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Giuseppe Pio Dachille
Maria De Paola
Roberto Nisticò

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Tommaso Nannicini

Guaranteed Minimum Income and Fertility

Giuseppe Pio Dachille
INPS, Rome

Maria De Paola
(INPS, Rome,
Department of Economics, Statistics and Finance, University of Calabria,
Institute for the Study of Labor (IZA), Bonn)

Roberto Nisticò
(Department of Economics and Statistics,
University of Naples "Federico II",
Institute for the Study of Labor (IZA), Bonn,
Center for Studies in Economics and Finance (CSEF), Naples II",
CESifo Network, Munich)

Guaranteed Minimum Income and Fertility

Giuseppe Pio Dachille [a], Maria De Paola [a, b, d], Roberto Nisticò [c, d, e, f] *

[a] *INPS, Rome*
[b] *Department of Economics, Statistics and Finance, University of Calabria*
[c] *Department of Economics and Statistics, University of Naples "Federico II"*
[d] *Institute for the Study of Labor (IZA), Bonn*
[e] *Center for Studies in Economics and Finance (CSEF), Naples*
[f] *CESifo Network, Munich*

Abstract: *This paper examines the impact of Italy's "Reddito di Cittadinanza" (RdC), a guaranteed minimum income program introduced in 2019, on fertility. Using administrative data from the Italian Social Security Institute and a Fuzzy Regression Discontinuity Design, we uncover regionally heterogeneous effects. While no significant impact is observed in the Centre-North, RdC recipients in the South are 1.5 percentage points more likely to have a child within two years compared to non-recipients—a 18% biennial increase. Additionally, we find no significant effect of the RdC on labor supply in the South. In contrast, beneficiaries in the Centre-North experience reductions in both months worked and labor earnings: over a nine-month period, women work 0.13 fewer months and earn €609 less, while men work 0.11 fewer months and earn €628 less—a 10% decline relative to the control group mean. These contrasting regional responses are driven by more traditional gender norms, greater financial constraints, and lower opportunity costs of childbearing in the South relative to the Centre-North.*

JEL classification: *H53; J13; C21.*

Keywords: *Fertility; Guaranteed Minimum Income; Gender Norms, RDD.*

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Giuseppe Pio Dachille: INPS Research Department, Istituto Nazionale della Previdenza Sociale Direzione Centrale Studi e Ricerche, Via Ciro il Grande 21, 00144 Roma, Italy. Email: giuseppepio.dachille@inps.it
Maria De Paola: INPS Research Department and Full Professor of Economics, Department of Economics, Statistics and Finance "G. Anania", University of Calabria, Via Ponte Bucci, 87036, Arcavacata di Rende, Italy. Email(s): maria.depaola@inps.it, m.depaola@unical.it
Roberto Nisticò (Corresponding author): Full Professor of Economics, Department of Economics and Statistics, University of Naples Federico II, Via Cintia 21, Monte S. Angelo, 80126, Napoli, Italy. E-mail: roberto.nistico@unina.it

Guaranteed Minimum Income and Fertility

Giuseppe Pio Dachille [a], Maria De Paola [a, b, d], Roberto Nisticò [c, d, e, f *]

[a] *INPS, Rome*
[b] *Department of Economics, Statistics and Finance, University of Calabria*
[c] *Department of Economics and Statistics, University of Naples "Federico II"*
[d] *Institute for the Study of Labor (IZA), Bonn*
[e] *Center for Studies in Economics and Finance (CSEF), Naples*
[f] *CESifo Network, Munich*

Abstract: *Questo studio analizza l'impatto del Reddito di Cittadinanza (RdC), un programma di reddito minimo garantito introdotto in Italia nel 2019, sulla fecondità. Utilizzando dati amministrativi dell'Istituto Nazionale della Previdenza Sociale (INPS) e un Fuzzy Regression Discontinuity Design, evidenziamo effetti eterogenei a livello regionale. Mentre non si osservano impatti significativi nel Centro-Nord, i beneficiari del RdC nel Mezzogiorno hanno una probabilità maggiore di 1,5 punti percentuali di avere un figlio entro due anni rispetto ai non beneficiari—un incremento biennale del 18%. Inoltre, non troviamo effetti significativi del RdC sull'offerta di lavoro nel Sud. Al contrario, nel Centro-Nord i beneficiari registrano una riduzione sia nei mesi lavorati sia nei redditi da lavoro: in un periodo di nove mesi, le donne lavorano 0,13 mesi in meno e guadagnano 609 euro in meno, mentre gli uomini lavorano 0,11 mesi in meno e guadagnano 628 euro in meno—una riduzione del 10% rispetto alla media del gruppo di controllo. Queste risposte divergenti tra regioni riflettono norme di genere più tradizionali, vincoli finanziari più stringenti e costi opportunità della maternità più bassi nel Sud rispetto al Centro-Nord.*

Classificazioni JEL: *H53; J13; C21.*

Parole chiave: *Fecondità; Reddito Minimo Gatantito; Norme di genere, RDD.*

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Giuseppe Pio Dachille: Direzione Centrali Studi e Ricerche dell'INPS, Via Ciro il Grande 21, 00144 Roma, Italia. Email: giuseppepio.dachille@inps.it
Maria De Paola: Direzione Centrali Studi e Ricerche dell'INPS e Professore Ordinario di Economia presso il Dipartimento di Economia, Statistica and Finanza "G. Anania", Università della Calabria, Via Ponte Bucci, 87036, Arcavacata di Rende, Italia. Email(s): maria.depaola@inps.it, m.depaola@unical.it
Roberto Nisticò (Corresponding author): Professore Ordinario di Economia, Dipartimento di Scienze Economiche e Statistiche dell'Università di Napoli Federico II, Via Cintia 21, Monte S. Angelo, 80126, Napoli, Italia. E-mail: roberto.nistico@unina.it

1. Introduction

Birth rates are declining globally, and high-income countries are experiencing severe baby shortages. As of 2023, the total fertility rate (TFR) in all rich countries, except Israel, was below the replacement level of 2.1, with countries like South Korea, Italy, and Spain falling below 1.3. This demographic shift has profound implications, with aging and shrinking populations posing significant pressure on social security systems and healthcare infrastructures. Low fertility rates also lead to reduced consumer demand, which hampers economic growth. Furthermore, with fewer people in the workforce, countries also face challenges in maintaining or increasing productivity levels, which are crucial for sustaining economic performance.

