to fathers (Kleven et al., 2019b).[1] [2] However, despite the relevance of understanding the drivers of this phenomenon to design effective policies to reduce gender inequality in the labor market,[3] current evidence still struggles to determine the importance of these mechanisms (Kleven, 2022). The challenge rests on the fact that the child penalty could come from the demand or supply side of the female labor force since mothers choose not to keep the same jobs after childbirth, and firms opt to dismiss them.[4] While the supply effect could come from women shifting preferences after giving birth,[5] the demand impact could be due to employers discriminating against mothers for viewing them as less productive.[6]

In this paper, we document the isolated effects of childbirth on productivity by exploring a setting that holds constant all the other possible mechanisms. We manage this task by analyzing judges in Brazil, a high-value job with strong employment stability, uniform allocation of work, and a relevant and precise measure of productivity. Looking at this particular occupation also enables us to assess how workers' performance in the public sector changes after having a child, a relevant open question. Its importance comes from the fact that bureaucrats are a class of workers that could affect the state's productivity, and decreases in individual performance could indicate social impacts (Hjort et al., 2023). On the other hand, it is still lacking evidence because measuring workers' productivity in the public sector is hard since they enjoy strong job security, and promotions and pay raises depend most on seniority rather than individual performance (Fenizia, 2022).

[1] The literature on gender inequality is reviewed by Altonji and Blank (1999) and Bertrand (2011). It relates to recent work on the impact of childbirth and parenthood (Cortés and Pan, 2020), and to work on the influence of social norms and culture (Fernández et al., 2004; Fernández and Fogli, 2009; Bertrand, 2020; Boelmann et al., 2021).

[2] Kleven (2022) highlights that the average child penalty in the US is currently 20% in annual employment, 24% in weekly employment, and 31% in earnings. These effects are larger than in Scandinavia and smaller in central Europe (Kleven et al., 2019a). Latin America has a 37% child penalty on annual employment, while Africa, Asia, and Oceania have, respectively, 4%, 14%, and 27% (Kleven et al., 2022).

[3] The literature on the impact of family policies is reviewed by Olivetti and Petrongolo (2017). For more research on parental leave schemes, see Lalive and Zweimüller (2009); Schönberg and Ludsteck (2014); Dahl et al. (2016). For more research on childcare subsidies, see Baker et al. (2008); Havnes and Mogstad (2011).

[4] Evidence on that is provided in Section 2.

[5] The literature has shown that female workers have different preferences than male ones. Female workers ask for significantly lower salaries in high-stakes environments (Roussille, 2021). They have lower salary expectations, negotiate less and receive lower salary offers (Bertrand, 2018; Goldin, 2014; Garbinti et al., 2018; Babcock et al., 2003; Bowles et al., 2005; Small et al., 2007; Babcock and Laschever, 2007). Cortés et al. (2022) highlight the gender differences in job search. Women accept jobs substantially earlier than men, with a clear gender earnings gap in accepted offers. These effects are partly explained by the greater risk aversion displayed by women and the higher levels of over-optimism displayed by men.

[6] There is evidence of changes in mothers' and fathers' job productivity across the transition to parenthood. Azmat and Ferrer (2017) show that female lawyers with young children are less productive than male lawyers with young children. Kim and Moser (2021) show evidence that highly educated women working as scientists are less productive during the childbearing years. They also have lower rates and slower speed promotion to tenure compared to fathers and other female scientists without kids. Gallen (2018) finds that mothers are substantially less productive than other workers, such as nonmothers, fathers, and nonfathers.

Due to the institutional context in Brazil, choosing the occupation of judge provide us with the perfect setting that overcomes all the practical difficulties in assessing the impacts of childbirth on productivity. Our first advantage in doing so is access to relevant official work performance measures for this worker class. As determined by law as one of the main determinants of judges' promotion, the measure of productivity is the total number of process sentences produced by the judge. Second, the occupation of a judge is a lifetime position, ensuring no wage reductions and dismissal risks. Like many other public sector workers with strong job security in Brazil,[7] their labor demand is fixed. Third, we have access to exclusive data from the Tax Authority, School Census, and government social aid beneficiaries, allowing us to identify the birthdays, fathers, and mothers of more than 60M children born from 1930 to 2020 in Brazil.

Therefore, using our rich data encompassing when all the Brazilian judges become parents, we explore the sharp changes around childbirth to study the impact of having a kid on productivity. Although the decision to have a child is endogenous, the precise timing of conception and childbirth serves as a shock to labor market outcomes and productivity, making the event study approach suitable for tracing the dynamic trajectory of the effects (Kleven et al., 2019b). Following a strategy similar to Britto et al. (2021) and Britto et al. (2022), we implement a dynamic difference-in-difference approach using our individual-level data on family links and judge productivity measures from 2015 to 2019. This strategy allows us to estimate dynamic treatment effects for up to two years after conception and placebo effects up to one year before conception.

We find that the difference in productivity for fathers and mothers between treatment and control groups is stable in the pre-conception period, supporting the common-trend assumption. After conception, fathers' productivity remains significantly unchanged. In contrast, the mother's productivity declines significantly right before birth, but the gap closes very quickly after the end of the maternity leave period. The short-lived reduction in productivity for mothers right after maternity leave seems to be a natural catching up of the mechanical effect mothers face during the maternity leave for being work absent. In other words, we find evidence that child penalties may not be driven by lower productivity since we do not have permanent changes in work performance for mothers. As expected, because of the lifetime position the judges have, we show that there is also no child penalty on employment and earnings for mothers and fathers.

The no effect on productivity and labor market outcomes is not exclusive to judges. In other words, judges are not the only group that these results are true. We show that the child penalty on productivity, employment, and earnings does not exist for other workers with fixed labor demand. First, we show that self-employed lawyers, a class of workers in the same area of the judge occupation whose labor demand does not depend on any firm, do not have decreases in proxies of productivity[8] when they have a child. Second, public sector workers, a group with strong job security, have fewer child penalties as their earnings increase, with no child penalty

[7]See Mocanu (2022) for more details on public sector workers in Brazil.

[8]We use the number of new cases and the number of won cases as proxies of lawyers' work performance.

for the bureaucrats above the first quartile. Also, we show that people similar to judges but in the private sector face indeed child penalty, indicating that the no effects found for the judges are due to the security of the occupation itself and not due to the people that became judges being special. Judges' siblings, cousins, workers with college degrees, lawyers in the private sector, and private workers that earn as much as judges face decreases in employment and earnings when they have a kid.[9]

Many factors could explain the constant productivity of parents after the maternity leave period. One such factor that could be responsible for this outcome is the role of technology in our setting. The Brazilian judiciary had made great strides in adopting technology since 2006 when legal proceedings were legally permitted to be conducted virtually.[10] Additionally, since 2009, a single system for the electronic processing of legal proceedings has been in place, allowing judges, civil servants, and other parties to interact and monitor the judicial process without physical interaction.

The literature on remote work has identified higher job performance, work satisfaction, and worker retention as benefits of remote work (Bloom et al., 2015; Choudhury et al., 2021; Angelucci et al., 2020). The flexibility of "smart-working"[11] increases workers' productivity and improves their well-being and work-life balance, with stronger effects for women (Angelici and Profeta, 2020). To test the role of technology in our setting, we exploit the availability of digital cases in the court where the judge works and examine if the existence of a single system for electronic processing legal proceedings has any impact. Our results show that remote work helps parents mitigate the child penalty, particularly for mothers during the maternity leave period.

Another factor is the reallocation of judges to larger cities with better services when they discover that they will have a baby. Findings of the literature on migration suggest that people tend to move to places with better welfare conditions when their family status changes (Meyer et al., 1998; Borjas, 1999; Kennan and Walker, 2011). The search for better living conditions is not restricted to low-earners (Kleven et al., 2013, 2014). After conception, mothers tend to work more intensely in courts located in metropolitan areas, regions with more health infrastructure,[12] and more access to child care and nannies.[13]

We check whether our results hide behavioral responses regarding parents adjusting their work to maintain productivity after maternity leave. We ensure that the results are not driven

[9] As far as we know, Britto et al. (2022) are the first to show the child penalty in Brazil regarding any occupation and even high-educated parents. They find that, for any occupation, mothers still have a 20% child penalty relative to the baseline on employment and earnings three years after the birth, while fathers remained unaffected. For highly educated parents (with college), mothers still have a child penalty of 10 to 15% three years after birth for both outcomes, while fathers remain unchanged.

[10] Link to the law: `https://www.planalto.gov.br/ccivil_03/_ato2004-2006/2006/lei/l11419.htm` (Accessed on February 13, 2023).

[11] We are following the definition of "smart-working" from Angelici and Profeta (2020): a new organizational model of work where, thanks to the use of technology, workers can work outside their workplace and with a flexible time schedule.

[12] In 2022, while 36% of private hospitals are located in large Brazilian cities with over 500 thousand people, only 13% are in small towns with a population under 20 thousand people (FBH and CNSaude, 2022).

[13] More than 70% of the cities in 6 Brazilian states in 2020 did not have private daycare centers. Even in the most developed state of Sao Paulo, 47% of the cities do not have nurseries (Exame, 2021).

by parents selectively choosing cases or judging differently to preserve their productivity once they know they will have a baby. Using detailed labor court data, we show that the institutional settings in the Brazilian judiciary leave little room for case selection by the judges. Almost 85% of the cases are randomly assigned to judges,[14] and even when cases are not randomly assigned to judges, the effects are similar. There is no evidence of judges sentencing more cases of specific characteristics, such as the initial value claimed by the plaintiff, the number of charges discussed in the case, the number of plaintiffs, or the number of defendants. Furthermore, we find no indication that judges alter the type of case they sentence the most after having a baby.

The effects of childbirth on productivity are not different due to the case's complexity. Looking at characteristics that proxy the case's difficulty, such as the number of charges in the process, the number of defendants, and the initial value claimed by plaintiffs, there is no evidence that the complexity of the case plays an important role in the effects of childbirth on productivity. Childbirth does not affect how judges sentence the cases when they become parents. The types of verdicts and the amount the defendants should pay to the plaintiffs as a result of the sentence do not change. Also, judges do not produce sentences with less quality. Their decisions are not contested more frequently after childbirth. Finally, judges do not take long to produce their decisions.

This paper adds to a new but extensive literature on the effects of parenthood on gender gaps giving evidence on the effects of childbirth on productivity. The child penalty is well documented through three labor market margins: labor force participation, hours worked conditional on employment, and earnings (Kleven et al., 2019b). Male and female workers evolve in parallel until the birth of their first child. After that, they diverge sharply immediately and do not converge again. This phenomenon is consistent across countries (Kleven et al., 2019a; Aguilar-Gomez et al., 2019; Andresen and Nix, 2019; Angelov et al., 2016; Barth et al., 2017; Bertrand et al., 2010) and explains much of the gender earning gap in high (Kleven et al., 2019b; Chung et al., 2017; Lundberg and Rose, 2000; Angelov et al., 2016) and low-income nations (Britto et al., 2022; Kleven, 2022; Kleven et al., 2022). However, the effect of childbirth on productivity is less understood due to the difficulty in finding great measures and data to assess this dimension. Separating the effects on productivity from the effects on employment and earnings is a true challenge.

The literature about child penalties on labor market outcomes is flourishing fast, but the findings about the mechanisms driving this phenomenon are still beginning. As stated by Kleven (2022), despite evidence ruling out explanations such as biology (Kleven et al., 2020b) and incentives created by government policy (Kleven et al., 2020a), no evidence conclusively rules in explanations. Our paper contributes to this literature by showing the importance of productivity, being the first, as far as we know, to show monthly dynamic effects on productivity measures related to cognitive work. Some research highlights productivity as a mechanism and its importance in explaining the gender wage gap but only accounts for productivity measures

[14] $\cong$ 12M of the 14.3M cases.

related to manual work.[15] Healy and Heissel (2022) explore the physical job performance of service members in the U.S. Marine Corps as a key precursor to productivity. They show negative impacts on parents' job performance two years after having a child, mainly among women.

There is evidence of changes in mothers' and fathers' job productivity across the transition to parenthood. Azmat and Ferrer (2017) show that female lawyers with young children are less productive than male lawyers with young children. Kim and Moser (2021) show evidence that highly educated women working as scientists are less productive during the childbearing years. They also have lower rates and slower speed promotion to tenure compared to fathers and other female scientists without kids. Gallen (2018) finds that mothers are substantially less productive than other workers, such as nonmothers, fathers, and nonfathers. We add to this literature by using monthly cognitive work performance, making us trace the dynamic effects of childbirth on productivity for mothers and fathers within the first year of work after becoming parents. Our contributions are also from the fact that we do not have selection problems since our setting provides a group of workers who do not decrease labor supply in response to childbirth. We show evidence that mothers return to previous productivity levels within the first year of parenthood if we net out the effects on employment and earnings.

We also contribute to the literature that studies public policies for boosting female labor force participation and reducing gender gaps (Kleven et al., 2020a). Our findings support the argument that the gender gap in labor market outcomes may not be solely solved through traditional government intervention. Since gender inequality would be driven mainly by equilibrium features of the labor market related to gender norms, culture (Bertrand, 2011; Kleven and Landais, 2017; Kleven et al., 2019a; Boelmann et al., 2021), and temporal flexibility of jobs (Goldin, 2014; Goldin and Katz, 2016), the solutions should account for their potential interaction with the formation of preferences and social norms regarding the family-career choices of men and women.

The paper is structured as follows. Section 2 details the institutional background and Section 3 describes the data. Section 4 presents the empirical strategy, and Section 5 examines the main results and related potential mechanisms. Section 6 concludes and Section 6 presents the tables and figures.

2 Institutional Background

2.1 Labor Market

Federal regulations govern the labor relations among firms and employees in Brazil. Job separations could happen unilaterally by the firm's will without the worker's approval (i.e.,

[15] We follow Autor et al. (2003) to classify cognitive and manual tasks. According to them, manual work demands physical activities, while cognitive work requires information processing, programming, creativity, and problem-solving.

"layoff") or by the worker voluntarily quitting (i.e., "quitting"). About 2/3 of all separations in Brazil from 2000 to 2018 are the first type, while the remaining cases are the second (Amorim et al., 2022). Among many benefits the formal worker is entitled to in Brazil (such as minimum wage, 13th monthly wage, 30 days of paid leave per year, and seniority account), there is Unemployment Insurance for workers dismissed against their will without a just cause.[16]

The employed worker in the formal sector has temporary stability (i.e., not being able to be dismissed without just cause) under 5 circumstances: if they suffer a work accident or injury due to their occupation; if they started the proceeding to retire; if collective bargaining agreement is taking place; if the worker is a union leader of the employees; and if the worker is pregnant. For the latter, women have stability from confirmation of pregnancy to five months after delivery. However, after this period, separations initiated by firms and workers increased. Figure 1a shows that many women quit after maternity leave, representing a lower female labor supply due to mothers unwilling to keep the same jobs. Figure 1b shows that many firms are reluctant to keep mothers after the maternity leave period, representing a lower female labor demand due to women displaced by firms. Different women's preferences could drive the supply side once they become mothers. The demand side could be caused by lower female productivity after childbirth.

The informality in the Brazilian labor market is as high as the other countries in Latin America due to the costs of formally hiring an employee and the low risk of detection (Gerard and Gonzaga, 2021; Ulyssea, 2018). 40.8% of all employed workers were in the informal labor market in 2017. The informality levels have been similar since 2012 and do not change much across gender: 40.8% of male employed workers and 40.7% of the female ones (IBGE, 2018).

2.2 Justice

The Brazilian Judiciary is divided into Common Justice (*Justiça Comum*) and Specialized Justice (*Justiça Especializada*). The former deals with civil and criminal cases, while the latter handles more specialized subjects. Common Justice is split into State and Federal Justice, and Specialized Justice comprises the Military, Electoral, and Labor Justices. These five branches of the judiciary system are structured in three instances: first, the judges; second, the court of appeals judges; and finally, the superior courts. These branches have a similar institutional model. At the bottom are the local courts called "*varas*". Above them, the local courts are grouped into courthouses called "*tribunais*". Then, we have the superior courts and the Brazilian Supreme Court at the top of the judicial system, regardless of the distinction between branches.

In contrast to other countries, judges are not elected in Brazil. They are admitted through a competitive civil service selection process that includes written and oral exams and the evaluation of academic and professional credentials. Recently admitted judges get an entry-level

[16]The current UI rules changed in 2015 (see Britto (2022) for analysis of the previous benefit rules). Nowadays, the monthly amount paid depends on the worker's average wage during the 3 months before the dismissal. The payment has a floor of 1 minimum wage (1,302.00 Brazilian Reais in 2023) and a ceiling of 2,230.97 Brazilian Reais. The benefit could be paid for 3 to 5 months, depending on how long the worker was employed.

position as substitute judges, responsible for working with or replacing regular judges on leave. Due to Article 95 of the Brazilian constitution,[17] the substitute judge gets a lifetime position after two years of tenure, ensuring no wage reductions[18] and low dismissal risks. There are only 6 possible disciplinary penalties that a judge with a lifetime position can get: warning; censorship; compulsory removal; availability with salaries proportional to the length of service; mandatory retirement with wages proportional to the length of service; and dismissal.[19] [20] Due to the lifetime status defined in the constitution, all the penalties against judges only can happen after a judicial action unless the judge is punished while being a substitute judge. The National Council of Justice (*Conselho Nacional de Justiça*, CNJ) is responsible for the administrative disciplinary control of judges. It evaluates judges' behavior, and it is responsible for their penalties.[21] To give a glimpse of how rare dismissal chances are, we show in Figure 2 all disciplinary processes judged by the CNJ from 2006 to 2020. Only 5 of the 118 suits resulted in dismissal, and in all of them, the judge did not have a lifetime position since her tenure was under 2 years.

When a regular judge position becomes vacant, the substitute judge with enough tenure and a good performance could be promoted to regular judge and assigned to the retired regular judge's local court. At the regular judge position, judges could be promoted to appellate judge by choice of the Brazilian president or by the governors from lists made by the other appellate judges in the courthouse. The superior courts and the supreme court members are chosen among the court of appeals judges by the president and approved by the Senate.

Judges are promoted via two criteria: seniority or merit.[22] Whether to assume administrative positions in the courts or to move to courts located in larger cities or higher courts, these two

[17]Link to the Brazilian constitution: https://normas.leg.br/api/binario/e4a41982-7e50-4627-a65c-0d1b6eea7a69/texto (Accessed on September 8. 2022).

[18]The initial salary is approximately BRL 26k per month and can reach up to BRL 39k, the ceiling stipulated for the position. In addition, there are some extra benefits that a judge could receive, such as food allowance, health allowance, pre-school allowance, moving allowance, funeral allowance, permanence allowance, vacation not taken, bonus for cumulative exercise, education allowance, bonus for a course or competition charge, Christmas bonus, birth allowance, housing allowance, an extra allowance for medical expenses regardless of the presentation of vouchers, money for the purchase of books, transportation allowance, indemnities. In the end, the judge's earnings can reach more than BRL 100k. Since the minimum wage in Brazil is around BRL 1k, judges are at the 99th percentile of the income distribution, receiving something between 20 and 100 times the minimum wage.

[19]Link to the complementary law that rules the subject: http://www.planalto.gov.br/ccivil_03/leis/lcp/lcp35.htm (Accessed on September 8. 2022).

[20]The definition of each penalty by order of severity: (1) Warning: applied in writing in the event of negligence in the performance of the duties of the office. (2) Censorship: the judge will not be able to participate in a merit promotion list for 1 year. (3) Compulsory removal: the judge is removed from the court where the illicit act was committed and transferred to another unit. (4) Availability with wages proportional to the length of service: removes the judge from their role and is prevented from performing other functions for 2 years, when the judge can request to return to work. (5) Mandatory retirement with wages proportional to the length of service: the maximum penalty in the administrative sphere, in which the judge can no longer act in the judiciary and receives remuneration proportional to the length of service. (6) Dismissal: applicable in the administrative scope only if the judges did not obtain the lifetime position; that is, they did not complete two years of career. For lifetime judges, it only occurs through a final and unappealable judicial decision.

[21]In addition, the courts in which the judges are linked have internal affairs that can carry out this disciplinary inspection.

[22]By law, these criteria are alternated when deciding which judge will be promoted. Link to the law: http://www.planalto.gov.br/ccivil_03/leis/lcp/lcp35.htm (Accessed on September 14, 2022).

criteria have to be obeyed. In promotion by seniority, the choice falls on the oldest judge, the one with the most extended service to the institution. Strictly speaking, the performance of the judge is disregarded. In promotion by merit, the objective of choice is to reach the name of the most deserving judge to access the position under dispute. Since a 2004 constitutional amendment,[23] the promotion by merit has to follow objective criteria of productivity, promptness in the exercise of jurisdiction, attendance, and success in official or recognized improvement courses. Although it is up to each courthouse to decide the exact details of the merit criteria, the majority of them use, as the productivity measure, the number of process sentences produced by the judge (Neto, 2009).

3 Data and Descriptive Statistics

3.1 Data

This section presents the data sources used according to their purpose in the paper. We start detailing the administrative registries we combined to link parents and children across generations. We also provide the main steps behind the linking process. Second, we introduce the justice datasets and explain how to connect our identified families with them. In addition, we describe the outcomes used from each of them and how they are constructed. Finally, we detail the official Brazilian employment registry and highlight the outcomes we recover from it.

3.1.1 Family Links

Three administrative registries are used in the family linking process:

Dependents' Claims: The Brazilian Tax Authority (*Receita Federal*) holds a Person Registry of all Brazilians with a registered CPF (*Cadastro de Pessoa Física*), Brazil's unique tax code identifier. This code is similar to the Social Security Number (SSN) in the United States. Almost every adult in Brazil has one because it is mandatory for many everyday tasks, such as opening bank accounts. Many kids also have CPF since this code is obligatory to hire a private health plan and claim the child a dependent[24] in tax filing. This Person Registry covers a large sample of the Brazilian adult population identified by CPF, including the full name, gender, date of birth, mother's full name, and the history of addresses of more than 250 million individuals. The Brazilian Tax Authority also maintains the administrative record of all dependents' claims in tax returns filled between 2006 and 2019. It provides a straightforward CPF-CPF pair of tax-filler parent and dependent child, similar to the dataset used by Chetty et al. (2014) to link generations of Americans. It is worth mentioning that, contrary to them,

[23] Constitutional Amendment nº 45, December 30, 2004. Link to the Amendment: http://www.planalto.gov.br/ccivil_03/constituicao/emendas/emc/emc45.htm (Accessed on September 8, 2022).

[24] 21 years old is the age limit to claim a child as a dependent in tax filing, and 24 years old is the age limit if the child is in college.

the link parent to the dependent child does not cover the whole population since usually the upper part of the income distribution in Brazil files tax and consequently claims dependents.

CadÚnico: The Federal Government maintains the *Cadastro Único* (CadÚnico), the administrative registry that tracks the socioeconomic conditions of low-income families from 2011 to 2020. The family is in CadÚnico if the family earns up to half a minimum wage per person or earns up to 3 minimum wages of total monthly income. This dataset also includes all individuals of every family that has ever been a beneficiary of a federal social welfare program in Brazil. With this dataset, we built a yearly panel with the information in CadÚnico from 2011 to 2020 containing the full name, gender, year of birth, race, addresses, mother's and father's full names, and income profiles of more than 110 million individuals identified by CPF. Also, we identify every individual by their NIS, an identification number designed explicitly for beneficiaries of social programs and the most reliable way to identify individuals in CadÚnico, given potential missing CPF information. Therefore, we merge CadÚnico with other administrative registries, such as Employment Registries (RAIS) and Tax Authority's Person Registry, to recover valid CPF numbers. We use NIS and a combination of full name and date of birth as keys to the merging process.

School Census: The school census is mandatory and filled by all public and private schools from 2008 to 2017. It contains detailed information on students and schools identified by a unique ID number. It can track children's enrollment, grades, class, demographic characteristics, and school characteristics. Parent-child links for students enrolled are available, for whom we have information on their student IDs in the School Census, full name, birth date, municipality of birth, and both parents' full names.

Concerning the family linking process, we follow three steps to build the parent-child links and execute them separately for mothers and fathers. First, we match the child's record in CadÚnico to their father's Person Registry record using the father's full name as the key. We follow two procedures. We begin merging children with only uniquely-named fathers, which is around 50% of the fathers' population, and then we also match children to males that have their father's full name and live at the same address as them. To avoid common misspellings and inconsistencies during the merge, we standardize all names and addresses across different administrative registries using some general conventions. As a result of the first step, from the usage of CadÚnico, we recover CPF-CPF pairs of children and fathers from the middle-lower part of the income distribution. The second step looks for males claiming their children as dependent from 2006 to 2019. These Dependents' Claims directly yield CPF-CPF pairs and complement CadÚnico's links in producing a representative sample since they cover mainly the upper part of the income distribution. We add the parent links directly available from the School Census in the third step.

The links between children with their mothers are built similarly to the fathers'. We begin matching children to uniquely-named mothers and complement matching children with females sharing the child's mother's full name and address. Then, we recover females claiming their child as dependent in tax returns and add the mother-child links directly available from the

School Census. However, we use extra information in the Person Registry to identify them. The mother's full name is available on the Person Registry, unlike the father's name. Therefore, we also recover mother-child links from the mother's name in the Person Registry.

As a result, the family linking process allows us to identify both father and mother for more than 60M children born from 1930 to 2020.

3.1.2 Justice data

We used two main justice datasets to link judges' outcomes of interest.

Monthly Productivity Module: The CNJ oversees the administrative and financial performance of the Brazilian Judiciary, in addition to controlling the fulfillment of duties by judges. It is also responsible for the official source of Judiciary statistics. One of them is the Monthly Productivity Module, a monthly panel since 2015 informing the amount of process sentenced by each Brazilian judge. The judges are identified by their full names, the type of the courthouses according to the branch of the Judiciary, the first instance courts, and the cities they are located.

We use the monthly amount of process sentences as our main productivity measure since it is the official definition of judge productivity used by CNJ to assess the judges' work. This is also the measure used to evaluate judges' productivity when they apply for promotion, one of the critical criteria for the decision. We only look for the data from 2015 to 2019 since it is the period when CNJ makes available the productivity measure for all the months of the year in each one of the courthouses' types. We are considering courthouses from three branches of the Brazilian Judiciary: Labor Justice, containing 24 courthouses and 2292 courts, Federal Justice, with 5 courthouses and 1512 courts, and State Justice, with 27 courthouses and 13109 courts.

Electronic Judicial Process: The CNJ developed a project in 2009 to maintain an electronic judicial process system capable of allowing the practice of procedural acts. The project's goal is to create the Electronic Judicial Process (PJe), a single system for the electronic processing of legal proceedings. This system allows judges, civil servants, and other procedural relationship participants to act and monitor the judicial process regardless of the physical interaction. In 2010, the Labor Justice officially adhered to the project, making all labor courthouses gradually migrate to use the system.

We had access to the Labor Justice PJe data, making available all case information on each suit in the system, such as the suit filing, hearing, and sentence dates; the case's charges; value claimed by the plaintiffs; the identification of each defendant and plaintiff by name and unique tax codes (i.e., CPF for the workers and CNPJ[25] for the firms); the court where the suit was filed; the judge of the case (identified by name and CPF); details of the sentence; indication if the suit was randomly assigned to the judge.

We use the PJe data to look at additional evidence of the effects of childbirth on productivity found in the CNJ data. We follow the same definition of CNJ to construct the monthly

[25]The CNPJ (*The Cadastro Nacional de Pessoa Jurídica*) is the unique tax code maintained by the Brazilian Tax Authority for all legal entities in Brazil.

productivity measure and link the judges to our family dataset using their CPF. Using the PJe data, we can assess if judges adjust their work to maintain constant productivity after maternity leave.

Other Crime Source: Kurier Tecnologia is a leading company providing information services to law firms all over Brazil. The company uses public case-level information available on the tribunals' websites and information from the courts' daily diaries to assemble a dataset of all criminal cases filed in all first-degree courts from 2009 to 2020. The dataset contains each case's start and termination date, court location, tags on the subjects being discussed, and defendant(s) and plaintiff(s) identified by their full name. We use the Kurier data to identify the precise timing when the court started having electronic processes. Therefore, we can assess the importance of remote work to reduce the child penalty for parents.

3.1.3 Labor Market

The *Relação Anual de Informações Sociais* (RAIS) is a Brazilian Government's registration of all employer-employee links between formal workers and formal firms in Brazil from 1985 to 2019. It contains information on each job spell, such as contracts' starting and ending dates, earnings, termination reason, and detailed employee demographic characteristics (e.g., date of birth, race, and education). Both workers and firms are identified by their full names and unique tax codes. We use RAIS to build a longitudinal administrative record of the Brazilian formal labor market from 2002 to 2019. Therefore, we can assess if a Brazilian worker is employed as a judge at a given moment, their earnings, wage and if they are absent due to maternity leave.

3.2 Descriptive Statistics

Judges are high-value jobs in Brazil, with strong employment stability and uniform work allocation (Dahis et al., 2020; Corbi et al., 2022). They are admitted through a competitive civil service selection process that includes the evaluation of academic and professional credentials. Therefore, people who end up as judges might be different from other workers. To provide evidence of how comparable people in the judicial profession are to other workers, we track in RAIS different types of workers employed at the end of 2016.[26]

Table 1 presents the results. The columns show the category of the worker's occupation and its mean and standard deviation for many variables. For each occupation type different from judges, we present the standard difference between that variable value for judges and for that category. We also show some information about the worker when they entered the formal labor market.[27]

The gender unbalance of women working as judges is close to full-time workers in Brazil. 39% of judges are female, while it is 42% for the full-time workers. Judges are high-educated

[26]We choose 2016 for simplicity. It is a year in CNJ data, and one year in RAIS already has much sample size to give a glimpse of workers' characteristics in Brazil.

[27]To track the information since the first time the worker appears in the labor market, we look at RAIS since 2002.

people with more than 16 years of schooling. The number is close to the years of study a random worker with a college degree in Brazil has.

People who end up as judges enter around 2 years later in the labor market compared to a formal worker in Brazil. Their last earnings are higher than the other categories, but they also start with higher wages ranging from 10 to 15 times the first earnings of any other worker in Brazil. Even though people that end up as judges do not necessarily begins their professional life as judges, they already start in high-payed jobs. Also, they have fewer jobs before their final occupation as judges when related to other professions. Judges have approximately 3 jobs throughout their life, while the other workers have something around 5. Employment stability is another thing that highlights this occupation. Once they become judges, workers have 15 years of tenure. This number is bigger even for the full-time public workers that have a tenure of 12 years.

Judges tend to work in developed cities, such as state capitals and cities in metropolitan regions. While 97% of judges work in state capitals, these places only employ 39% of the formal Brazilian workers. This disparity is smaller when we look at metropolitan regions. They employ 98% of the judges and 71% of the formal workers.

To provide more evidence about the judge profession in Brazil, we present in Table 2 descriptive statistics on the complete CNJ productivity data.[28] The judges in the CNJ dataset are identified by their full names. We keep only judges with unique names to avoid namesake judges when creating descriptive statistics. We identify them by checking the CPFs that appear in RAIS from 2003 to 2019 working as judges. Then, we merge them with the Brazilian Tax Authority's Person Registry, keeping the matched observation. Finally, we keep the judges in the CNJ data with unique names in this last sample. Since Brazilians often hold several last names, precise matches on names are feasible. From the 18063 names in the CNJ productivity data, 16140 are unique. Therefore, this dataset has more than 17 million observations at the judges-court-month level, 16 thousand judges, and 15 thousand courts.

As expected, some judges' demographic information is close to the ones presented in Table 1. Only 38% of judges are female, 47% are white, and they are hired as judges at the age of 31. Judges have high mobility across courts within the courthouse but very low mobility across courthouses.[29] Judges work in 15 courts per month but in only 1 courthouse. On average, judges sentence 130 times per month, similar to the total sentences produced in each court. Both judges and courts have similar values also for the number of months we observed them in the panel: 69 months. Almost 15 judges work in a single court per month, while more than 300 judges work in a single courthouse per month. 21% of the courts are dedicated to hearing civil cases, 13% to criminal, 11% to labor, and only 5% are responsible for federal suits.

[28]We follow some measures created by Dahis et al. (2020) to show descriptive statistics on the "old" CNJ productivity data. They used information from the Open Justice System (*Sistema Justiça Aberta*), an online platform maintained by the CNJ that was extinguished in 2015 and replaced by the Monthly Productivity Module. As stated by them, the new dataset is not strictly comparable to the data they use.

[29]This low mobility across courthouses makes sense since each courthouse has its competitive civil service selection process.

4 Empirical Strategy

4.1 Main Specification

We exploit sharp changes around childbirth to study the impact of having a child on productivity. As elucidated by Kleven et al. (2019b), although fertility choices are not exogenous, the event of having a child creates significant changes in labor market outcomes that are orthogonal to unobserved determinants of those outcomes as they should evolve. In other words, although the decision to have a child is endogenous, the precise timing of conception and childbirth serves as a shock to labor market outcomes and productivity. Therefore, the event study approach is suitable for tracing the dynamic trajectory of the effects, exploiting individual-level variation at the time of birth.

Our individual-level data on family links and judge productivity cover 2015-2019. To implement a difference-in-differences strategy, we follow an approach similar to Britto et al. (2021) and Britto et al. (2022). We select as our treatment group all judges that had their first child in 2016, which allows us to estimate dynamic treatment effects for up to two years after conception and placebo effects up to one year before conception. The candidate control pool comprises all judges who had their first child in 2019. We then match each treated judge with a controlling parent who (i) has the same gender, (ii) works at the same courthouse, and (iii) is the one with the nearest birth date to the treated candidate.

In practice, we estimate the following difference-in-differences equation on the sample of treated and (matched) control parents:

$$Y_{it} = \sum_{\tau=-k}^{K} \beta_\tau \left(Treat_i \times Time_\tau\right) + \delta_i + \lambda_t + \epsilon_{it} \tag{1}$$

Parents are identified by the subscript i, and $Treat_i$ is a dummy indicating that the parent belongs to the treatment group. $Time_\tau$'s are dummies identifying months since conception, which we can define very precisely because of the exact dates of childbirth reported in our data. Therefore, $\tau = 0$ for the month of conception, $\tau = 9$ for the month of childbirth, and so on. Thus, the coefficients $\{\beta_0, ..., \beta_T\}$ identify dynamic treatment effects, whereas $\tau = -1$ is the baseline omitted period and $\{\beta_{-k}, ..., \beta_{-2}\}$ estimate anticipation effects. Finally, δ_i and λ_t are parent and period fixed effects, respectively. We cluster the standard errors at the control judge level. Since the same control judge could be matched to more than one treated judge, we allow any correlation in the error term among the treated judges and the control judge matched to them.

4.2 Alternative Specifications

We run other matching and clustering strategies to show the consistency of the results.[30] Related to the matching procedures, we always keep step (i), so we can compare mothers to eventual

[30] We present them in Section 5.2.

mothers and fathers to eventual fathers. However, we selected treated and control units from different childbirth years and chose other steps after the first.

One exercise consists in keeping as the treatment group judges giving birth in 2016, while the control group is defined via 3 different matching periods. These three groups are judges conceiving a baby during the first year after the childbirth of the treated judge,[31] judges conceiving a baby during the second year after the childbirth of the treated judge,[32] and judges giving birth in 2018.

We also replicate our main analysis but only change step (ii). Instead of looking at judges that work at the same courthouse, we match each treated judge with a controlling parent who works in a courthouse of the same Brazilian judiciary branch.[33] In another exercise, we match each treated judge with a controlling parent who works in a courthouse in the same state.

Finally, we do other strategies that do not restrict the childbirth years of potential treated and control judges to a single year. First, we select as our treatment group all judges that had their first child in 2016 or 2017, and the candidate control pool comprises all judges who had their first child in 2018 or 2019. Then, we replicate steps (i) and (ii) and keep as remained potential controlling the ones that conceive a baby after the first year post the childbirth of the treated judge.[34] Finally, among them, we select as the controlling judge the one with the most distant birth date from the treated judge within a 3-year bandwidth.[35] We replicate the same steps mentioned before but only change the procedure after steps (i) and (ii). We allow to keep as remained potential controlling the ones that conceive a baby after one and a half year post the childbirth of the treated judge,[36] so we can have more 6 months of estimations to look without any contamination concerns.

Related to the other clustering strategies, we assume 3 different assumptions to the Standard Errors. First, we cluster at the parent fixed effects level, assuming that errors are correlated within each parent cluster across time. Second, we assume that errors are heteroskedastic, using the White correction. Third, we assume that the errors are homoskedastic and not correlated. For each one of the other matching and clustering strategies, the results are consistent with the ones from the main analysis.

4.3 Specification for the other Occupations

To show that the no effect on productivity and labor market outcomes is not exclusive to judges, we show that the child penalty on productivity, employment, and earnings does not exist for other workers with fixed labor demand. Also, we show that people similar to judges but in the

[31] From the 21st to the 33rd month after the treated conception month.

[32] From the 33rd to the 45th month after the treated conception month.

[33] As shown in Section 3.1.2, the CNJ productivity data comprises courthouses of the following branches of the Brazilian judiciary: Labor Justice, Federal Justice, and State Justice.

[34] From the 21st month after the treated conception month onwards.

[35] We selected a 3-year bandwidth because it is the mean distance between birth dates among treated and control parents in the main analysis strategy.

[36] From the 27th month after the treated conception month onwards.

private sector face indeed child penalty, indicating that the no effects found for the judges are due to the security of the occupation itself and not due to the people that became judges being special.

To do so, first, we look to self-employed lawyers, a class of workers in the same area of the judge occupation whose labor demand does not depend on any firm in Brazil. Using the PJe dataset, we identify as self-employed lawyers all lawyers working in cases from 2015 to 2019 who are not employed in RAIS through this same period. We select as our treatment group all lawyers that had their first child in 2016, and the candidate control pool comprises all lawyers who had their first child in 2019. We then match each treated lawyer with a controlling parent who (i) has the same gender, (ii) is located in the same municipality according to the Tax Revenue data, and (iii) is the one with the nearest birth date to the treated candidate. Then, we run for them the equation equal to Equation 1, but looking at two outcomes in the PJE data that would proxy the lawyer's productivity: the number of new cases and the number of won cases.

Second, we consider individuals working in different occupations in the formal sector to highlight that for the professions in the public sector with similar job security as the judges, there are no child penalties in earnings and employment; and for people similar to judges but in the private sector, the child penalties still exist. Therefore, to identify people in the formal sector in different occupations, we select the individuals employed at the end of 2013, 2014, or 2015 in RAIS working in the professions of interest. Then, following Britto et al. (2022), for each of these years, we select as our treatment group the individuals that had their first child in the next year, and the candidate control pool comprises all individuals in the same occupation who had their first child 3 years after the treatment group. We then match each treated individual with a controlling parent who (i) has the same gender, (ii) works at the same municipality according to the RAIS information, (iii) belongs to the same annual birth cohort, (iv) has the same presence status in RAIS during the previous year of treated parent childbirth,[37] (v) has the same presence status in CadÚnico during the previous year of treated parent childbirth,[38] (vi) has the same schooling level.[39] When treated parents are matched with multiple controls, one control unit is randomly selected. Then, we run the equation equal to Equation 1.