In this context, understanding the factors that influence fertility rates is critical for developing policies that can mitigate the negative economic consequences of low fertility. This paper focuses on Italy's *Reddito di Cittadinanza (RdC)* to study the impact of guaranteed minimum income programs on fertility decisions. By leveraging administrative individual-level data from the Italian Social Security Institute (INPS), covering the universe of *RdC* applicants, and applying a Fuzzy Regression Discontinuity Design (RDD) based on the policy's income thresholds, we contribute new evidence on the interplay between income support policies and fertility outcomes. Our findings reveal significant regional differences in the impact of income support, with fertility increases observed exclusively among households in the Southern Italy and mediated by more traditional gender norms and worse economic conditions.

The prevailing view in fertility research is that declining fertility rates are largely driven by professional women postponing childbearing. This perspective argues that women are constrained by limited time to have as many children as they desire before their childbearing years end. This notion is reinforced by evidence showing that child-rearing and household responsibilities often limit women's career opportunities and contribute to income disparities (Feyrer et al., 2008; Sevilla-Sanz, 2010), further exacerbating gender inequality and hindering economic mobility. As a result, policy interventions typically focus on tax incentives and subsidized childcare to help women balance family and career.

However, the effectiveness of such incentives remains hotly debated. An article in The Economist recently argued that government cash transfers or financial rewards often fail to boost fertility meaningfully.[1] A significant portion of the fertility decline in wealthy countries is, in fact, concentrated among younger, economically disadvantaged women who are delaying childbirth,

[1] See the article "Why paying women to have more babies won't work", which is accessible at: https://www.economist.com/leaders/2024/05/23/why-paying-women-to-have-more-babies-wont-work

leading to fewer children overall. In the U.S., for instance, the average age at first childbirth for mothers without a university degree was 20 in 1994. Today, nearly two-thirds of women in their 20s without a degree are yet to have their first child.[2] While historically, wealthier individuals have had fewer children, more recent evidence suggests that this relationship has flattened (Bar et al., 2018) or even reversed in some high-income settings, with wealthier families exhibiting higher fertility rates (Doepke et al., 2022). This shift underscores the need for policies that address not only the career-family trade-off for professional women but also the financial and social barriers faced by younger, lower-income women.

Becker's economic theory of fertility (1960) posits that the demand for children is influenced by the marginal cost of childbearing (i.e., the price effect), with income changes (i.e., the income effect) having an ambiguous impact depending on whether children are considered normal or inferior goods. Empirical studies largely support the price effect hypothesis, showing that fertility increases with child-related welfare benefits (Cohen et al., 2013; González, 2013; González and Trommlerová, 2023; Sandner and Wiynck, 2023) as well as with expanded maternity leave provisions (Lalive and Zweimüller, 2009; Malkova, 2018; Raute, 2019).[3]

The evidence on the income effect is, instead, more mixed. Previous studies primarily focused on the impact of cash transfers on fertility. Results for developing countries often highlight negative effects, that are driven by reduced teenage pregnancies (Baird et al., 2011; Olson et al., 2019). In contrast, results from developed countries varies across contexts and groups of individuals (Gauthier, 2007). For instance, lottery studies report positive effects of lottery wealth on the fertility of men in some cases (Cesarini et al., 2023) and null or little effects on total fertility in others (Bulman et al., 2022). Studies on family cap policies also show mixed results, with some reporting no effect on birth rates (Grogger and Bronars, 2001; Kearney, 2004; Levine, 2002; Wallace, 2009), while others note a decrease (Camasso, 2004; Horvath-Rose et al., 2008; Jagannathan et al., 2004; Sabia, 2008).[4] Inconclusive evidence emerges also from studies examining child tax credits, such as the Earned Income Tax Credit (EITC), with state-level variations in the U.S. showing either no effect (Baughman and Dickert-Conlin, 2003, 2009) or a positive effect for white married mothers with one child (Duchovny, 2001), and findings from Canada (Milligan, 2005) and Europe (Azmat and González, 2010 for Spain; Laroque and Salanie, 2013 for France) pointing to small though positive effects.

[2] In Italy, the mean age of first-time mothers reached 32 in 2023, the highest in Europe.
[3] See Olivetti and Petrongolo (2017) for a review of the relevant literature.
[4] Examining the effects of a UK welfare reform on fertility, Brewer et al. (2012) find no increase in births among single women and an increase in births among coupled women, while Francesconi and Van der Klaauw (2007) find instead a reduction in fertility of single mothers.

However, the extant literature has largely overlooked the impact of minimum income schemes. Unlike other cash transfer programs designed to target specific groups (e.g., families with children, unemployed individuals), minimum income schemes are often universal, providing financial support to all individuals below a specified income threshold. To the best of our knowledge, Yonzan et al. (2024) is the only study to examine the fertility effects of a universal cash transfer program in the rich world, focusing on the Alaska Permanent Fund Dividend (APFD) introduced in 1982. Using a synthetic control approach, they compare fertility trends in Alaska with a counterfactual U.S. state, failing however to show a good pre-treatment match on fertility rates between the synthetic and the actual Alaska.