We also consider as individuals similar to judges in the private sector their siblings and cousins since they would share the same family background. To identify them, first, we select all judges registered in RAIS from 2003 to 2019. Then, using our family linking process, we can go up and down in the judges' family tree, making it possible to identify their siblings and cousins. Therefore, we flag these individuals in our sample of workers employed in RAIS at the end of 2013, 2014, or 2015. Next, for each of these years, we select as our treatment group

[37] It is a dummy variable indicating 1 if the person is in RAIS during the previous year of treated parent childbirth.

[38] It is a dummy variable indicating 1 if the person is in CadÚnico during the previous year of treated parent childbirth.

[39] Schooling level is measured by a dummy variable indicating 1 if the person has at least 13 years of education, meaning that the individual has some college education.

the siblings or cousins that had their first child in the next year, and as the candidate control pool consisting of all individuals that are nonsiblings and noncousins who had their first child 3 years after the treatment group. We then match each treated individual with a controlling parent who (i) has the same gender, (ii) works at the same municipality according to the RAIS information, (iii) belongs to the same annual birth cohort, (iv) has the same presence status in RAIS during the previous year of treated parent childbirth, (v) has the same presence status in CadÚnico during the previous year of treated parent childbirth, (vi) has the same schooling level, (vii) have the same occupation.[40] [41] When treated parents are matched with multiple controls, one control unit is randomly selected. Then, we run the equation equal to Equation 1.

5 Results

5.1 Main Results

5.1.1 Productivity and Labor Market

Figure 3 shows the effect of childbirth on productivity.[42] Table 3 presents the descriptive statistics of the final sample after the matching procedure used in the main analysis. We find that the difference in productivity for fathers and mothers between treatment and control groups is stable in the pre-conception period, supporting the common-trend assumption. After conception, fathers' productivity remains significantly unchanged. In contrast, the mother's productivity declines significantly right before birth, but the gap closes very quickly after the end of the maternity leave period.

The short-lived reduction in productivity for mothers right after maternity leave seems to be a natural catching up of the mechanical effect mothers face during the maternity leave for being work absent.[43] Figure 4 shows evidence of our hypothesis. Using RAIS data, we show the effects of childbirth on judges being absent from work due to maternity leave or any request.

[40] In RAIS, occupations are classified following the Brazilian Classification of Occupations (*Classificação Brasileira de Ocupações*, CBO), a 6-digit code. Each number, from left to right, indicates more and more details about the occupation. For example, the code 225124 indicates that: 2 is for the science and arts professionals; 22 is for professionals in biological, health, and related sciences; 225 is for medicine professionals; 2251 is for clinical doctors; and 225124 is for pediatricians. To have a higher matching chance, we consider only the first 3-digits of the CBO.

[41] Before the matching process, we restrict the treated and potentially controlling parents to individuals that are not judges.

[42] As identified by Dahis et al. (2020) when looking at the "old" CNJ productivity data, we also find clear instances of incorrect entries for the productivity variable. There are judges sentencing hundreds of thousands of cases in a single month. Therefore, we drop a judge before the matching if they are sentencing in any month in the 99th percentile of the productivity measure distribution. The 99th percentile is 1512 sentences in a single month.

[43] By law, female judges can take 120 days of maternity leave with no monetary deduction, with the possibility of a 60-day extension if requested. The break could start on the day of birth, on the first day of the ninth month of pregnancy, or before if following medical needs. Male judges can also take paternity leave with no monetary deduction. The break is of 5 days beginning from the day of birth and can be extended for more 15 days if requested. Link to the law: https://www.csjt.jus.br/c/document_library/get_file?uuid=1040cbb5-f5b9-46b5-95d3-1e3e43d65133&groupId=955023 (Accessed on September 10, 2022).

We also display the probability of zero sentencing by the judge since they would not be working during the break. The graphs show an increase in the outcomes right before the 8th-month post conception and a return to previous levels after the maternity leave period.

Figure 5 shows the effect of childbirth on labor market outcomes. As expected, due to judges' lifetime occupation, we find no child penalty on employment and earnings for mothers and fathers. The slight decrease in mothers' earnings during the maternity leave period makes sense since they are likely to be not working,[44] and judges have extra earnings benefits related the daily work activity, as detailed in Section 2.

5.1.2 External Validity

The no effect on productivity and labor market outcomes is not exclusive to judges. In other words, judges are not the only group that these results are true. We show that the child penalty on productivity, employment, and earnings does not exist for other workers with fixed labor demand.

Figure 6 shows the effect of childbirth on the productivity of self-employed lawyers, a class of workers in the same area of the judge occupation whose labor demand does not depend on any firm in Brazil. We find no effect on the proxies of productivity we considered: the number of new cases and the number of won cases. Figure 7 shows the childbirth effects on the labor outcomes of public sector workers, a class of workers with fixed labor demand due to their job security. We find that public sector workers have fewer child penalties as their earnings increase, with no child penalty for the bureaucrats above the first quartile.

Also, we show in Figure 8 that people similar to judges but in the private sector face indeed child penalty, indicating that the no effects found for the judges are due to the security of the occupation itself and not due to the people that became judges being special. Judges' siblings, cousins, workers with college degrees, lawyers in the private sector, and private workers that earn as much as judges face decreases in employment and earnings when they have a kid.

5.1.3 Mechanisms

Many factors in our setting could explain the constant productivity of parents after the maternity leave period. The literature on remote work has identified higher job performance, work satisfaction, and worker retention as benefits of remote work (Bloom et al., 2015; Choudhury et al., 2021; Angelucci et al., 2020). The flexibility of "smart-working" increases workers' productivity and improves their well-being and work-life balance, with stronger effects for women (Angelici and Profeta, 2020).

We test the role of technology in our setting by the existence of digital cases in the court the judge works. Digital judicial cases could increase smart working ability, making parents net the child penalty out once they know they will have a baby. Figure 9 shows the heterogeneous effect of childbirth on productivity due to the electronic process in the court where the judge works.

[44] As shown in Figure 4.

We find that remote work makes parents attenuate the child penalty, especially during the maternity leave period for mothers. Using the PJe platform has similar effects. Figure 10 shows the heterogeneous effects of childbirth on productivity due to a single system for electronic processing legal proceedings.[45]

Another factor could be the reallocation of judges to larger cities with better services when they discover that they will have a baby in the future, following the finding of the literature on migration that people tend to move to places with better welfare conditions when their family status changes (Meyer et al., 1998; Borjas, 1999; Kennan and Walker, 2011).[46] Since the mother will need more medical attention through the gestation period, it would be reasonable that they move to places with better health infrastructure.[47] Also, to attenuate the burden of raising the child, they would prefer regions that provide more access to child care and nannies.[48]

Using the CNJ dataset, we can check the precise location (in terms of the municipality) the judge was working in a given month. Therefore, Figure 11 shows the effects of childbirth on migration, where we use the probability of the court the judge most produce sentence is located in a metropolitan region as an outcome. We find that after conception, mothers tend to work more intensely in courts located in economically developed areas.

5.2 Robustness exercises

5.2.1 Other matching and clustering strategies

Figure 12 shows the effect of childbirth on productivity using the CNJ dataset but with different periods to define the control group. We keep as the treatment group judges giving birth in 2016, while the control group is defined via 3 different matching periods. These three groups are judges conceiving a baby during the first year after the childbirth of the treated judge,[49] judges conceiving a baby during the second year after the childbirth of the treated judge,[50] and judges giving birth in 2018. We also present the matching results of our main analysis, which defines the control group of judges giving birth in 2019. Note that independent of the choice of the period for the control group, the results are consistent.

Figure 13 replicates our main analysis changing step (ii). Instead of looking at judges that work at the same courthouse, we match each treated judge with a controlling parent who works in a courthouse of the same branch of the Brazilian judiciary.[51] In another exercise, we match each treated judge with a controlling parent who works in a courthouse in the same state. For

[45] Since we only have detailed data from PJe to labor courts, we restrict our sample from the CNJ dataset to courts of the Labor branch.

[46] The search for better living conditions is not restricted to low-earners (Kleven et al., 2013, 2014).

[47] In 2022, while 36% of private hospitals are located in large Brazilian cities with over 500 thousand people, only 13% are in small towns with a population under 20 thousand people (FBH and CNSaude, 2022).

[48] More than 70% of the cities in 6 Brazilian states in 2020 did not have private daycare centers. Even in the most developed state of Sao Paulo, 47% of the cities do not have nurseries (Exame, 2021).

[49] From the 21st to the 33rd month after the treated conception month.

[50] From the 33rd to the 45th month after the treated conception month.

[51] As shown in Section 3.1.2, the CNJ productivity data comprises courthouses of the following branches of the Brazilian judiciary: Labor Justice, Federal Justice, and State Justice.

both, the results are similar to our main analysis.

We display in Figure 14 the other strategies that do not restrict the childbirth years of potential treated and control judges to a single year. First, we select as our treatment group all judges that had their first child in 2016 or 2017, and the candidate control pool comprises all judges who had their first child in 2018 or 2019. Then, we replicate steps (i) and (ii) and keep as remained potential controlling the ones that conceive a baby after the first year post the childbirth of the treated judge.[52] Finally, among them, we select as the controlling judge the one with the most distant birth date from the treated judge within a 3-year bandwidth.[53] We replicate the same steps mentioned before but only change the procedure after steps (i) and (ii). We allow to keep as remained potential controlling the ones that conceive a baby after one and a half year post the childbirth of the treated judge,[54] so we can have more 6 months of estimations to look without any contamination concerns. Note that independent of the choice of the period, the results are consistent.

Figure 15 shows the other clustering strategies. We assume 3 different assumptions to the Standard Errors. First, we cluster at the parent fixed effects level, assuming that errors are correlated within each parent cluster across time. Second, we assume that errors are heteroskedastic, using the White correction. Third, we assume that the errors are homoskedastic and not correlated. For each one of the clustering strategies presented, the results are consistent with the ones from the main analysis.

5.2.2 Adjustment over the productivity margins

It would be worrying if judges adjusted their work over productivity margins to maintain constant productivity after the maternity leave. They could be selecting cases or judging differently to keep their productivity levels unchanged once they know they will have a baby. To provide evidence on these aspects, we use detailed data on labor courts from PJe.

First, we show in Figure 16 that the effect of childbirth on productivity using the PJe dataset is similar to the ones in our main analysis. The difference in outcomes between treatment and control groups is stable in the pre-conception period, supporting the common-trend assumption. After conception, fathers' productivity remains significantly unchanged. In contrast, the mother's productivity declines significantly right before birth, and the gap closes very quickly after the end of the maternity leave period.

The institutional settings in the Brazilian judiciary leave little room for case selection by the judges. Figure 17 shows the heterogeneous effect of childbirth on productivity due to randomness of suit assignment. In the PJe data, the cases that are not randomly assigned to judges represent only 16% of the sample.[55] Even when cases are not randomly assigned to judges, the dynamic of the effects is similar to the previous patterns we found. The difference in outcomes between

[52] From the 21st month after the treated conception month onwards.

[53] We selected a 3-year bandwidth because it is the mean distance between birth dates among treated and control parents in the main analysis strategy.

[54] From the 27th month after the treated conception month onwards.

[55] $\cong$ 2.3M of the 14.3M cases.

treatment and control groups is stable in the pre-conception period, supporting the common-trend assumption. After conception, fathers' productivity remains significantly unchanged, and the gap closes very quickly after the end of the maternity leave period for the mothers.

We also assess if the judge sentences more intensely cases with some particular characteristics. Figure 18 shows the effect of childbirth on different case characteristics, such as the initial value claimed by the plaintiff in the process, the number of charges discussed in the case, the number of plaintiffs, and the number of defendants. Then, we look if judges change the type of case they sentence the most. For this, we follow Britto et al. (2023) and aggregate the main issues for suing in the PJe dataset in 9 different categories.[56] Figure 19 shows the results for the probability of the cases sentenced to be in each one of these groups. For both figures, there is no evidence that judges select cases with some particular characteristics due to childbirth.

The effects of childbirth on productivity could be different due to the case's complexity since it would be harder to analyze and need more attention from the parent. Therefore, we look at the heterogeneous effects due to some case characteristics that would proxy the case's difficulty. Figure 20 examine the importance of the number of charges in the process, Figure 21 assess the relevance of the number of defendants, and Figure 22 focus on initial value claimed by plaintiffs. For all of them, there is no evidence that the complexity of the case plays an important role in the effects of childbirth on productivity.

Childbirth could also affect how judges sentence the cases when they become parents. Figure 23 shows the results on case outcomes, such as the types of verdicts and the amount the defendants should pay to the plaintiffs as a result of the sentence. It seems that mothers became more prone to sentence cases as settlements and less inclined to give partial win decisions. Fathers do not change their decision patterns.

However, judges could be producing sentences with less quality. But this not seems to be the case. Figure 24 shows the results for the probability that a case sentenced by the judge goes to appeals courts. Their decisions are not contested more frequently after childbirth. Also, the judges could be taking longer to produce their decisions. Figure 25 displays the effects on the duration of the cases, which seems to be not affected too.

6 Conclusion

We explore the sharp changes around childbirth to study the impact of having a child on productivity. We provide evidence from a unique setting that holds constant all the other possible mechanisms for child penalty on labor outcomes. Due to the institutional context in Brazil, choosing the occupation of judge overcomes all the practical difficulties in assessing the impacts of childbirth on work performance since they have relevant official productivity measures and fixed labor demand.

[56]The categories are: Worker's registration; Firm's social contributions, such as pensions, taxes, and withholdings; Hours, such as overtime, vacation, etc.; Cash and in-kind mandated benefits; Payments at separation; Unemployment insurance; Other separation issues; Civil prosecution; Other subjects.

We implement a dynamic difference-in-difference approach using our individual-level data on family links and judge productivity measures from 2015 to 2019. We find that fathers' productivity remains significantly unchanged while mothers' productivity declines significantly right before birth, and the gap closes very quickly after the end of the maternity leave period. As expected, given the lifetime status for the judge occupation, there is no child penalty on employment and earnings for mothers and fathers. The short-lived reduction in productivity for mothers right after maternity leave seems to be a natural catching up of the mechanical effect mothers face during the maternity leave for being work absent.

The no effect on productivity and labor market outcomes is not exclusive to judges. We show that the child penalty on productivity, employment, and earnings does not exist for other workers with fixed labor demand. First, we show that self-employed lawyers do not have decreases in proxies of productivity when they have a child. Second, public sector workers have fewer child penalties as their earnings increase, with no child penalty for the bureaucrats above the first quartile. Also, we show that people similar to judges but in the private sector face indeed child penalty, indicating that the no effects found for the judges are due to the security of the occupation itself and not due to the people that became judges being special. Judges' siblings, cousins, workers with college degrees, lawyers in the private sector, and private workers that earn as much as judges face decreases in employment and earnings when they have a kid.

Regarding policy recommendations, our results suggest that the child penalties may not be driven by lower productivity since we do not have permanent changes in work performance for mothers in a setting that holds constant all the other possible mechanisms. Therefore, to design effective policies to reduce gender inequality in the labor market, the gender disparities may not be solely solved through government interventions that focus primarily on boosting mothers' productivity, such as better parental leave schemes and childcare subsidies (Kleven et al., 2020a). The solutions should rest in accounting for the role of social norms in the workplace (Cullen and Perez-Truglia, 2023), focusing on family-career choices of women and discrimination in the work environment.

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Tables and Figures

Table 1: Descriptive statistics of judges and other occupation categories

	Judges		Formal Workers			Workers with College			Full-time Workers			Full-time Private Workers			Full-time Public Workers		
	Mean	SD	Mean	SD	Std Diff	Mean	SD	Std Diff	Mean	SD	Std Diff	Mean	SD	Std Diff	Mean	SD	Std Diff
Female	0.39	0.49	0.44	0.50	0.08	0.59	0.49	0.39	0.42	0.49	0.06	0.40	0.49	0.02	0.55	0.50	0.31
White	0.48	0.50	0.54	0.50	0.13	0.65	0.48	0.35	0.54	0.50	0.12	0.56	0.50	0.16	0.44	0.50	-0.07
Schooling	16.14	0.73	11.78	3.13	-1.92	16.11	0.66	-0.04	11.67	3.10	-1.98	11.53	2.83	-2.23	13.00	3.31	-1.31
Last Age	31.84	6.67	32.26	10.24	0.05	32.27	8.90	0.05	32.34	10.21	0.06	32.43	10.31	0.07	31.27	9.23	-0.07
First Age	28.47	5.97	26.23	8.84	-0.30	26.08	7.53	-0.35	26.23	8.84	-0.30	25.83	8.88	-0.35	27.56	8.04	-0.13
Last Earning	29162.82	3540.42	2493.46	3277.38	-7.82	5476.96	5804.90	-4.93	2494.96	3301.29	-7.79	2162.08	2855.89	-8.39	4169.85	4579.22	-6.11
First Earning	20380.36	12082.49	1474.03	2204.09	-2.18	2870.68	4076.25	-1.94	1467.57	2200.31	-2.18	1302.79	1853.97	-2.21	2294.02	3335.41	-2.04
Tenure	15.02	9.19	5.53	7.16	-1.15	8.10	8.74	-0.77	5.43	7.05	-1.17	3.94	5.08	-1.49	12.46	10.00	-0.27
Spells	3.38	2.04	4.97	4.12	0.49	5.52	3.49	0.75	4.98	4.13	0.49	5.12	3.56	0.60	4.34	2.84	0.39
State Capital	0.97	0.17	0.39	0.49	-1.58	0.53	0.50	-1.17	0.39	0.49	-1.58	0.38	0.49	-1.62	0.53	0.50	-1.19
Met. Region	0.98	0.16	0.71	0.45	-0.78	0.78	0.41	-0.62	0.71	0.45	-0.77	0.74	0.44	-0.72	0.70	0.46	-0.80
Population	4310538.71	4334939.31	2177002.36	3730509.79	-0.53	2997846.30	4262622.18	-0.31	2202017.20	3758981.48	-0.52	2291535.12	3857957.66	-0.49	2226993.18	3561855.76	-0.53
GDP per capita	41098.01	13333.39	37235.21	24189.39	-0.20	40449.71	25504.44	-0.03	37429.06	24344.67	-0.19	38596.25	24586.62	-0.13	33900.62	23576.66	-0.38
Observations	15888		44186742			8758186			42001582			32169595			6739542		

Notes: This table shows descriptive statistics of workers employed in RAIS at the end of 2016. The columns show the category of the worker's occupation and its mean and standard deviation for many variables. For each occupation type different from judges, we present the standard difference between that variable value for judges and for that category. The 6 occupation categories are Judges; Formal Workers (i.e., any worker in RAIS); Workers with College (i.e., workers with at least 16 years of schooling); Full-time Workers (i.e., workers that work more than 30 hours per week); Full-time Private Workers (i.e., Full-time workers working in the private sector); Full-time Public Workers (i.e., Full-time workers working in the public sector). We look at 13 different variables: Female (i.e., dummy = 1 if the worker is female); White (i.e., dummy = 1 if the worker is white); Schooling (i.e., years of education the worker have the moment they were hired at the job they are employed at the end of 2016); Last Age (i.e., age the worker have the moment they were hired at the job they are employed at the end of 2016); First Age (i.e., age the worker have the first time they appear in RAIS); Last Earning (i.e., earning the worker have the moment they were hired at the job they are employed at the end of 2016); First Earning (i.e., earning the worker have the first time they appear in RAIS); Tenure (i.e., time between hiring date and dismissal/retirement date of the worker for the job they are employed at the end of 2016); Spells (i.e., number of job spells the worker have since the first time they appear in RAIS); State Capital (i.e., dummy = 1 if the worker is working in a state capital at the job they are employed at the end of 2016); Met. Region (i.e., dummy = 1 if the worker is working in a metropolitan region at the job they are employed at the end of 2016); Population (i.e., the population of the city the worker is working at the job they are employed at the end of 2016); GDP per capita (i.e., the GDP per capita of the city the worker is working at the job they are employed at the end of 2016). To track the information since the first time the worker appears in the labor market, we look at RAIS since 2002. All monetary variables are in Brazilian Reais at 2015 price levels.

Table 2: Descriptive statistics of the complete CNJ productivity data

	Mean	SD	Observations
Panel A: Judges			
Female	0.38	0.49	
White	0.47	0.50	
Age	31.11	6.14	
# Courts by judge	15.62	20.14	
# Courthouse by judge	1.04	0.20	
# Months by judge	69.67	0.92	
Productivity at judge-month level	130.82	179.11	
Panel B: Courts			
# Judges by court	15.89	20.96	
# Months by court	69.72	0.85	
Productivity at court-month level	133.14	249.80	
Civil courts	0.21	0.41	
Criminal courts	0.13	0.34	
Labor courts	0.11	0.32	
Federal courts	0.05	0.23	
Panel C: Courthouses			
# Judges by courthouse	305.11	396.97	
# Months by courthouse	69.69	0.86	
Productivity at courthouse-month level	38393.97	65115.13	
Panel D: General Information			
Judges			16140
Courts			15860
Courthouses			55
Judge-court pairs			252032
Judge-courthouse pairs			16781
Judge-court-month pairs			17642240
Judge-courthouse-month pairs			1174670

Notes: This table shows descriptive statistics of the complete CNJ productivity data. We follow some measures created by Dahis et al. (2020) in the analysis of the "old" CNJ productivity data. Since the judges in the CNJ dataset are identified by their full names, we keep only judges with unique names to avoid namesake judges when creating descriptive statistics. We identify them by checking the CPFs that appear in RAIS from 2003 to 2019 working as judges. Then, we merge them with the Brazilian Tax Authority's Person Registry, keeping the matched observation. Finally, we keep the judges in the CNJ data with unique names in this last sample. Since Brazilians often hold several last names, precise matches on names are feasible. The columns show the mean, standard deviation, and the number of observations. The variable that the name is not self-explanatory are: Female (i.e., dummy = 1 if the judge is female); White (i.e., dummy = 1 if the judge is white); Age (i.e., age the judge has the moment they were hired as a judge); Civil courts (i.e., dummy = 1 if the court is dedicated to hearing civil cases); Criminal courts (i.e., dummy = 1 if the court is dedicated to hearing criminal cases); Labor courts (i.e., dummy = 1 if the court is dedicated to hearing labor cases); Federal courts (i.e., dummy = 1 if the court is dedicated to hearing federal cases).

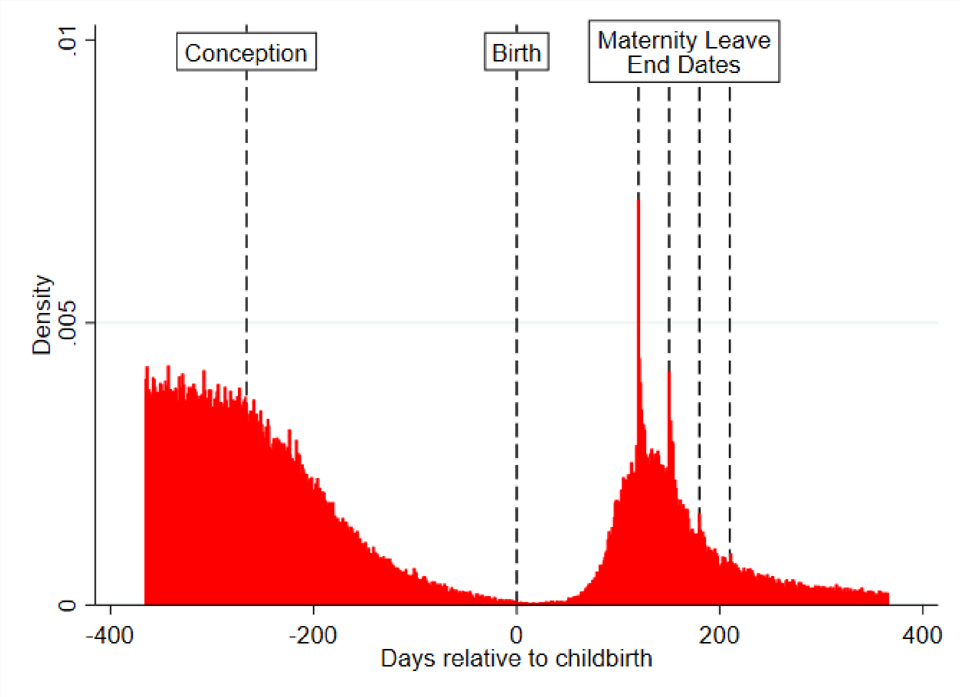
Table 3: Descriptive statistics of treated and control units in the main analysis sample

	Male					Female				
	Control		Treat			Control		Treat		
	Mean	SD	Mean	SD	Std Diff	Mean	SD	Mean	SD	Std Diff
Employed	1.00	0.00	1.00	0.00		1.00	0.00	1.00	0.00	
Earnings	29470.95	3277.22	29554.75	3042.45	-0.03	29016.35	2572.06	29226.03	2108.47	-0.09
Wage	25853.89	6604.45	25451.15	7698.92	0.06	23588.84	9367.02	24129.38	9247.18	-0.06
Process Sentences	116.52	147.25	118.28	112.60	-0.01	119.11	150.02	119.17	129.03	0.00
Work in State Capital	0.95	0.23	0.98	0.15	-0.16	0.92	0.27	0.92	0.27	0.01
Work in Met. Region	0.97	0.16	0.96	0.19	0.05	1.00	0.00	1.00	0.00	
Schooling	16.26	0.77	16.21	0.72	0.08	16.10	0.43	16.08	0.40	0.04
Year of Birth	1976.80	5.37	1976.22	6.49	0.10	1979.81	3.23	1978.71	3.74	0.32
Year of Hiring	2007.16	5.42	2006.09	6.60	0.18	2009.14	3.96	2007.43	4.58	0.40
White	0.46	0.50	0.50	0.50	-0.09	0.31	0.47	0.42	0.50	-0.23
Observations	194		194			104		104		

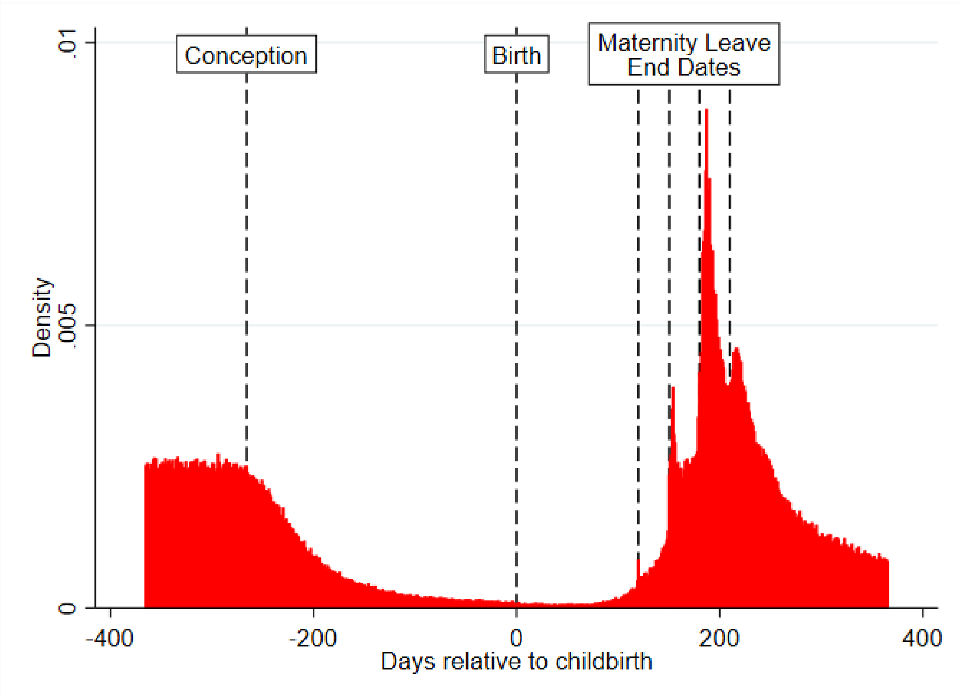
Notes: This table shows descriptive statistics of the final sample after the matching procedure used in the main analysis. The columns show the mean, standard deviation, and standard difference for many variables by treatment status and gender. We look at 10 different variables at t = -1: Employed (i.e., dummy = 1 if the judge is employed); Earnings (i.e., the judge's earnings); Wages (i.e., the judge's wage); Process Sentences (i.e., the judge's productivity measure); Work in State Capital (i.e., dummy = 1 if the judge is working in a court located in a state capital); Work in Met. Region (i.e., dummy = 1 if the judge is working in a court located in a metropolitan region); Schooling (i.e., years of education the judge had the moment they were hired); Year of Birth (i.e., the year the judge was born); Year of Hiring (i.e., the year the judge was hired as a judge); White (i.e., dummy = 1 if the judge is white). All monetary variables are in Brazilian Reais at 2015 price levels.

Figure 1: Dismissals around childbirth for female workers in Brazil

(a) Quittings around childbirth



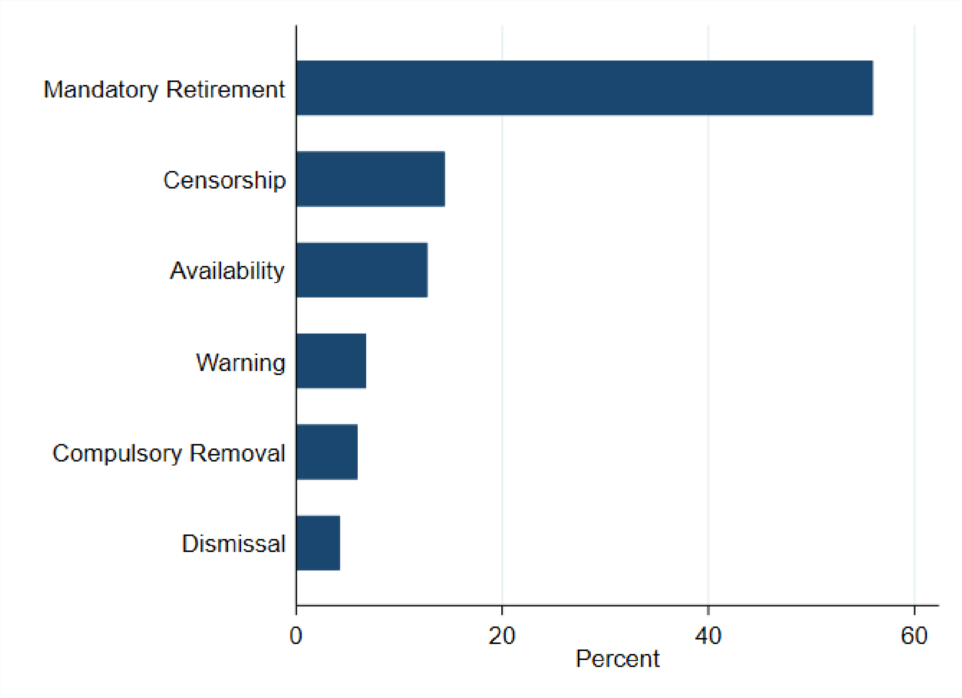
(b) Layoffs around childbirth



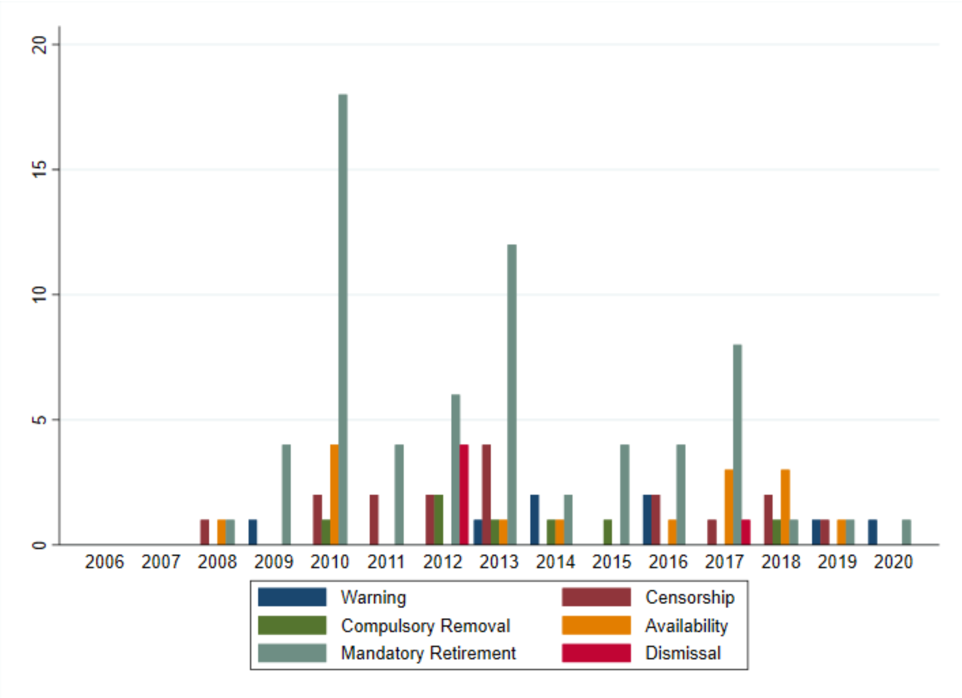
Notes: This figure shows the dismissals of female workers around childbirth. We look at the distribution of dismissals within 1-year bandwidth around childbirth for mothers in RAIS from 2014 to 2019. The vertical lines represent, respectively: the conception moment, the childbirth, the 4th month after birth, the 5th month after birth, the 6th month after birth, and the 7th month after birth.

Figure 2: Disciplinary penalties applied to judges

(a) Distribution of disciplinary penalties applied to judges

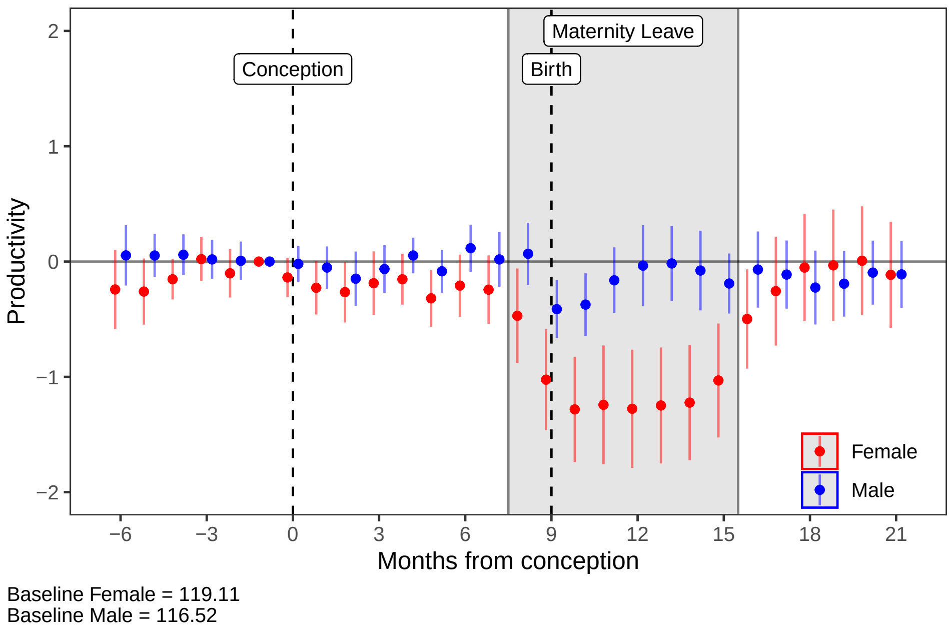


(b) Timeline of disciplinary penalties applied to judges



Notes: This figure shows all the disciplinary penalties applied to judges by the CNJ from 2006 to 2020. All the dismissals were applied to substitute judges with no lifetime position due to tenure shorter than 2 years.

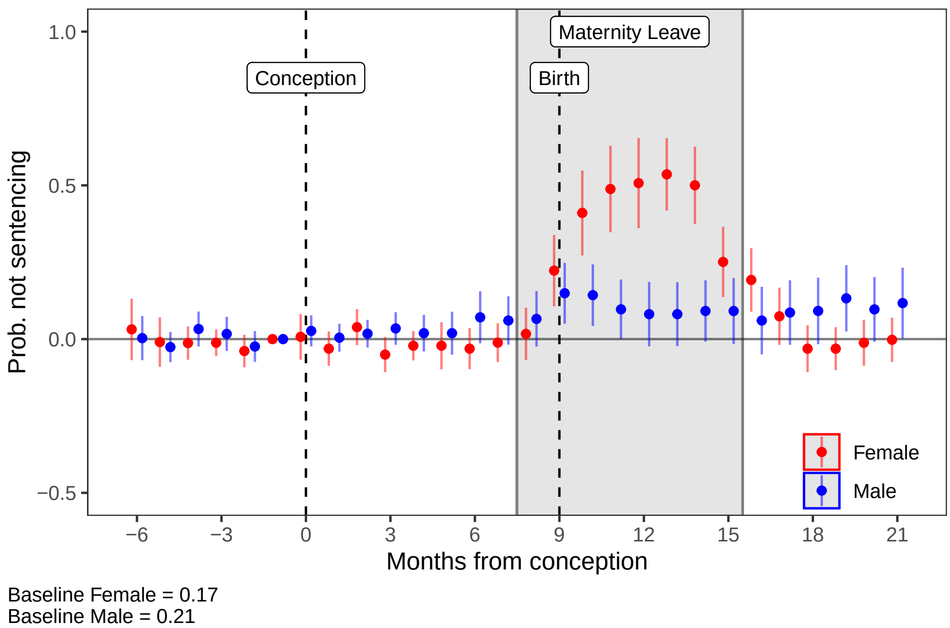
Figure 3: Effect of childbirth on productivity



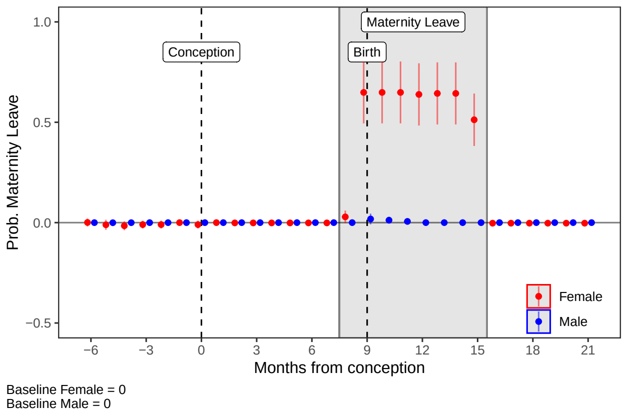
Notes: This figure shows the effect of childbirth on productivity using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 4: Effect of childbirth on work absence