Our study addresses this key gap in the literature by investigating the fertility response to Italy's *RdC*, a minimum income program introduced in 2019 to combat poverty, that we use as an exogeneous source of variation in household income. With respect to Yonzan et al. (2024), our research offers several innovations. First, the *RdC* program provides a unique opportunity to examine the causal impact of income support on reproductive behavior at the household level. Second, we employ an RDD estimation strategy that allows us to provide more credible evidence of causality. Third, our possibility to analyse the entire population of *RdC* applicants from administrative records enhances the external validity of our results, making them more generalizable across the broader context of unconditional cash transfer policies. Fourth, differently from Yonzan et al. (2024), who look at the birth spacing, birth parity, and abortion as potential mechanisms for the observed increase in fertility, we explore the role of other key dimensions, such as gender norms, financial constraints, and the opportunity cost of childbearing. Finally, our focus on Italy provides insights from a very-low fertility setting that mirrors other rich countries, particularly in Southern Europe. In contrast to Alaska, which registered one of the highest fertility rates across the U.S., with more than 60 births per 1,000 women aged 15–44 in 2022 (over 9 births per 1,000 residents), Italy had one of the lowest in Europe, with slightly more than 30 births per 1,000 women aged 15–44 in 2023 (about 6 births per 1,000 residents).

Identifying the causal impact of income on fertility presents several econometric challenges. First, reverse causation complicates the analysis, as having children may reduce household income capacity. Second, unobserved confounding factors may simultaneously affect income and fertility decisions. Third, comparing recipients and non-recipients of income support is problematic because the former typically face greater socio-economic vulnerabilities, making it challenging to construct an appropriate counterfactual. To address these challenges, we employ a Regression Discontinuity Design (RDD), leveraging the strict eligibility criteria of the *RdC,* which restrict access to households below specified income and wealth thresholds.

Our analysis focuses on household income as the primary determinant of eligibility, given that approximately 73% of applications met the income threshold, and 90% of acceptance or rejection decisions were based on this criterion. To mitigate potential biases, we restrict the sample to the first three months of program implementation (April–June 2019), when strategic behavior to manipulate income eligibility was unlikely due to the reliance on pre-existing 2018 income levels. To account for the dynamic nature of eligibility, including the possibility of reapplication or benefit loss, we use a Fuzzy RDD and define "effective recipients" as individuals who received income support for at least six months after their application outcome. Our analysis focuses on women of childbearing age (16-45), aligning with standard demographic definitions of reproductive age and targeting the population most likely influenced by income changes in fertility decisions.

Our findings reveal no overall impact of the *RdC* on fertility; however, this null effect masks significant regional heterogeneity. While the program had no observable effect in the Centre-North, it significantly increased fertility in Southern Italy. In the South, *RdC* recipients were 1.5 percentage points more likely to conceive a child within two years of receiving the benefit, representing a 18% increase in the biennial (between June 2019 and June 2021) fertility rate relative to the control group mean. These results are robust to manipulation tests, balance checks, non-parametric estimations, and progressively smaller bandwidths. We also observe more pronounced effects among older women, those with at least one existing child, women without disabled household members, and those living in rented accommodations. Our analysis of the mechanisms suggests that the regional differences we detect are driven by contrasting social norms and economic conditions, with Southern Italy characterized by more traditional family structures and greater financial constraints compared to the Centre-North.

Moreover, we find no overall impact of the *RdC* on either margin of labor supply, suggesting that income support does not create negative work incentives through substitution effects. However, while this null effect persists in the South, *RdC* recipients in the Centre-North show a significant reduction in the intensive margin of labor supply and in individual labor earnings. Specifically, over the nine-month period from June 2019 to February 2020, women worked 0.13 fewer months (approximately 4 fewer days) and men 0.11 fewer months (about 3 fewer days), representing a 10% and an 8% decline, respectively, relative to the control group mean.[5] Correspondingly, labor earnings fell by €609 for women and €628 for men, equivalent to declines of 10% and 11%, respectively, relative to

[5] We decided to focus on the period before the outbreak of the Covid-19 pandemic as this might have affected recipients and non-recipients differently.

the control group mean. These reductions are driven primarily by fewer days worked, rather than changes in daily wages.

We further enrich these findings with insights from a comprehensive survey by the Italian National Institute for Public Policy Analysis (INAPP), which allows to combine detailed individual-level information on labor market outcomes with other key variables such as income, education, family background, health, as well as measures of trust and wellbeing. The 2021 wave of the survey asks respondents whether they applied to the *RdC* program and whether they received or not the benefit in the past 12 months. By focusing exclusively on *RdC* applicants and comparing recipients to non-recipients, we find that the program not only increased fertility intentions but also had significant effects on other key outcomes. Specifically, we note that income support significantly alleviated beneficiaries' financial constraints, improved health outcomes, and boosted job search efforts. Moreover, additional evidence suggests that the observed positive effect on fertility may not be solely driven by increased income. Instead, it could also stem from the reduced economic uncertainty and the enhanced sense of stability and self-confidence associated with participation in the program.

Overall, our findings suggest that, although not the intended consequence of the *RdC* program, government minimum income schemes can serve as effective pro-natalist policy tools, given the substantive effects we estimate. The size of our estimates suggests that an average (potentially permanent) monthly cash transfer of €500 increases the probability of having a child within two years of almost 20%. This effect is comparable to the 15% annual fertility increase among women aged 20-44 reported by Yonzan et al. (2024) after the introduction of the APFD, which provides an annual cash transfer of $2,000. Our estimates also align with other studies examining the effects of cash transfers on fertility. For instance, Milligan (2005) investigates the effects of the Quebec Allowance for Newborn Children which paid $500 for the first child, $1000 for the second child, and up to $8000 for the third child. Using Canadian Census data and a triple-difference approach leveraging differences in benefits across family types, he finds that a one-time $500 transfer increased the likelihood of having a child by 10%. Compared to these studies, our analysis highlights the regional heterogeneous effects of minimum income programs like the *RdC* and offers novel insights into the mechanisms driving the observed shifts in fertility.