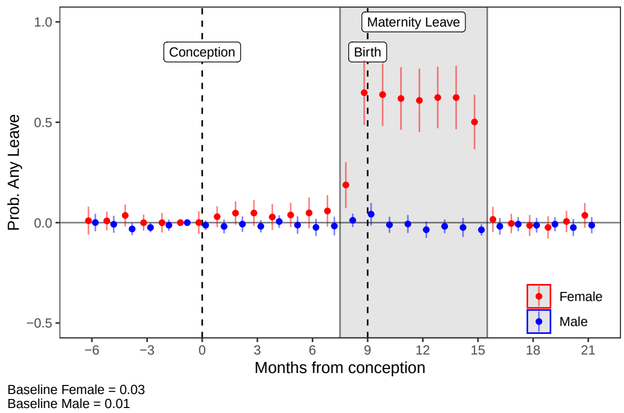
(a) The probability of the judge giving no sentence



(b) The probability of absence due to Maternity Leave



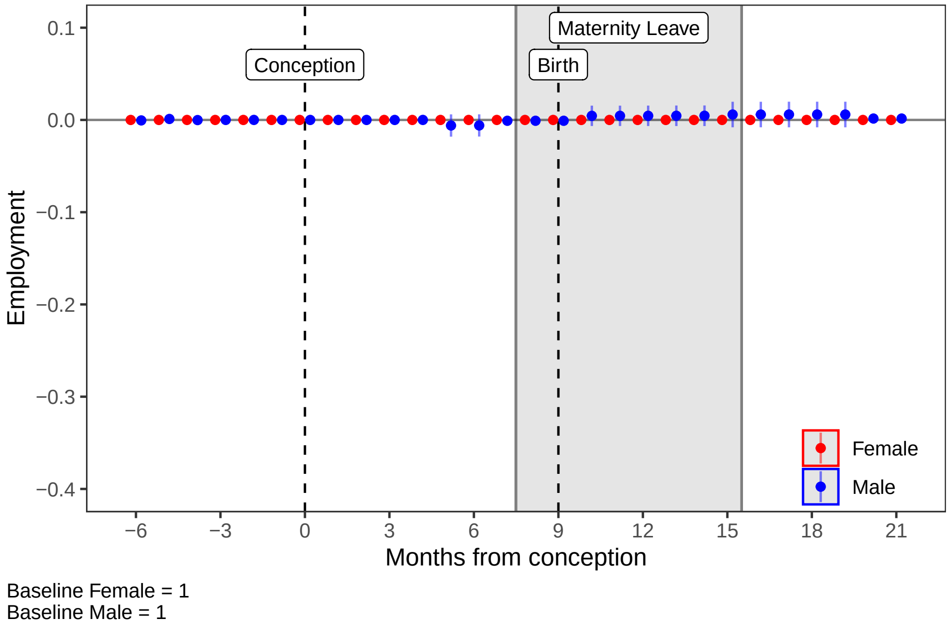
(c) The probability of absence due to Any Leave



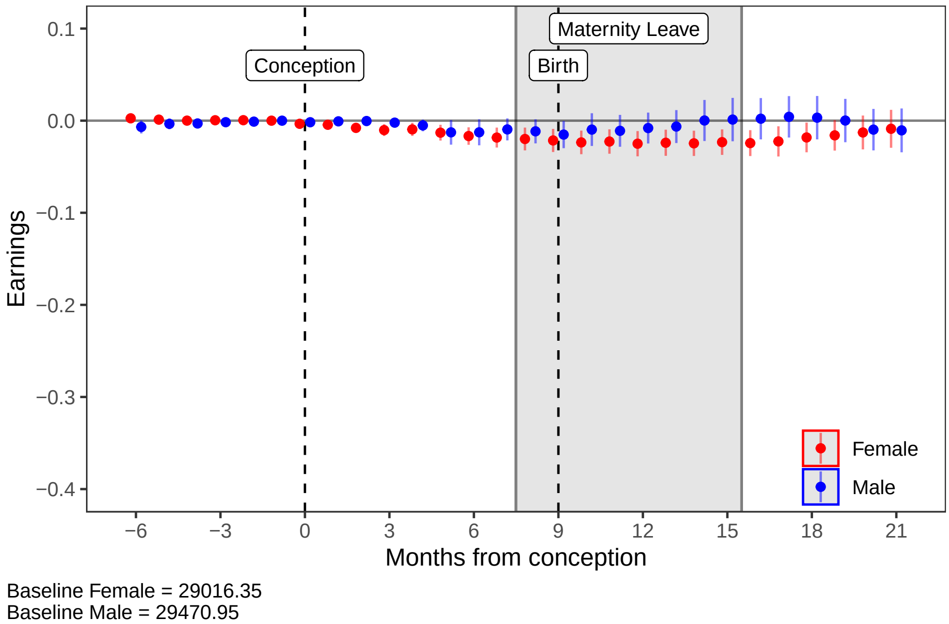
Notes: This figure shows the effect of childbirth on the absence of work due to Maternity Leave or any kind of Leave (using the RAIS data) and the probability of no sentencing by the judge (using CNJ data). These effects are estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) displays the effect on the probability of the judge giving no sentence, Panel (b) shows the effect on the probability of absence due to Maternity Leave, and Panel (c) shows the effect on the probability of absence due to any kind of Leave.

Figure 5: Effect of childbirth on labor outcomes

(a) Employment



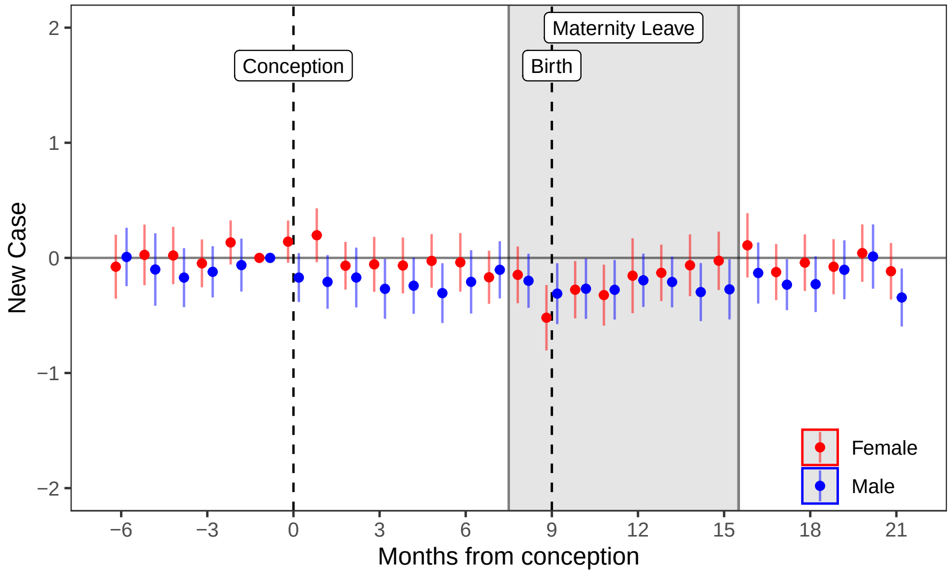
(b) Earnings



Notes: This figure shows the effect of childbirth on labor market outcomes using the RAIS data, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) shows the effect on the probability of being employed, and Panel (b) shows the effects on earnings. Earnings are measured in Brazilian Reais at 2015 price levels. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

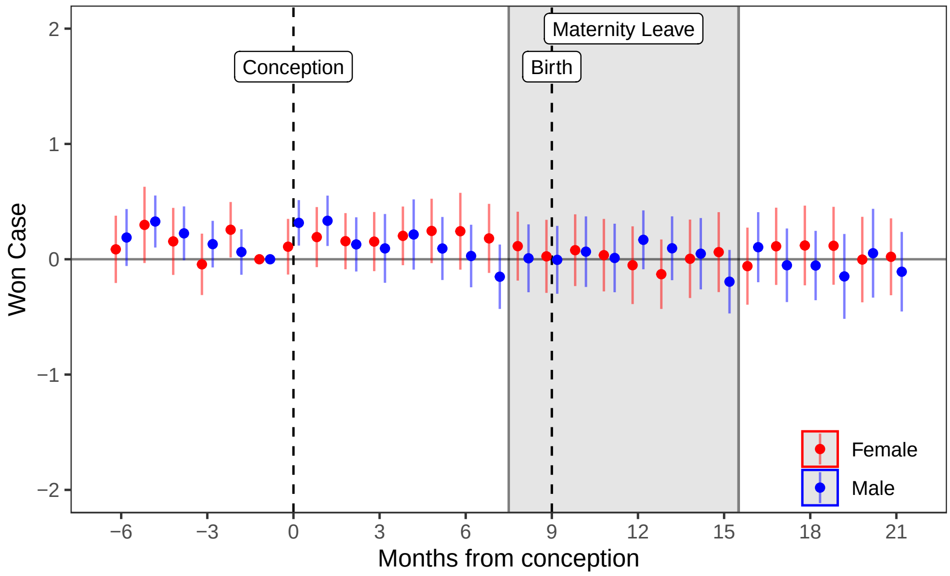
Figure 6: Effect of childbirth on self-employed lawyer's productivity

(a) Number of New Case



Baseline Female = 2.12
Baseline Male = 3.04

(b) Number of Won Case

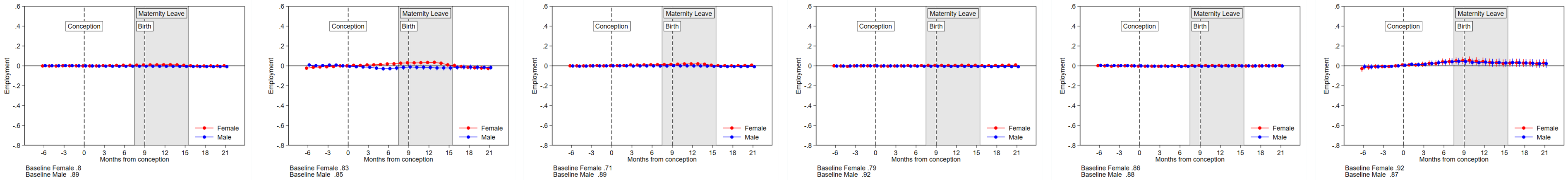


Baseline Female = 1.14
Baseline Male = 1.83

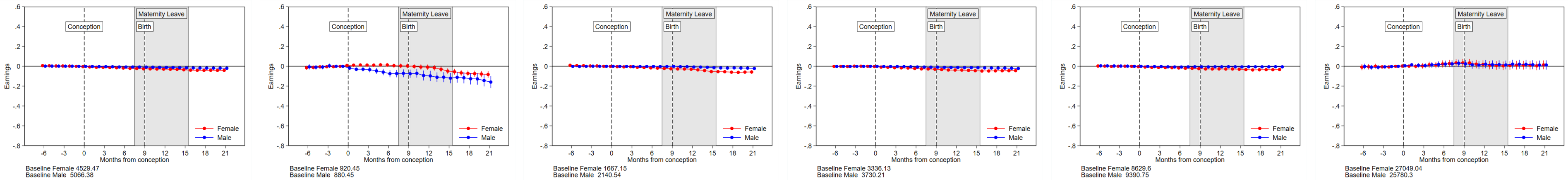
Notes: This figure shows the effect of childbirth on self-employed lawyers' productivity using proxies from PJe data, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises self-employed lawyers giving birth in 2016, while the control group is defined via matching among self-employed lawyers giving birth in 2019. Panel (a) shows the effect on the number of new cases, and Panel (b) shows the effects on the number of won cases. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 7: Effect of childbirth on public worker's labor outcomes

(a) Employment (b) Emp. 1st Quartile (c) Emp. 2nd Quartile (d) Emp. 3rd Quartile (e) Emp. 4th Quartile (f) Emp. Top Earners



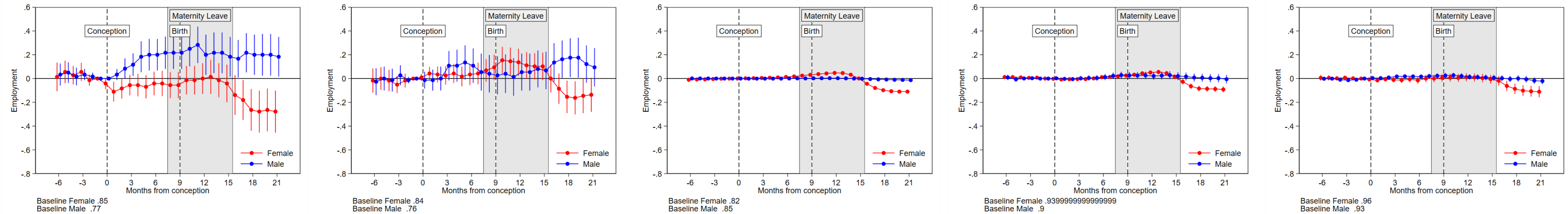
(g) Earnings (h) Earn. 1st Quartile (i) Earn. 2nd Quartile (j) Earn. 3rd Quartile (k) Earn. 4th Quartile (l) Earn. Top Earners



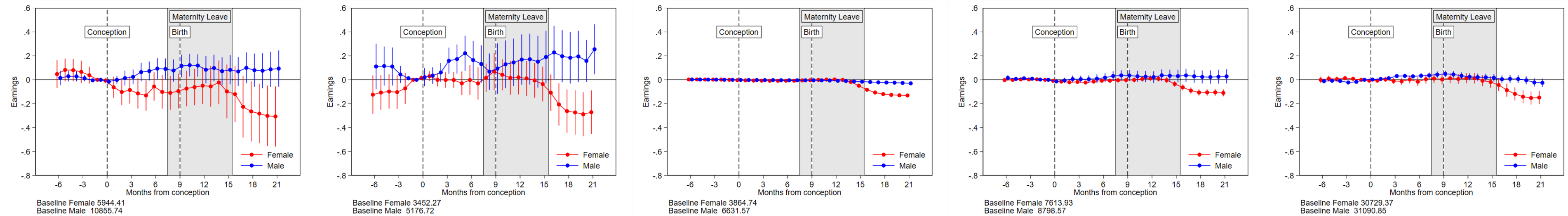
Notes: This figure shows the effect of childbirth on public workers' labor market outcomes using the RAIS data, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises individuals employed at the end of 2013, 2014, or 2015 in RAIS working as public workers that have their first child in the next year, while the candidate control pool comprises individuals employed in the same year as public worker that have their first child 3 years after the treatment group. The panels of the first row show the effect on the probability of being employed, and the ones in the second row show the effects on earnings. We display the effects without restrictions on our matched sample (first column) and separately according to the distribution of the public workers' earnings during the years we selected them in RAIS. We define as top earners the public workers earning at least BRL 25K, the initial wage of a judge in Brazil. Earnings are measured in Brazilian Reais at 2015 price levels. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 8: Effect of childbirth on labor outcomes of people similar to judge in the private sector

(a) Emp. Sibling (b) Emp. Cousin (c) Emp. Worker with College (d) Emp. Lawyer (e) Emp. Top Earner

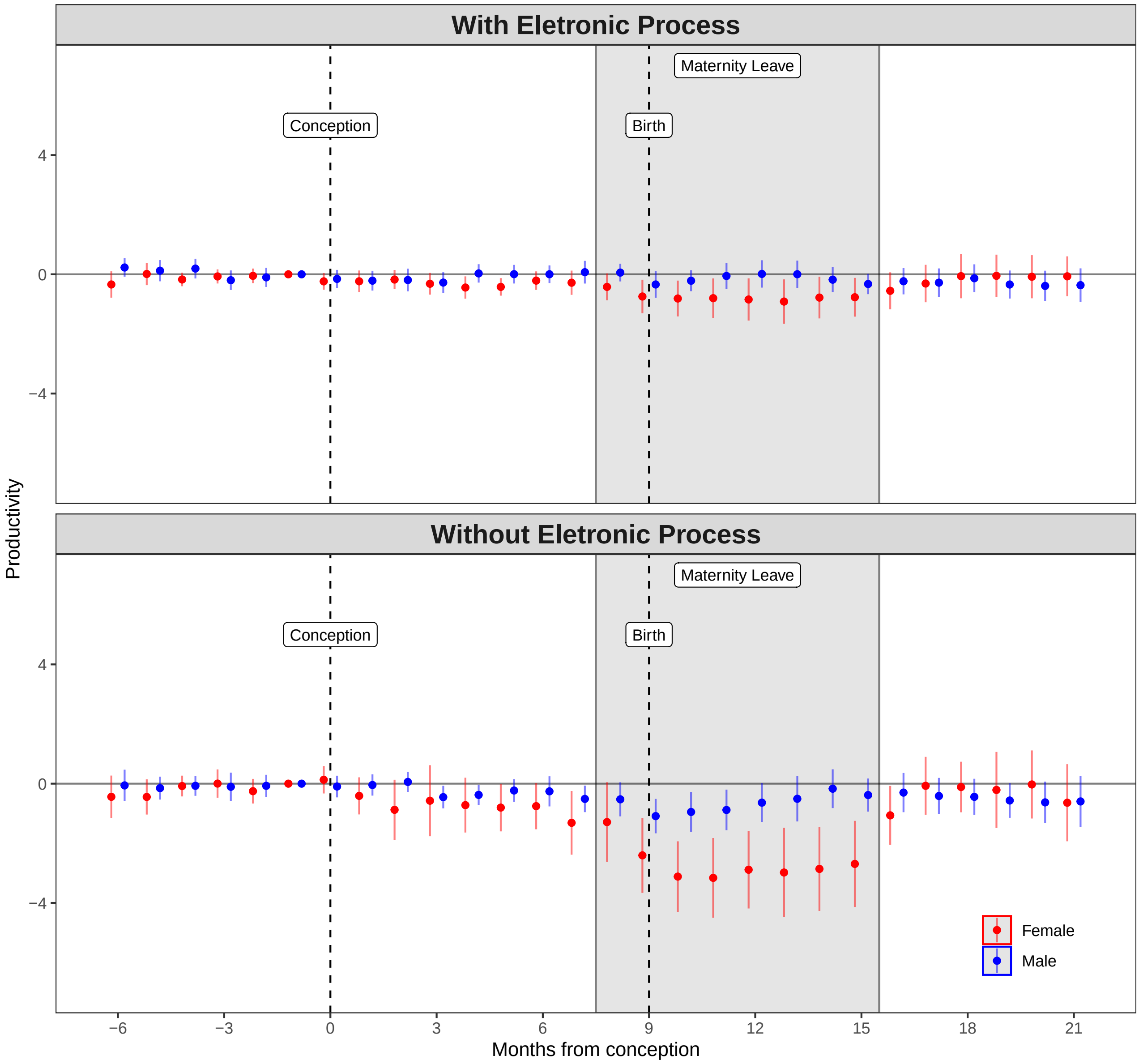


(f) Earn. Sibling (g) Earn. Cousin (h) Earn. Worker with College (i) Earn. Lawyer (j) Earn. Top Earner



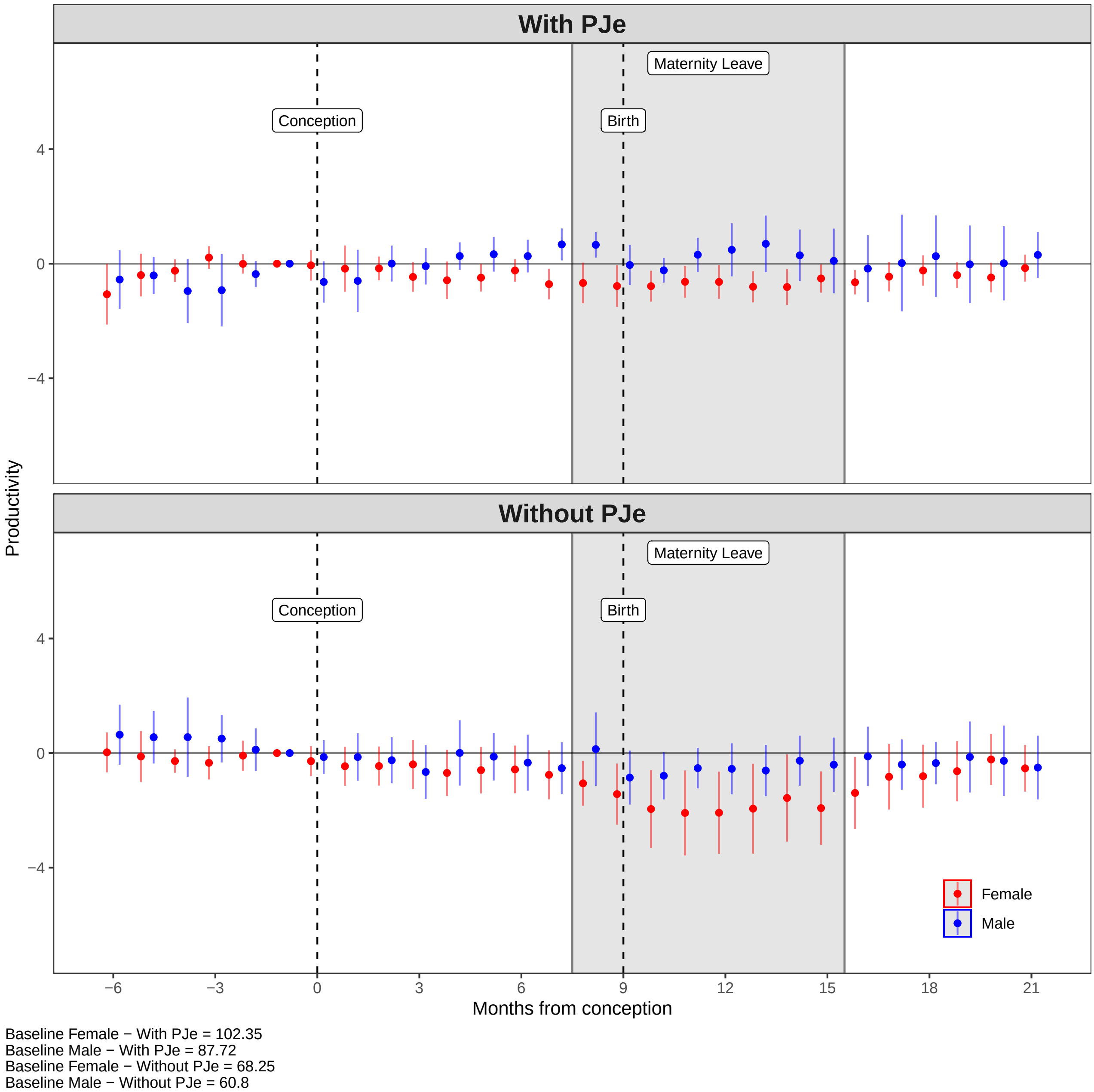
Notes: This figure shows the effect of childbirth on labor outcomes of people similar to a judge in the private sector using the RAIS data, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment groups comprise individuals employed at the end of 2013, 2014, or 2015 in RAIS working in the private sector that have their first child in the next year, are siblings of judges, are cousins of judges, have college degrees, work as lawyers, or is top earners (a private worker earning at least BRL 25K, the initial wage of a judge in Brazil). The candidate control pool comprises individuals employed in the same year as a worker in the private sector that have their first child 3 years after the treatment group and belongs to one of the 5 groups of interest. See Section 4 for more details on the matching procedure, especially for the control group of siblings and cousins. The panels of the first row show the effect on the probability of being employed, and the ones in the second row show the effects on earnings. Earnings are measured in Brazilian Reais at 2015 price levels. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 9: Heterogeneous effect of childbirth on productivity due to remote work technology



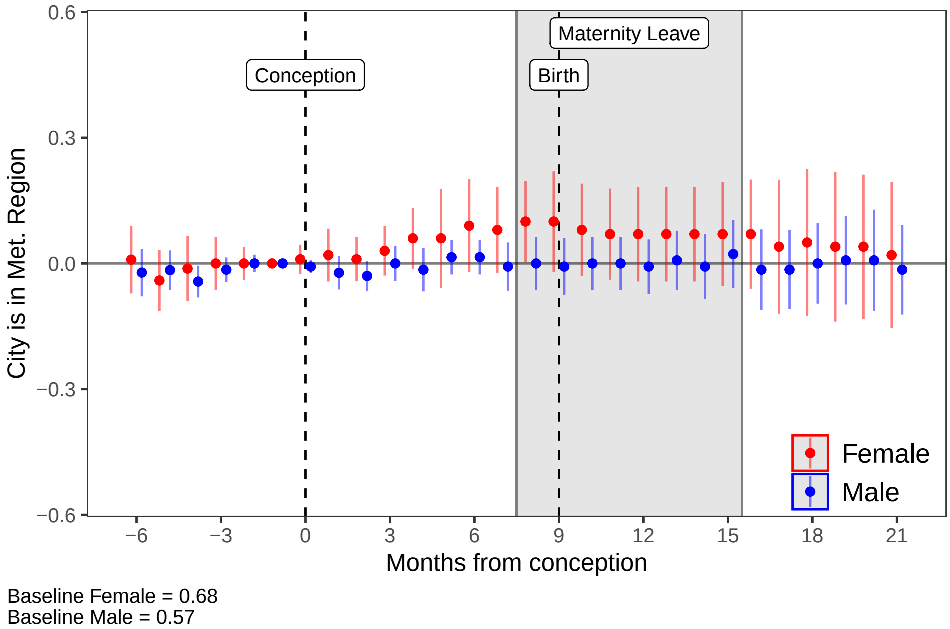
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to the existence of electronic process in the court using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. We use the Kurier data to identify the precise timing when the court started having electronic processes. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 10: Heterogeneous effect of childbirth on productivity due to PJe technology



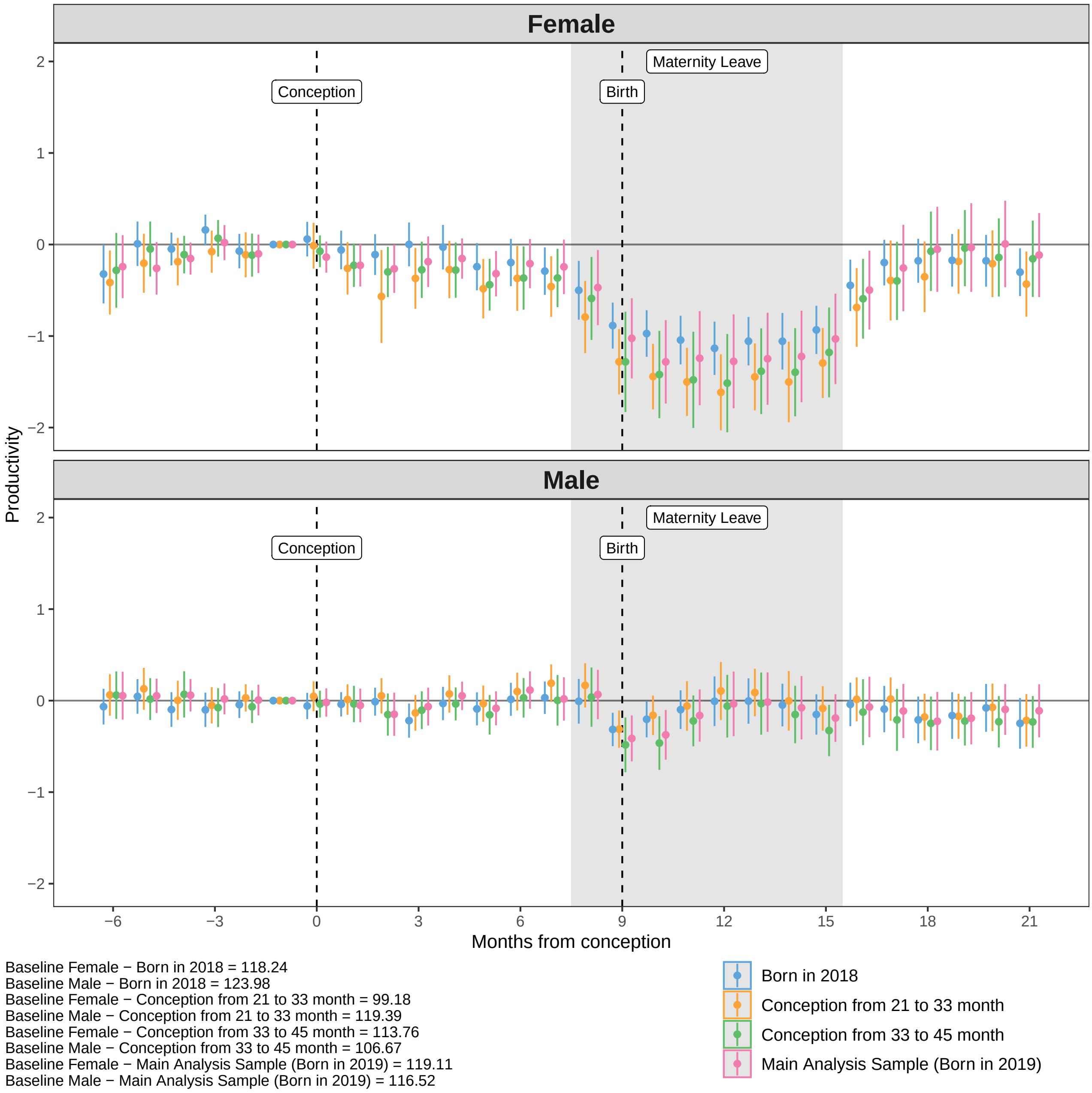
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to the existence of a single system for electronic processing legal proceedings in the court using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. We use the PJe data to identify the precise timing when the court started using this platform. Since we only have detailed data from PJe to labor courts, we restrict our sample from the CNJ dataset to courts of the Labor branch. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 11: Effect of childbirth on migration



Notes: This figure shows the effect of childbirth on the probability of the court the judge most produce sentence is located in a metropolitan region. We use the CNJ dataset to perform the estimations from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019.

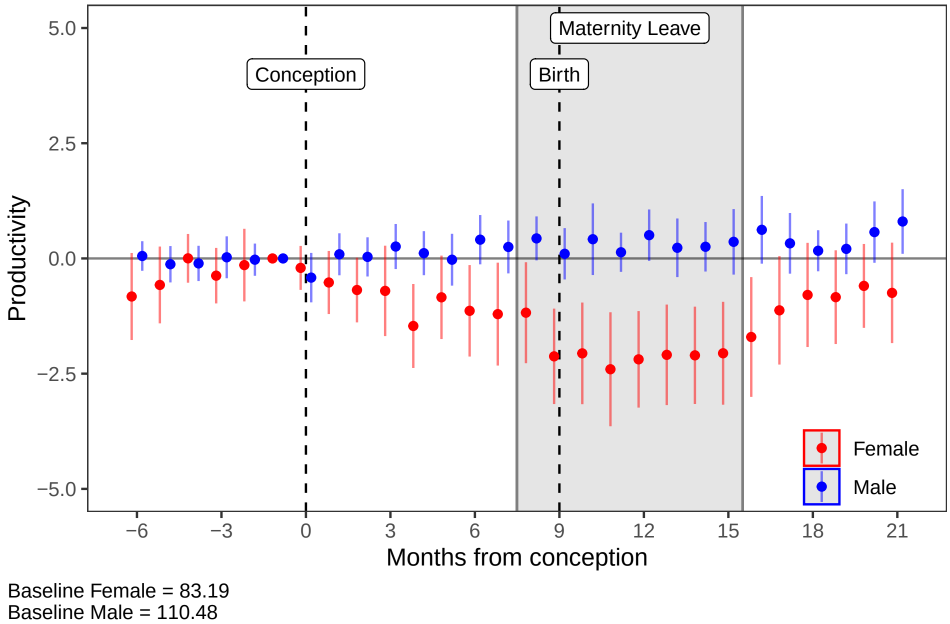
Figure 12: Effect of childbirth on productivity using different matching strategies: Control group in 3 different matching periods



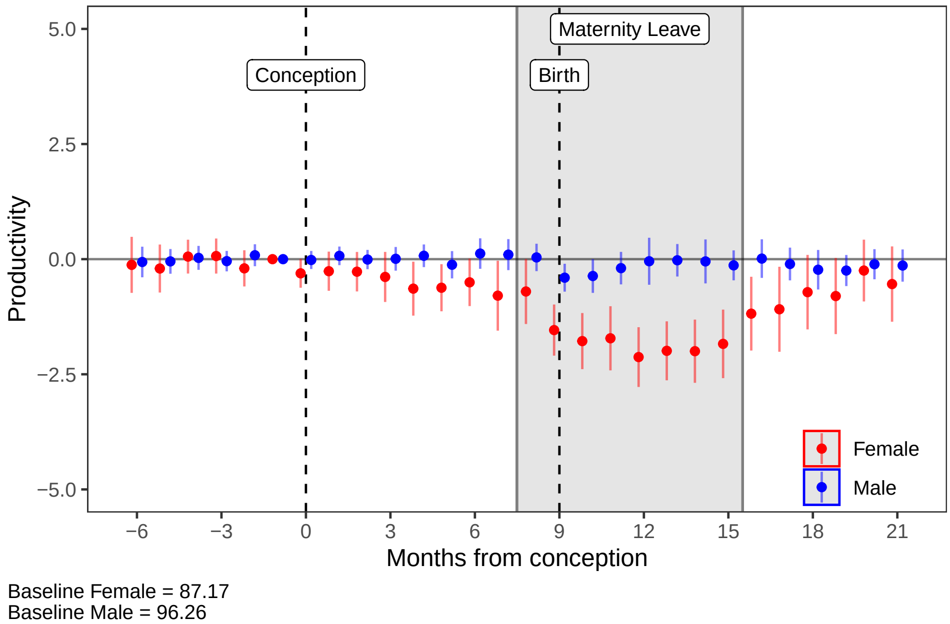
Notes: This figure shows the effect of childbirth on productivity using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via 3 different matching periods. These three groups are judges conceiving a baby during the first year after the childbirth of the treated judge (from the 21st to the 33rd month after the treated conception month), judges conceiving a baby during the second year after the childbirth of the treated judge (from the 33rd to the 45th month after the treated conception month), and judges giving birth in 2018. We also present the matching results of our main analysis (judges giving birth in 2019). All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 13: Effect of childbirth on productivity using different matching strategies: Changing step (ii)

(a) Control works in a courthouse of the same judiciary branch



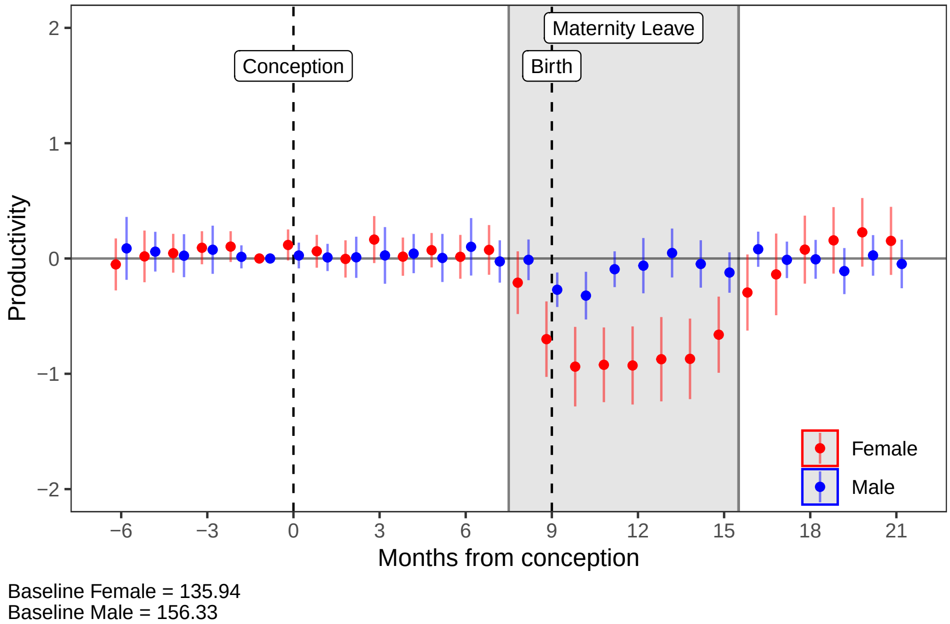
(b) Control works in a courthouse in the same state



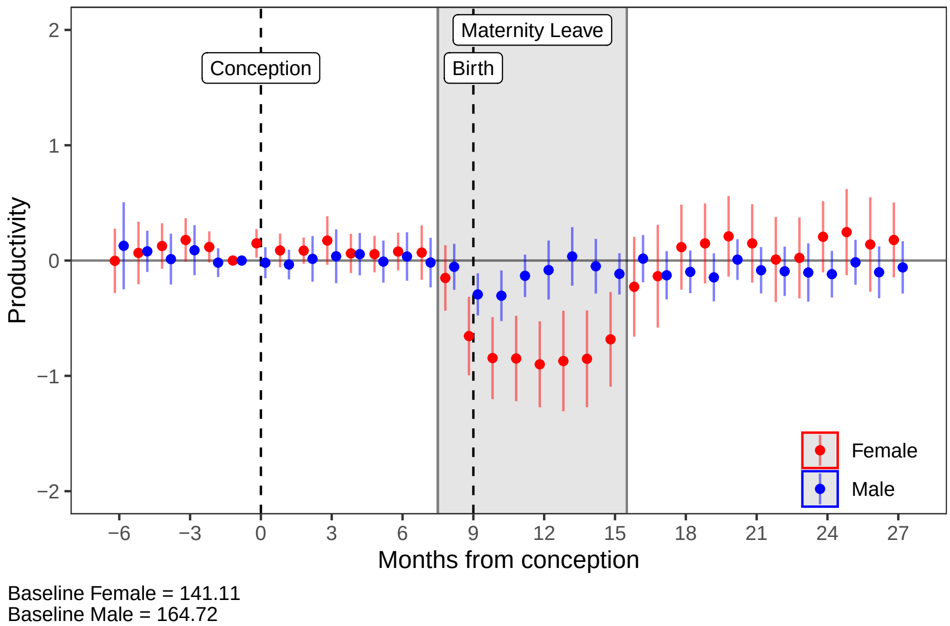
Notes: This figure shows the effect of childbirth on productivity using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) replicates the main analysis changing step (ii), so we match each treated judge with a controlling parent who works in a courthouse of the same branch of the Brazilian judiciary. Panel (b) changes step (ii), so we match each treated judge with a controlling parent who works in a courthouse in the same state. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 14: Effect of childbirth on productivity using different matching strategies: Not restricting the childbirth years to a single year

(a) Remained potential controlling conceive a baby after the first year post the childbirth of the treated judge



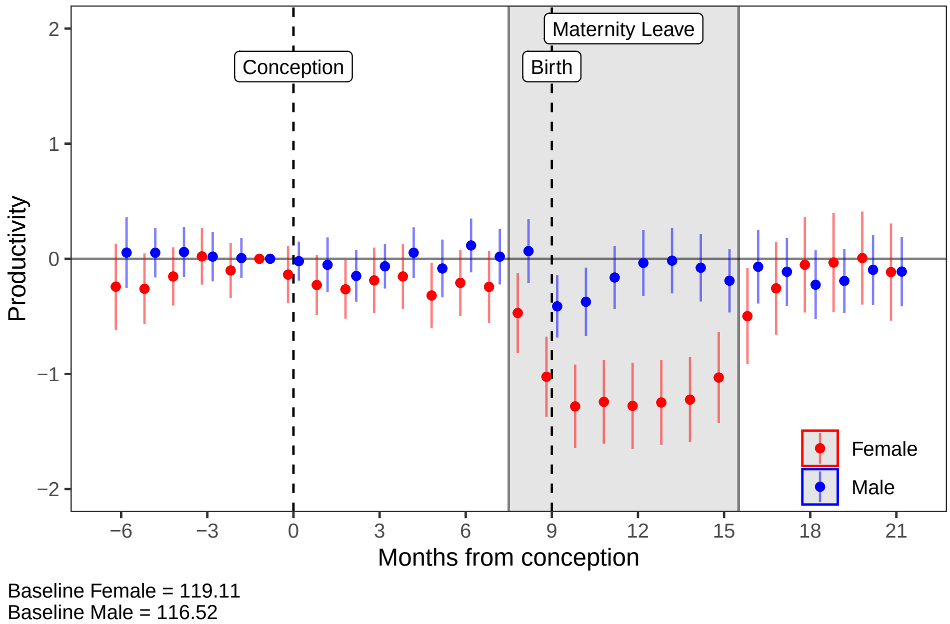
(b) Remained potential controlling conceive a baby after one and a half year post the childbirth of the treated judge