Our study also contributes to the broad literature examining how income changes influence fertility, whether through employment variations, changes in broader economic conditions, or housing market fluctuations. Studies have documented significant fertility effects arising from changes in employment (Adsera, 2005; Autor et al., 2019; Currie and Schwandt, 2014; Del Bono et al., 2012; Huttunen and Kellokumpu, 2016; Lindo, 2010), job security (Clark and Lepinteur, 2022; De Paola et al., 2021), economic uncertainty (Kearney and Wilson, 2018; Schaller, 2016), housing prices (Daysal et al., 2021; Dettling and Kearney, 2014; Lovenheim and Mumford, 2013), and mortgage interest rates (Cumming and Dettling, 2023). We contribute to these lines of research by showing how income support programs affect fertility decisions, particularly in economically disadvantaged regions with conservative social norms.

The reminder of the paper is structured as follows: Sections 2 describes the institutional framework. Section 3 describes the data. Section 4 presents the identification strategy, and the validity checks of our RDD. Section 5 discusses the main results, the heterogeneous effects, and the mechanisms. Section 6 concludes.

2. Institutional setting

The Italian *RdC*, a guaranteed minimum income program designed to combat poverty, was introduced in March 2019 through Law Decree 4/2019 (later converted into Law 26/2019) and remained in effect until January 2024. During its implementation, the program aided approximately 3 million individuals, with an average monthly benefit of around €500. The *RdC* aimed to combine financial support for households below a certain income threshold with an active labor market policy (ALMP), requiring beneficiaries to actively engage in job searching or social inclusion programs. However, the ALMP component was only partially implemented throughout the program's duration.[6]

Eligibility for the *RdC* was subject to several criteria. First, households had to meet four income and wealth-related requirements:[7] *(a)* household taxable income must not exceed €6,000 (€9,360) for households in rented (non-rented) accommodation; *(b)* financial assets must be less than €6,000; *(c)* excluding the primary residence, total real estate holdings could not exceed €30,000; *(d)* the household's Indicator of the Equivalized Economic Situation (ISEE) must be below €9,360.[8] Table 1

[6] ANPAL (2021) documented that among the beneficiaries eligible to the ALMP, the take-up rate of the participation to the program was 45.6 percent. It must be taken into consideration that one of the requirements related to the participation to ALMP of unemployed beneficiaries was the acceptance of at least one of three adequate job offers provided by the Italian employment centers. This requirement turned out to be quite slack in practice, as the definition of adequacy of the job offer was "within 200 km" for the first one, "within 100 km" for the second one in case the first is refused and anywhere for the third one in case the second is refused; after 12 months a job offer is considered adequate within 250 km. The extent of success of this policy has been documented in ANPAL (2021), where it turns out that only the 10.8 percent of those who have participated to the ALMP reached a stable occupation in the years 2019-2021.

[7] These conditions were self-declared through the "*DSU*" ("*Dichiarazione Sostitutiva Unica*") form, which applicants were required to complete at a tax assistance center either prior to or simultaneously with their application. All values reported in the *DSU* referred to year t-2 with respect to the declaration, except for household income, which was required to be updated if more recent values were higher.

[8] ISEE is a composite indicator weighting household income, real estate, financial wealth, and household composition. The analytical formula to retrieve ISEE value is $\frac{ISR+0.2\times ISP}{ISEE\ equivalence\ scale}$, where ISR (Indicator of the household income situation) is the total amount of household income in *t-2*, ISP (Indicator of the household wealth situation) is the total amount of financial and real estate assets in *t-2* and the ISEE equivalence scale is as follows: 1 (1 component); 1.57 (2

summarizes the eligibility criteria and associated thresholds for single-person households. For multi-person households, the taxable income threshold was adjusted using the RdC equivalence scale, which considers the household's size and composition. Also, the financial asset threshold was increased by €2,000 for each additional household member, up to a maximum of €10,000.

An additional wealth requirement *(e)* was related to the ownership of luxury vehicles or boats. Eligibility was disqualified for applicants who owned vehicles registered within six months prior to the application, high-powered cars registered within the past two years, or ships and pleasure boats. Moreover, individuals had to meet specific residency or citizenship criteria - requirement *(f)*. They needed to be Italian or EU citizens or be close relatives of an Italian or EU citizen. Alternatively, they could be permanent residents or have lived continuously in Italy for at least 10 years. A final eligibility condition - requirement *(g)* - was participation in the ALMP for unemployed individuals.

Eligibility criteria were slightly different for households with all members aged 67 or older, referred to as the "*Pensione di Cittadinanza*". In this case, the criteria outlined in Table 1 applied, except for households in non-rented accommodation, where the household taxable income threshold was raised to €7,560 (instead of €6,000) and adjusted by the *RdC* equivalence scale.

Table 1. Requirements and thresholds for eligibility of single-person households.

		(1) Household in non-rented house	(2) Household in rented house
a.	Household taxable income	€9,360	€6,000
b.	Financial assets	€6,000	€6,000
c.	Real estate (excluding main residence)	€30,000	€30,000
d.	ISEE value	€9,360	€9,360
e.	Luxury vehicles or boats	NO	NO
f.	Residency-citizenship	YES	YES
g.	Participation in ALMP if unemployed	YES	YES

The duration of the benefit was 18 months, with the possibility of renewal after a 1-month break. There was no explicit limit on the number of renewals. This implies that the benefit was perceived as permanent, especially for early applicants, who are the focus of our analysis. The financial support consisted of two components: 1) a cash transfer aimed at supplementing household income up to a defined threshold, and 2) a contribution towards rent or mortgage payments, with caps of €3,360 per year for tenants and €1,800 for mortgagers, respectively. For a single-person household, the first component topped up annual income to €6,000. The amount of the cash transfer had a minimum of €480 and increased with family size, following the *RdC* equivalence scale up, up to a maximum of

components); 2.04 (3 components); 2.46 (4 components); 2.85 (5 components); these values are incremented by 0.35 in case of each further component, by 0.2 in case of 3 children, by 0.35 in case of 4 children and by 0.5 in case of 5 children; these values are further incremented by 0.2 and by 0.3 for the presence of children under the age of 18 and 3, respectively.

€20,592 per year.[9] To mitigate the potential negative effects on labour supply, the cash transfer was temporarily extended for up to one year after a beneficiary entered the labour market or increased her work hours. Specifically, 80% of additional labour income counted toward the updated household taxable income requirement during this period.[10] After one year, the benefit expired if the household income exceeded the eligibility threshold, resulting in a marginal implied tax rate on labor supply of 80% within the first year, rising to 100% thereafter.

Starting January 1, 2024, the *RdC* was replaced by two new measures: the *Assegno di Inclusione* (*AdI*) and the *Sistema Formazione Lavoro (SFL)*. The *AdI* is similar to the *RdC*, with comparable economic eligibility requirements, but targets a smaller group of households. Specifically, it applies to households with at least one member who meets any of the following criteria: disability, under 19 years old, over 59 years old, or in disadvantaged circumstances supported by social services. The benefit structure mirrors the *RdC*, lasting 18 months with the possibility of a 12-month renewal. From January to April 2024, around 643,000 households, or 1.6 million individuals, received at least one monthly payment of the *AdI*, with an average monthly amount of €619. The *SFL* targets individuals aged 18-59 with an ISEE not exceeding €6,000 annually, who do not qualify for the *AdI*. It aims to integrate employable individuals at risk of social exclusion by providing training, career guidance, and job placement support. Participants also receive a financial benefit of €350 per month for up to 12 months, non-renewable, provided they engage in the required activities. In our analysis, we focus exclusively on the *RdC* and will explore the effects of the new measures in future research.

3. Data and descriptive statistics

We utilize several data sources provided by the Italian Social Security Institute to conduct our analysis. To identify applicants and beneficiaries of the *RdC*, we focus on data from the universe of applications submitted and processed by June 2019, which includes 2,828,767 individuals. Our initial selection includes only those applications that were accepted or rejected based on the household income eligibility requirement —requirement *(a)* in Table 1. As shown in Table 2, the majority of rejections are due to this income eligibility criterion, with a rejection rate of about 27%. This criterion is complex, as it is based on the sum of all household members' incomes from two years prior (year t-2), minus any welfare benefits from previous years, and adjusted for current-year welfare benefits. In contrast, the other economic and wealth conditions (requirements (b)-(f) in Table 1) are easier to

[9] The amount of the benefit was then calculated as: Benefit = [(Income Threshold x Equivalence Scale) - Household Income] + Rent/Mortgage support.
[10] As the benefit is a complement to a threshold, a reduction in taxable income reflects an increase in the benefit amount.

predict. Typically, individuals who know in advance that they exceed these thresholds do not apply. Therefore, we exclude applications rejected based on requirements (b)-(f), that is, 2,582,840 individuals.

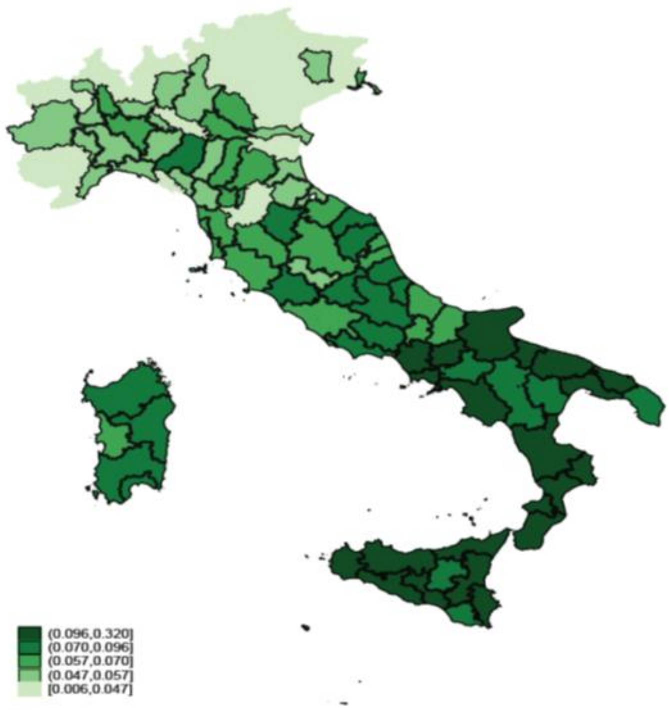
Table 2. *RdC* met requirements distribution.

Requirement	Met requirement N	Met requirement %
a. Household income	4,108,165	73.6
b. Financial assets	5,177,167	92.7
c. Real estate	5,473,675	98.0
d. ISEE value	5,493,954	98.3
e. Luxury vehicles	5,582,073	99.9
f. Residency-Citizenship	5,441,751	97.4
Requirements b-f	5,038,235	90.2
Requirements a-f	3,920,244	70.2

Notes: Sample includes the universe of 5,584,393 *RdC* applicants between April 2019 and April 2021. Source: INPS data.

As shown in Table 2, 90.2% of applications meet requirements (*b)-(f)*, while 70.2% of applications meet all eligibility thresholds, including requirement *(a)*. We then narrow our sample to focus exclusively on women of childbearing age (between 16 and 45 years), who make up 20% of the initial sample. This further selection leaves us with a final sample of 532,430 women. Figure 1 illustrates the geographical distribution of applicants in this sample. The map reveals a clear North-South divide, with the majority of applicants residing in the Southern regions of Italy, the country's poorest area.

Figure 1: Share of *RdC* applicants in April-June 2019 by province.



Notes: The figure illustrate the distribution of the share of *RdC* applicants in the total population at the province level. Darker green areas reflect higher shares of *RdC* applicants. Sample includes the universe of 532,430 female applicants aged 16-45, whose application was processed by June 2019 and was either accepted or rejected based on the household income eligibility requirement—requirement (a) in Table 1. Source: INPS data.

As shown in Table 3, where we report some descriptive statistics, about 61% of the women in our sample live in the South. The average age is 31, and the average household consists of about four members, including 1.5 minors (children under 18) and 0.2 disabled individual. About 25% of applicants in the sample are non-Italian and about 45% of them live in rented accommodation.