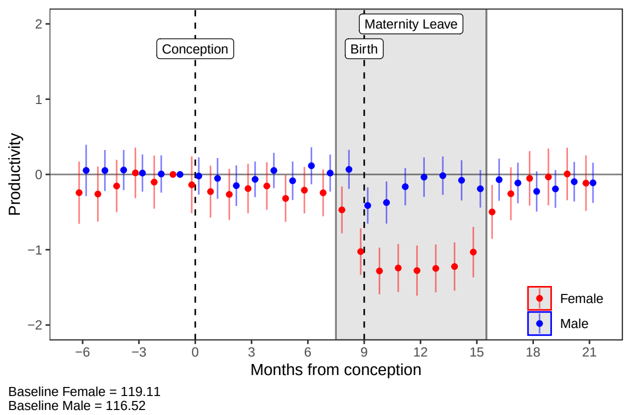
Notes: This figure shows the effect of childbirth on productivity using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges that had their first child in 2016 or 2017, and the candidate control pool comprises all judges who had their first child in 2018 or 2019. Panel (a) keeps as remained potential controlling the ones that conceive a baby after the first year post the childbirth of the treated judge (from the 21st month after the treated conception month onwards). Panel (b) keeps as remained potential controlling the ones that conceive a baby after one and a half year post the childbirth of the treated judge (from the 27th month after the treated conception month onwards). All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 15: Effect of childbirth on productivity using different clustering strategies

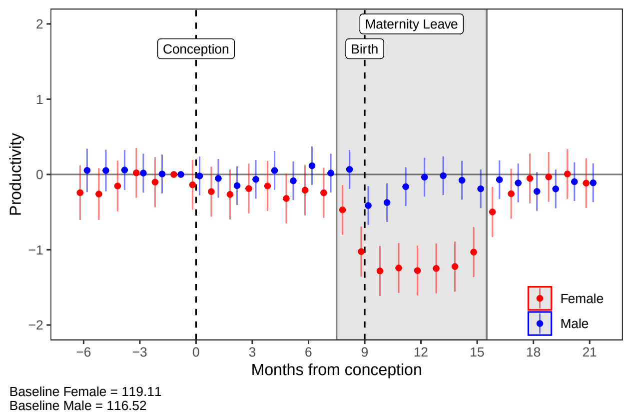
(a) Cluster at the parent fixed effects level



(b) Standard Error robust to heteroscedasticity

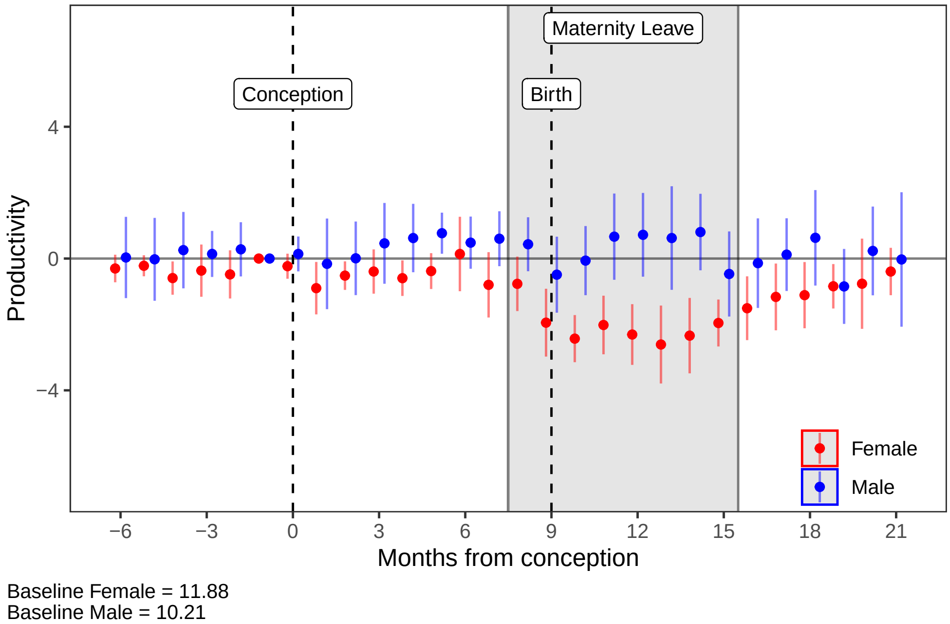


(c) Standard Error assuming homoscedasticity and no correlation



Notes: This figure shows the effect of childbirth on productivity using the CNJ dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) clusters at the parent fixed effects level, assuming that errors are correlated within each parent cluster across time. Panel (b) assumes that errors are heteroskedastic, using the White correction. Panel (c) assumes that the errors are homoskedastic and not correlated. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

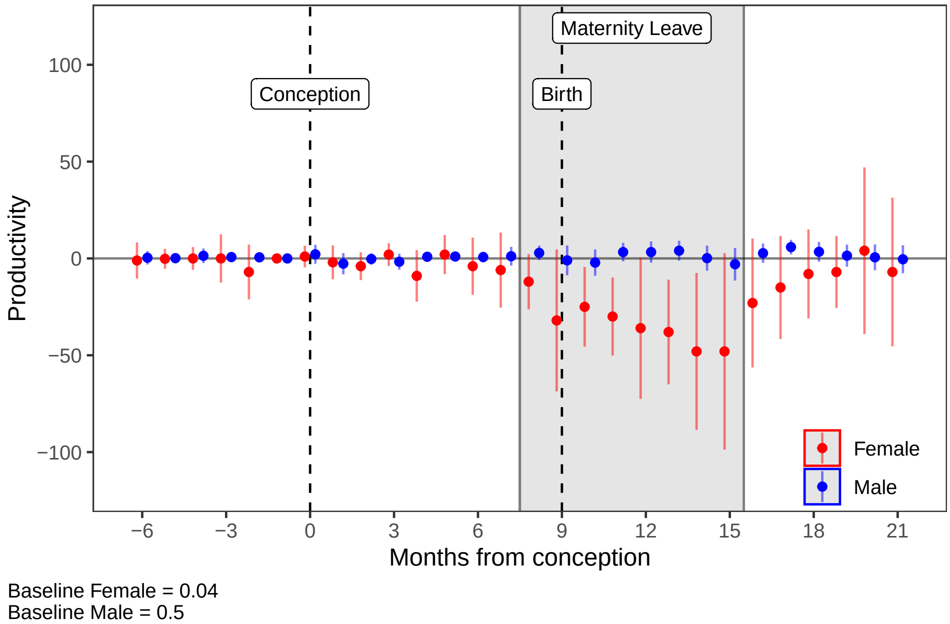
Figure 16: Effect of childbirth on productivity using PJe data



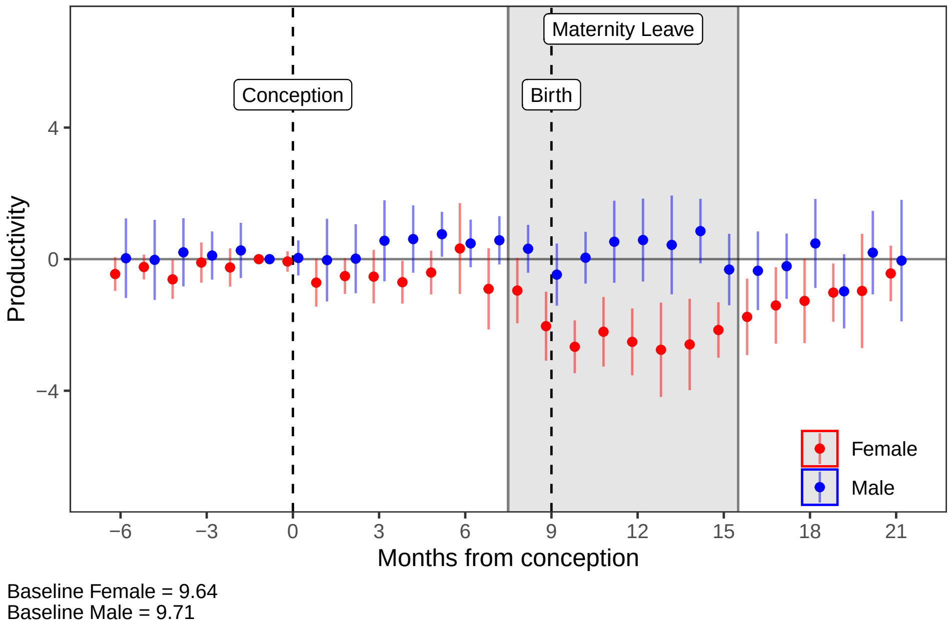
Notes: This figure shows the effect of childbirth on productivity using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 17: Heterogeneous effect of childbirth on productivity due to randomness of suit assignment

(a) Suit not randomly assigned

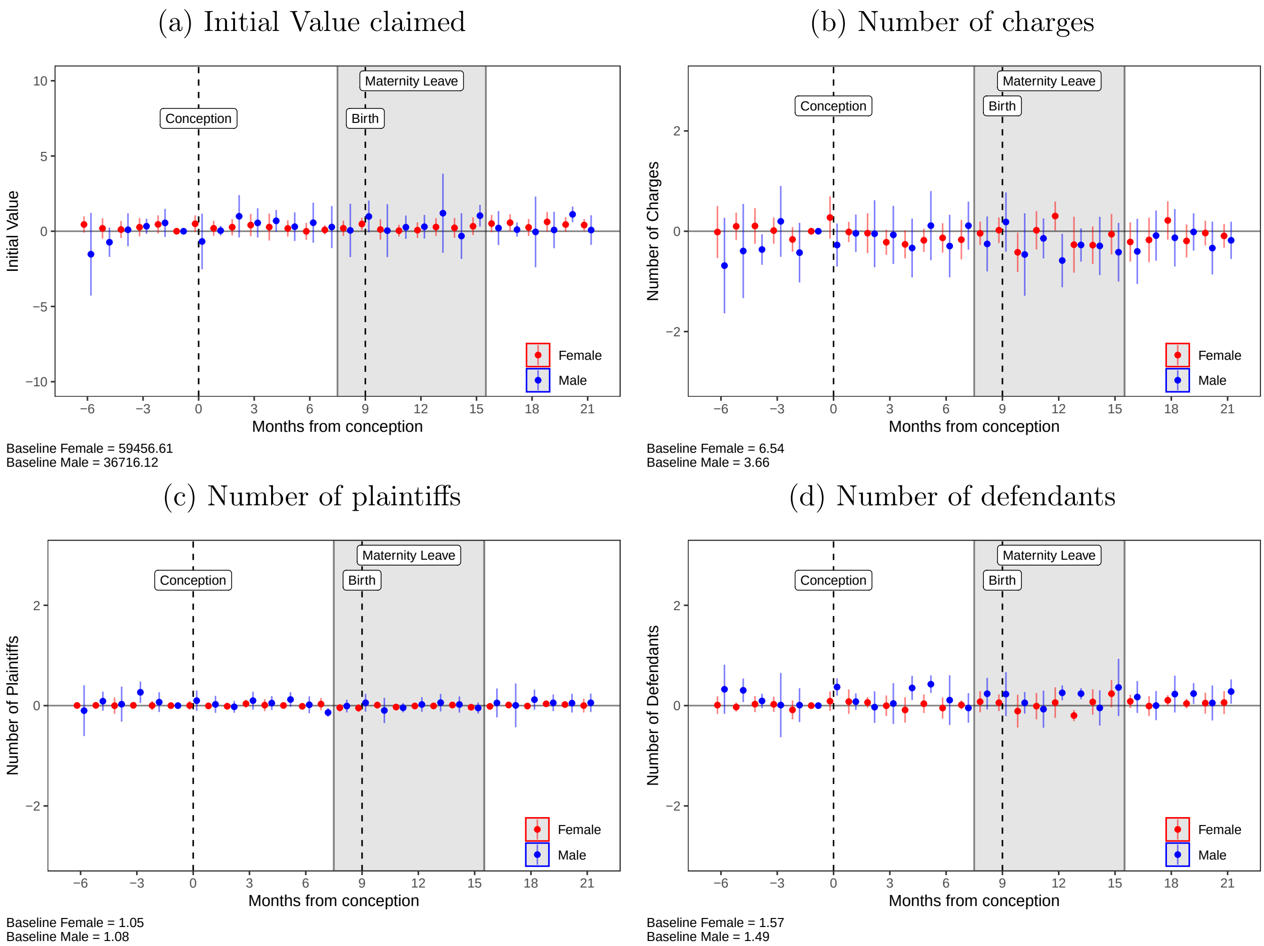


(b) Suit randomly assigned



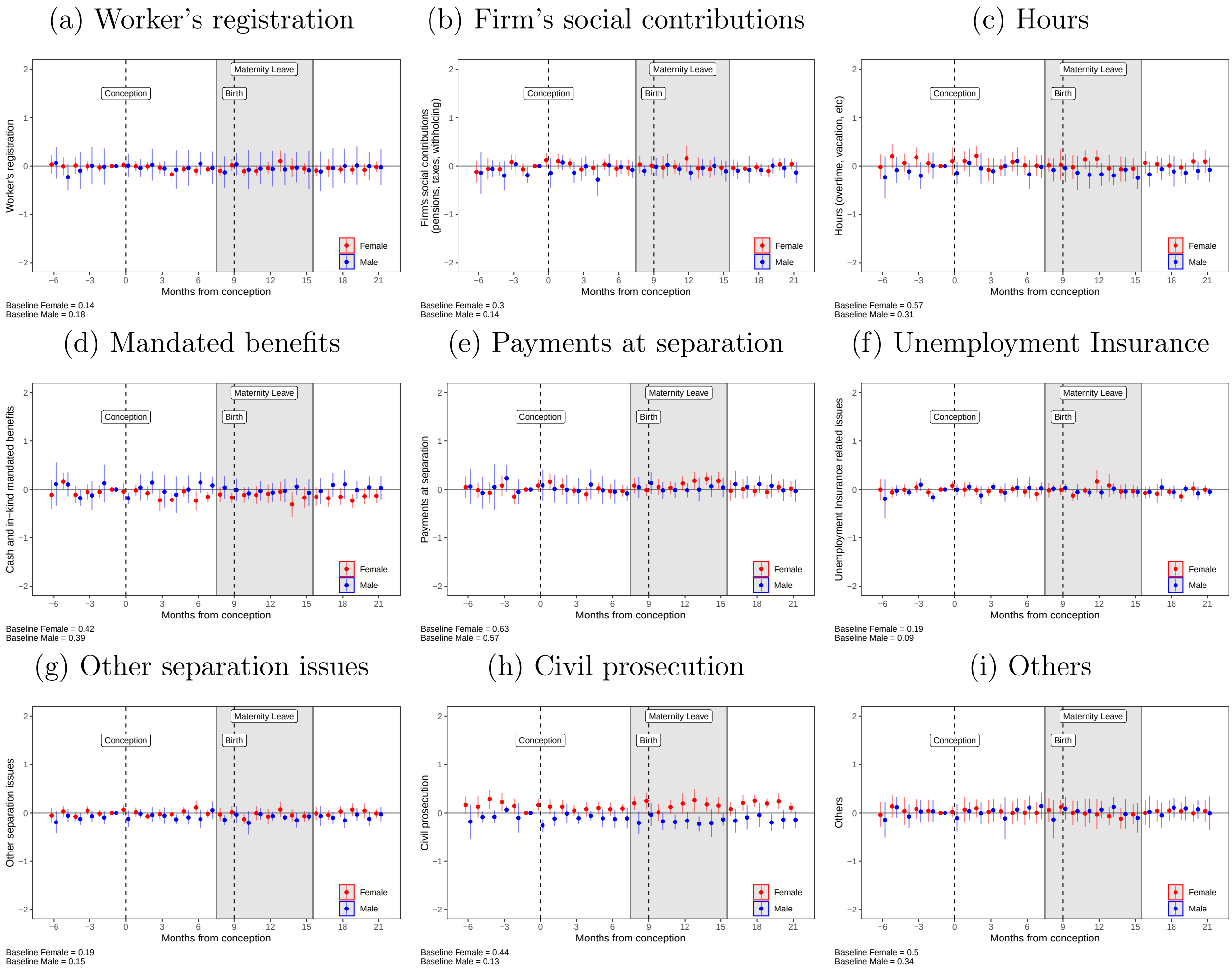
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to randomness of suit assignment using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) shows the results only for the suits not randomly assigned to the judges. Panel (b) shows the results for the suits randomly assigned to the judges. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 18: Effect of childbirth on different case characteristics



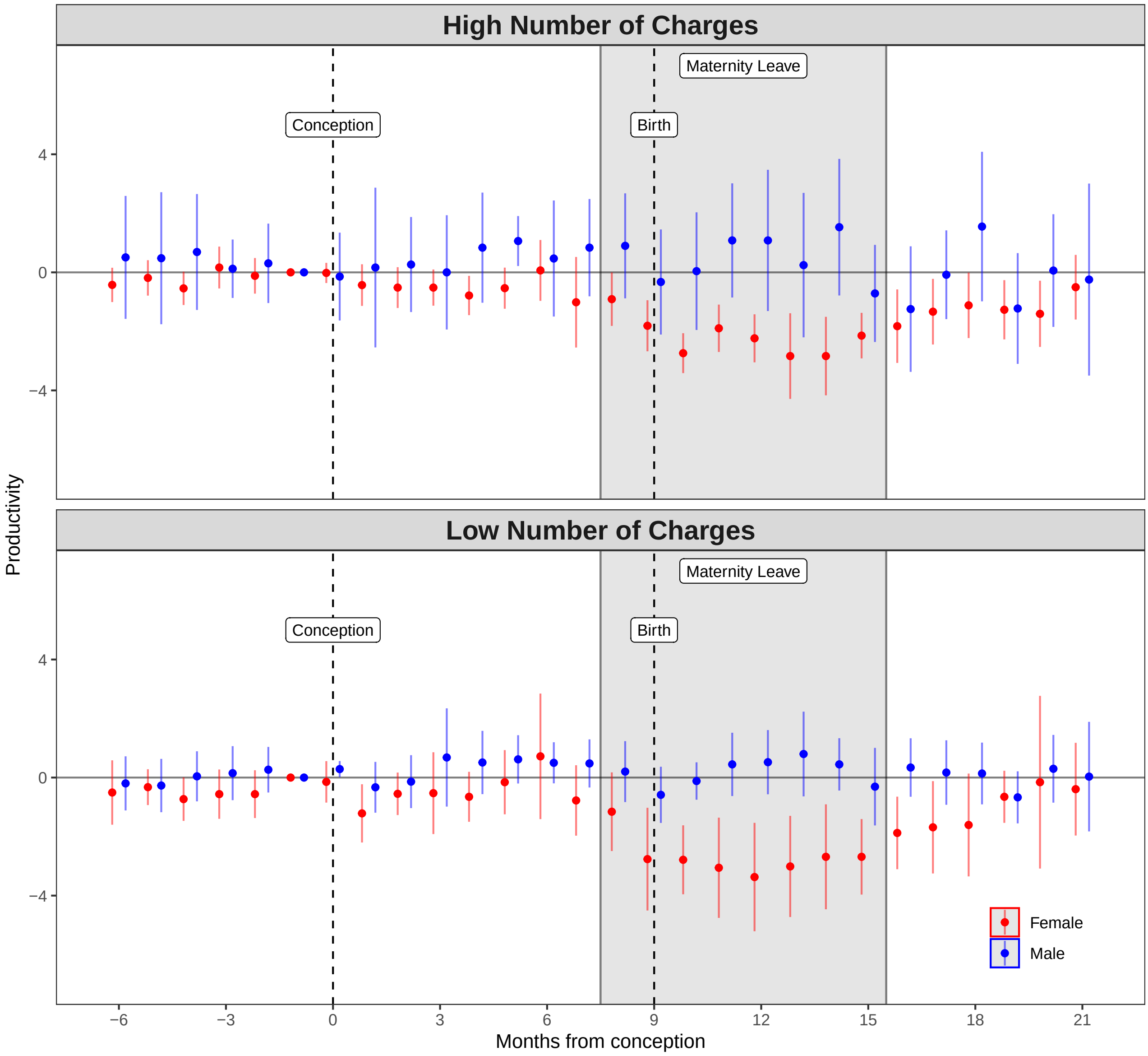
Notes: This figure shows the effect of childbirth on different case characteristics using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) shows the effect on the initial value claimed by the plaintiff in the process. Panel (b) displays the results for the number of charges discussed in the case. Panel (c) shows the effect on the number of plaintiffs. Panel (d) shows the results for the number of defendants. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 19: Effect of childbirth on different main issues for suing by aggregate categories



Notes: This figure shows the effect of childbirth on different main issues for suing by aggregate categories using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. We follow Britto et al. (2023) to aggregate the main issues for suing in the PJe dataset in 9 different categories. Panel (a) shows the effects on the probability that the main issue is related to Worker's registration. Panel (b) shows the effects on the probability that the main issue is related to the Firm's social contributions, such as pensions, taxes, and withholdings. Panel (c) shows the effects on the probability that the main issue is related to Hours, such as overtime, vacation, etc. Panel (d) shows the effects on the probability that the main issue is related to Cash and in-kind mandated benefits. Panel (e) shows the effects on the probability that the main issue is related to Payments at separation. Panel (f) shows the effects on the probability that the main issue is related to Unemployment insurance. Panel (g) shows the effects on the probability that the main issue is related to Other separation issues. Panel (h) shows the effects on the probability that the main issue is related to Civil prosecution. Panel (i) shows the effects on the probability that the main issue is related to Other subjects.