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Birth	0.079	0.270	0	1
RdC (recipient)	0.762	0.426	0	1
Below (relative threshold)	0.744	0.437	0	1
Distance (from relative threshold)	4929.733	7098.727	-16015.619	19166.170
South	0.613	0.487	0	1
Age	31.092	8.996	16	45
Household size	3.887	1.542	1	21
Non-Italian	0.245	0.430	0	1
No. of minors	1.468	1.191	0	13
No. of disabled	0.188	0.466	0	7
Rented house	0.448	0.497	0	1

Notes: Sample includes the universe of 532,430 female applicants aged 16-45, whose application was processed by June 2019 and was either accepted or rejected based on the household income eligibility requirement—requirement (a) in Table 1. Source: INPS data.

We define our treatment variable, *RdC*, as a dummy variable taking the value of one for women who were admitted to the program between April and December 2019 and received the benefit for at least 6 months. Based on this definition, 76% of women in our sample are considered effective beneficiaries. This proportion is slightly higher than the 74% of women who, by June 2019, had a household income below the eligibility threshold (which defines our instrumental variable, denoted as Below). This difference occurs because some individuals (4,905, or 1% of the sample) who were initially excluded due to income exceeding the threshold were later admitted, while others (14,479, or 3% of the sample) initially admitted were soon excluded, ending up with less than 6 months of income support during the study period.

We build a variable called *Distance from relative household income threshold*, which represents the difference between the household income declared by applicants and the income threshold set by the law for their specific household type. This threshold varies according to the household's size and composition, and whether the household lives in rented or non-rented accommodation. On average, this variable has a value of €4,930.

To measure fertility, we use data from the Universal Child Allowance, a child benefit program introduced in 2022 that covers all families with children under the age of 21. With a high take-up (about 98% for children born between 2019 and 2021), this allowance serves as a reliable indicator of birth rates in Italy during the sample period. Using this data, we define our dependent variable, *Birth*, as an indicator for women who conceived a child within two years of receiving the outcome of their application (i.e., by the end of June 2021). As shown in Table 3, approximately 8% of women in our sample gave birth during the observation period.[11]

We apply the Mean Squared Error (MSE) optimization criterion to select the optimal sample for our empirical analysis from the 532,430 women previously described. To account for the asymmetric distribution of applicants (with recipients outnumbering non-recipients), we use an asymmetric bandwidth in the selection process. In our preferred specification (discussed in Section 3), we include applications accepted and rejected for differences from the threshold of -€3,044 and +€3,362 in the Overall sample, -€3,002 and +€3,606 in the Centre-North sub-sample, and -€2,313 and +€4,252 in South sub-sample. After applying the optimal bandwidth criterion, we are left respectively with 118,464 observations in the Overall sample (60% of which are *RdC* recipients), 54,999 observations in the Centre-North sub-sample (57% of which are *RdC* recipients), and 47,512 in the South sub-sample (74% of which are *RdC* recipients).

Table 4 presents a comparison of the summary statistics between women in the initial samples and those in the optimal-bandwidth samples used for analysis.

Table 4: Descriptive statistics in the original and optimal bandwidth samples.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Overall		Centre-North		South	
Variable:	Initial	Optimal	Initial	Optimal	Initial	Optimal
Birth	0.079	0.080	0.074	0.079	0.082	0.081
RdC (recipient)	0.744	0.596	0.641	0.571	0.837	0.741
Below (relative threshold)	0.762	0.548	0.614	0.507	0.825	0.697
Distance (from relative threshold)	4,930	468	2,859	420	6,234	1,243
South	0.613	0.553	0	0	1	1
Age	31.092	31.482	31.504	31.752	30.833	31.179
Household size	3.887	3.815	3.956	3.880	3.843	3.735
Non-Italian	0.245	0.288	0.501	0.535	0.083	0.086
No. of minors	1.468	1.412	1.632	1.601	1.365	1.255
No. of disabled	0.188	0.167	0.182	0.158	0.191	0.173
Rented house	0.448	0.426	0.654	0.666	0.319	0.231
Observations	532,430	118,464	205,808	54,999	326,622	74,512

Notes: Reported are mean values. Overall initial sample includes the universe of 532,430 (205,808 in the Centre-North and 326,622 in the South of Italy) female applicants aged 16-45, whose application was processed by June 2019 and was either accepted or rejected based on the household income eligibility requirement—requirement (a) in Table 1. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample for the empirical analysis. Source: INPS data.

The comparison is made for the Overall sample (columns 1-2), the Centre-North sub-sample (columns 3-4), and the South sub-sample (columns 5-6), respectively. In the Overall optimal-

[11] Considering that we focus on births occurring from June 2019 to June 2021, this share is comparable with that found by De Paola et al. (2021), who use data from the Italian Labor Force Survey and measure fertility based on employees' declaration of having been absent from work due to Compulsory Maternity Leave. About 3.7% of women in their sample were on Maternity leave during a year.

bandwidth sample, the average probability of conceiving a child is 8%, which is nearly identical to the 7.9% in the initial sample of 532,430 women, with 60% *RdC* recipients compared to 74% in the initial sample. In the Centre-North optimal-bandwidth sub-sample, the average probability of conceiving a child is 7.9%, slightly higher than the 7.4% in the initial sample of 205,808 women, with 57% *RdC* recipients compared to 64% in the initial sample. In the South optimal-bandwidth sub-sample, the average probability of conceiving a child is 8.1%, almost identical to the 8.1% in the initial sample of 326,622 women, with 74% of women receiving *RdC* benefits, compared to 84% in the initial sample.

4. Identification strategy

To investigate the effect of the *RdC* program on fertility, we employ a Fuzzy Regression Discontinuity Design (RDD), leveraging the threshold-based structure of the scheme. More precisely, we instrument the effective treatment indicator, i.e. whether an individual is an actual recipient of the *RdC*, with a dummy variable for individuals whose household income, as of June 2019, was below the relevant threshold. Household income serves as the running variable, and we compare households whose applications were rejected or accepted close to the income threshold (requirement *(a)* in Table 1), given that all other requirements were met. We estimate the following structural model:

$$Birth_i = \beta_0 + \beta_1 RdC_i + \beta_2 f(Distance_i) + \beta_3 RdC_i * f(Distance_i) + \beta_4 X_i + \varepsilon_i \qquad (1)$$

$$RdC_i = \alpha_0 + \alpha_1 Below_i + \alpha_2 f(Distance_i) + \alpha_3 Below_i * f(Distance_i) + \alpha_4 X_i + \mu_i \qquad (2)$$

where equation (1) represents the main outcome equation, while equation (2) is the first stage. $Birth_i$ is a binary outcome variable that takes the value of 1 for individuals who conceived a child between June 2019 and June 2021, and 0 otherwise. RdC_i is a binary variable equal to 1 for *RdC*-recipient, defined as individuals who received income support for at least 6 months since the notification of the application's outcome, and 0 otherwise; $f(Distance_i)$ is a flexible functional form relating the distance of the household income from the relative threshold to the probability of having a child. We also include the interaction term between RdC_i and the running variable $f(Distance_i)$ to allow for different functional forms of the two sides of the cut-off. $Below_i$ is a dummy variable for individuals whose household income was below the relative threshold in June 2019, signifying their eligibility for the *RdC*. This variable is used as an instrumental variable for RdC_i. X_i is a vector of individual characteristics, including age, age squared, migration status, household size, number of children under the age of 18, number of disabled household members, and a full set of macro-regional dummies (North-East, North-West, Center, South, Islands) to capture geographical variations.[12] ε_i and μ_i represent the error terms in equation (1) and (2), respectively. We cluster standard errors at the level of the forcing variable.

We estimate our model using a Local Linear Regression (LLR) approach in the neighbourhood of the MSE-optimal bandwidth around the cut-off, as proposed by Calonico, Cattaneo and Farrell (2020). Additionally, we estimate separate functions for both sides of the threshold by including interaction terms between the running variable $f(Distance_i)$ and the treatment indicator RdC_i, which we instrument with the interaction term between $f(Distance_i)$ and $Below_i$. Under the assumption that the relationship between fertility and household income is continuous near the cutoff, the treatment assignment can be rated as good as random (Lee and Lemieux, 2010) and any discontinuity or jump in the outcome variable can be interpreted as a causal effect of the program.

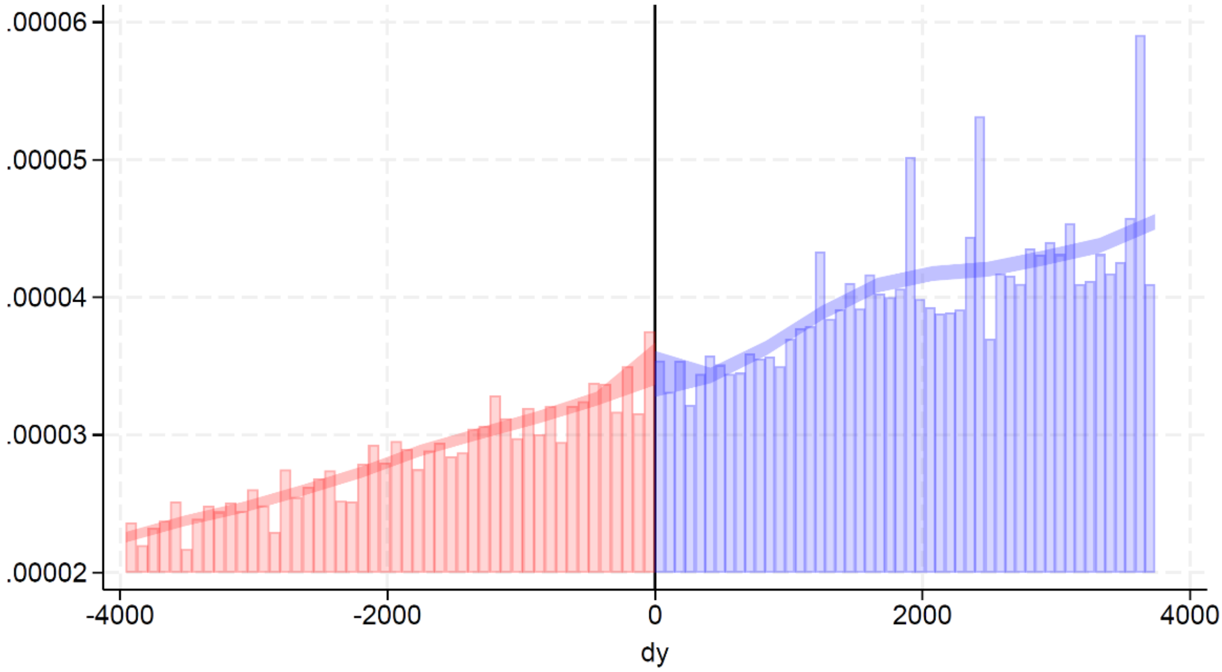
4.1. RDD validity checks

Before presenting our results, we discuss the main assumption underlying the estimation strategy. We first present the McCrary test for the continuity of the forcing variable (household income), conducted using a kernel local linear regression of the log density on either side of the threshold (McCrary, 2008). A discontinuity at the cut-off point would indicate that *RdC* applicants might have manipulated their household income to fall below the threshold for program eligibility. For example, individuals could reduce their working hours to meet the household income criterion. However, such behaviour is unlikely in our context, as the household income used for eligibility in 2019 applications was from two years prior. Therefore, individuals could not have anticipated the program's technical details or eligibility conditions in advance. The McCrary test results in Figure 2 support our expectations.

As shown in the Figure, the log density of household income on both sides of the threshold exhibits no discontinuity (t-statistic = 0.5753, p-value = 0.5651) for women in the Overall optimal-bandwidth sample. Thus, we fail to reject the null hypothesis of no jump in household income density at the threshold. Additional results for the Centre-North and South sub-samples, presented in Figures A.1 and A.2 in the Appendix, reinforce this conclusion. These findings reassure us that households did not manipulate the forcing variable to gain program access.