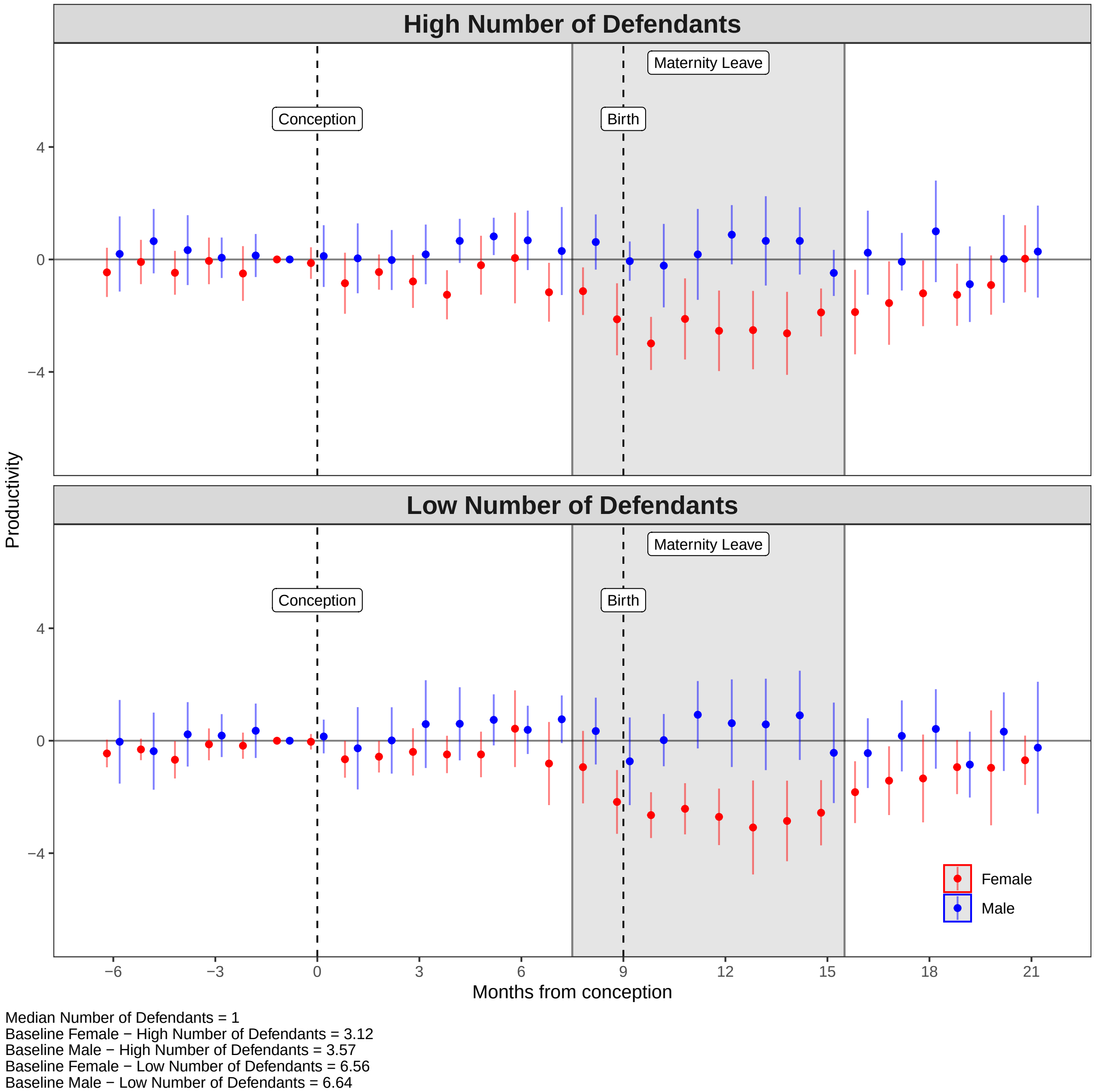
Figure 20: Heterogeneous effect of childbirth on productivity due to the number of charges



Median Number of Charges = 3
Baseline Female − High Number of Charges = 6.12
Baseline Male − High Number of Charges = 3.5
Baseline Female − Low Number of Charges = 3.56
Baseline Male − Low Number of Charges = 6.71

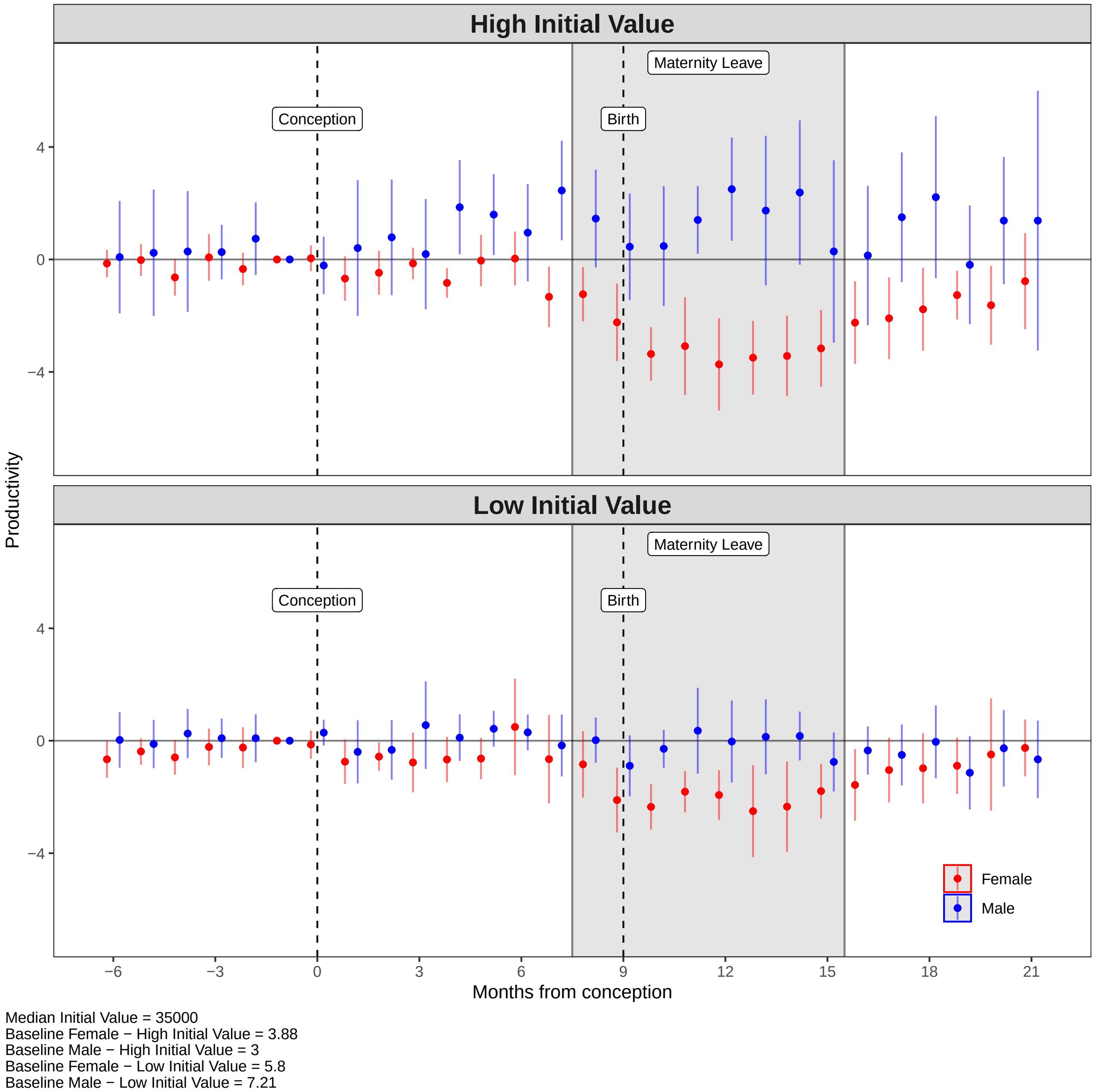
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to the number of charges in the suit using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 21: Heterogeneous effect of childbirth on productivity due to the number of defendants



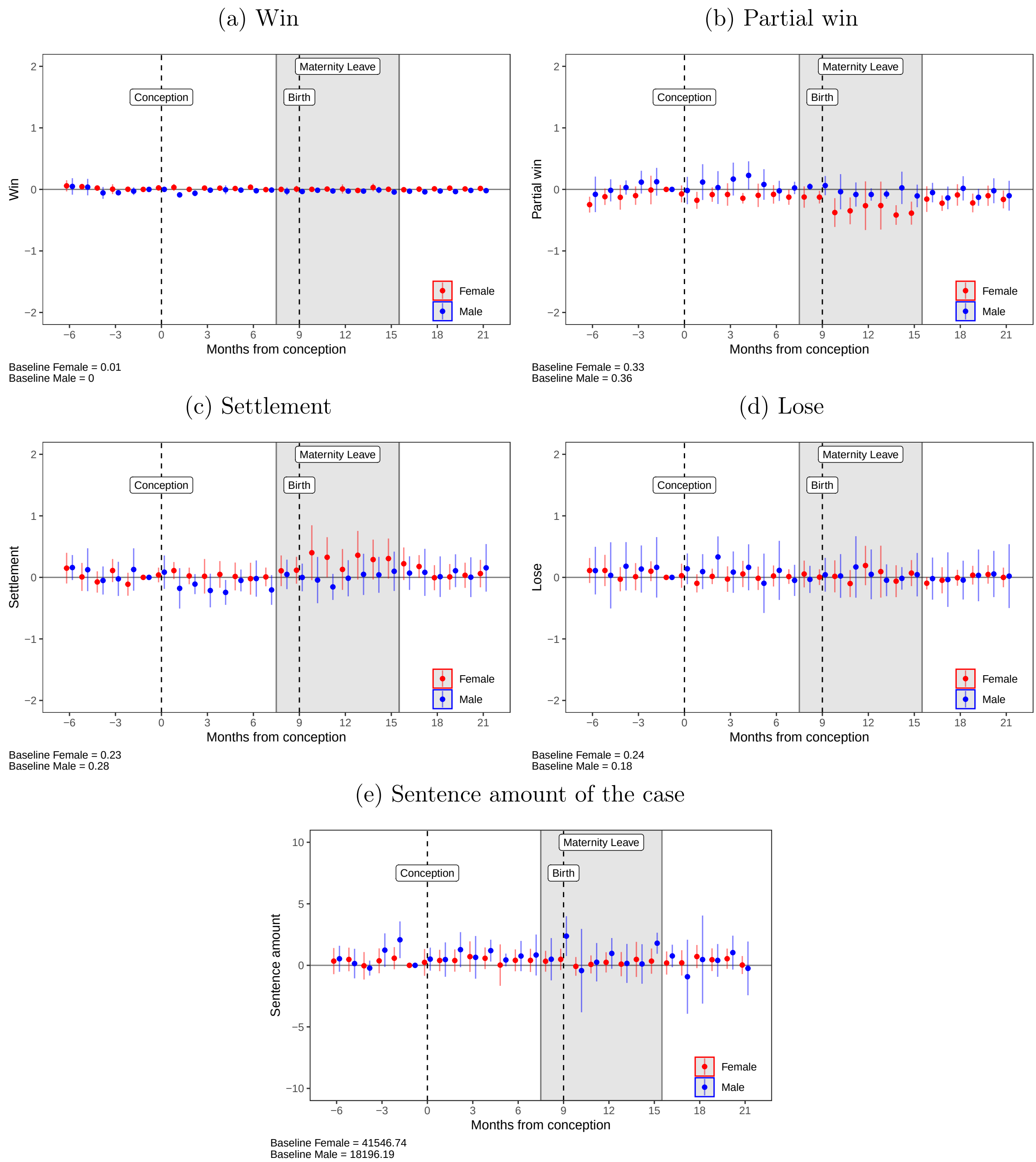
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to the number of defendants in the suit using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 22: Heterogeneous effect of childbirth on productivity due to the initial value claimed



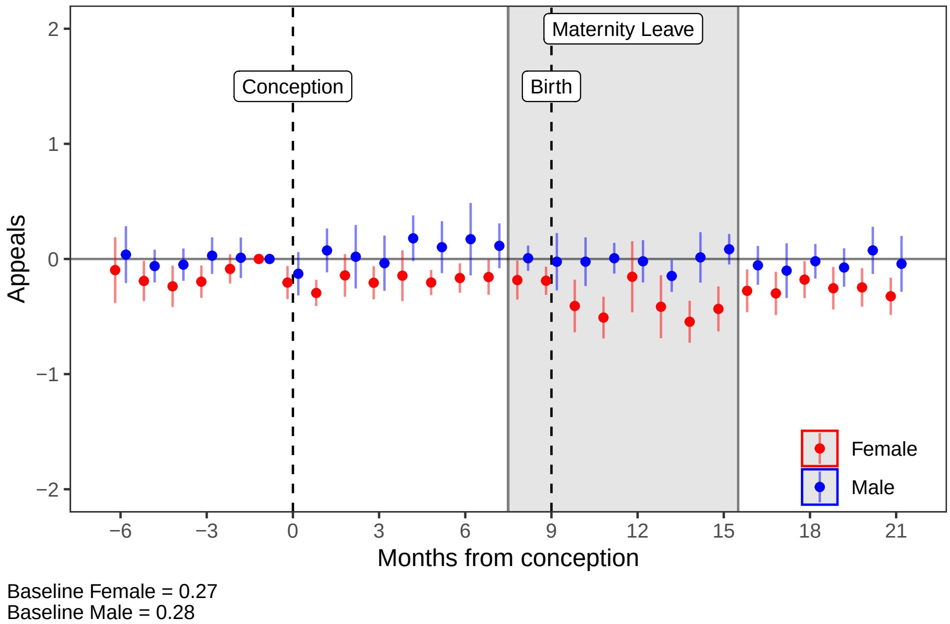
Notes: This figure shows the heterogeneous effect of childbirth on productivity due to the initial value claimed in the suit using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 23: Effect of childbirth on different case outcome



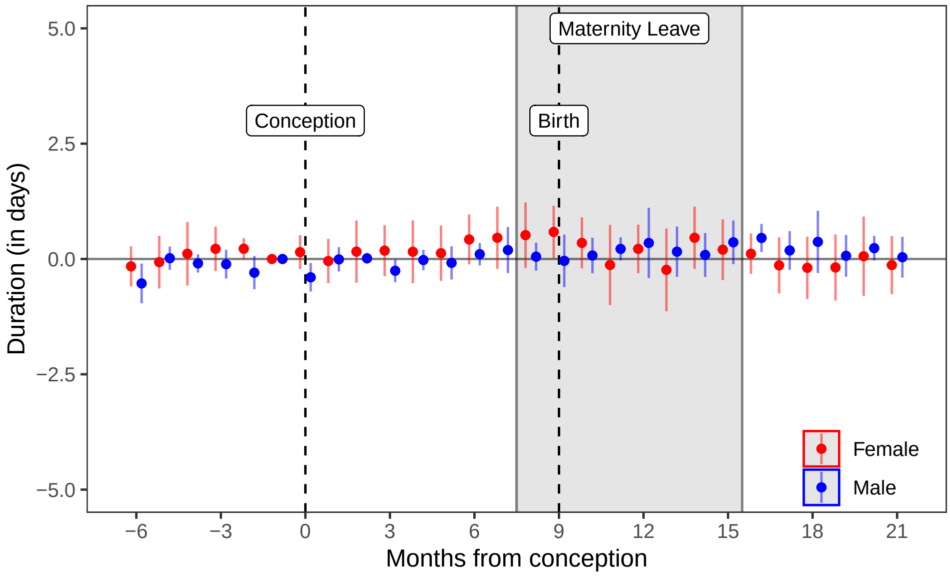
Notes: This figure shows the effect of childbirth on different case outcomes using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. Panel (a) shows the effects on the probability the verdict of the case is Win. Panel (b) shows the effects on the probability the verdict of the case is Partial win. Panel (c) shows the effects on the probability the verdict of the case is Settlement. Panel (d) shows the effects on the probability the verdict of the case is Lose. Panel (e) shows the effects on the amount the defendants should pay to the plaintiffs as a result of the sentence. Only Panel (e) has its coefficients rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.

Figure 24: Effect of childbirth on sentencing quality



Notes: This figure shows the effect of childbirth on the probability that a case sentenced by the judge goes to appeals courts using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019.

Figure 25: Effect of childbirth on duration



Baseline Female = 323.75
Baseline Male = 204.27

Notes: This figure shows the effect of childbirth on the duration in days of the case using the PJe dataset, as estimated from the difference-in-difference Equation 1 - along with 95% confidence intervals. The treatment group comprises judges giving birth in 2016, while the control group is defined via matching among judges giving birth in 2019. All coefficients are rescaled by the average value of the outcome in the control group at t = -1, which is also reported as Baseline.