[12] In some specifications, we use region dummies instead of macro-region dummies and results are unchanged.

Figure 2. McCrary test. Overall sample.



Notes: The figure depicts the estimates of the McCrary test in the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. Histograms represent the log density of the running variable, computed as the difference between the threshold and the applicant's household income. Blue histograms on the right refer to *RdC* recipients, while red histograms on the left refer to non-recipients. Source: INPS data.

We also examine the continuity of observable individual and household characteristics used as covariates in our RDD analysis at the cut-off point. Specifically, we regress each covariate on a first- or second-order polynomial of the forcing variable, including a treatment indicator. A statistically insignificant coefficient on the treatment dummy supports local random assignment (see, among others, Caughey and Sekhon, 2011; Lee, 2008). The estimates, reported in Table 5, show that our treatment is not significantly associated with any of the covariates included in the model. These balance checks confirm that individuals' characteristics do not change sharply at the threshold.

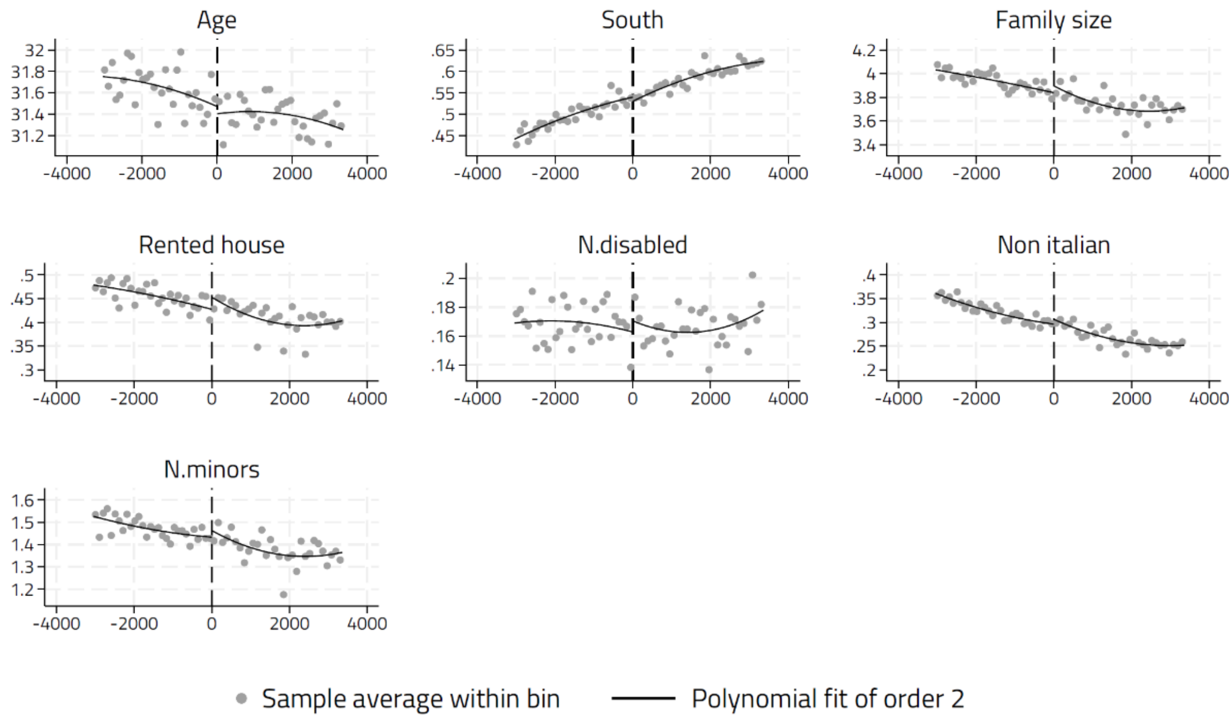
For visual inspection, Figure 3 presents descriptive graphs of the predetermined characteristics plotted against the household income around the threshold in the Overall sample. Figures A.3 and A.4 in the Appendix provide similar graphs for the Centre-North and South sub-samples, respectively. Each panel displays cell means of predetermined characteristics near the income threshold, along with locally weighted second-order regression fits. Overall, Figure 3 and Figures A.3–A.4 confirm that covariates show no significant jumps at the threshold, further supporting our assumptions.

Table 5: Balance checks.

Sample:	(1) Overall	(2) Centre-North	(3) South
Dependent Variable:			
South	-0.0022		
	(0.0056)		
Age	-0.0306	-0.0048	-0.0095
	(0.0957)	(0.1387)	(0.1335)
Non-Italian	0.0013	0.0092	-0.0023
	(0.0050)	(0.0088)	(0.0051)
Household size	-0.0049	-0.0088	-0.0122
	(0.0189)	(0.0240)	(0.0276)
No. of minors	0.0017	-0.0019	0.0148
	(0.0132)	(0.0179)	(0.0185)
No. of disabled	-0.0017	-0.0073	-0.0017
	(0.0062)	(0.0087)	(0.0087)
Rented house	0.0041	0.0105	0.0048
	(0.0077)	(0.0107)	(0.0096)
Observations	118,464	54,999	74,512

Notes: Sample includes female applicants aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each column. Reported are coefficients of the effect of *RdC* on the 8 different variables listed in the "Dependent variable" column. The treatment variable in each regression is *RdC*, a dummy taking value 1 for *RdC* recipients. Controls are 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Figure 3. Continuity of the observable characteristics at the threshold in the Overall sample.



Notes: The figure depicts the values of each individual characteristic plotted against the running variable, computed as the difference between the threshold and the applicant's household income. Estimates are from the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. Source: INPS data.

5. Results

Table 6 reports the first stage results from estimating equation (2) in Section 3. The estimates suggest that having a household income below the relative threshold as of June 2019 strongly predicts the likelihood of being an *RdC* beneficiary.

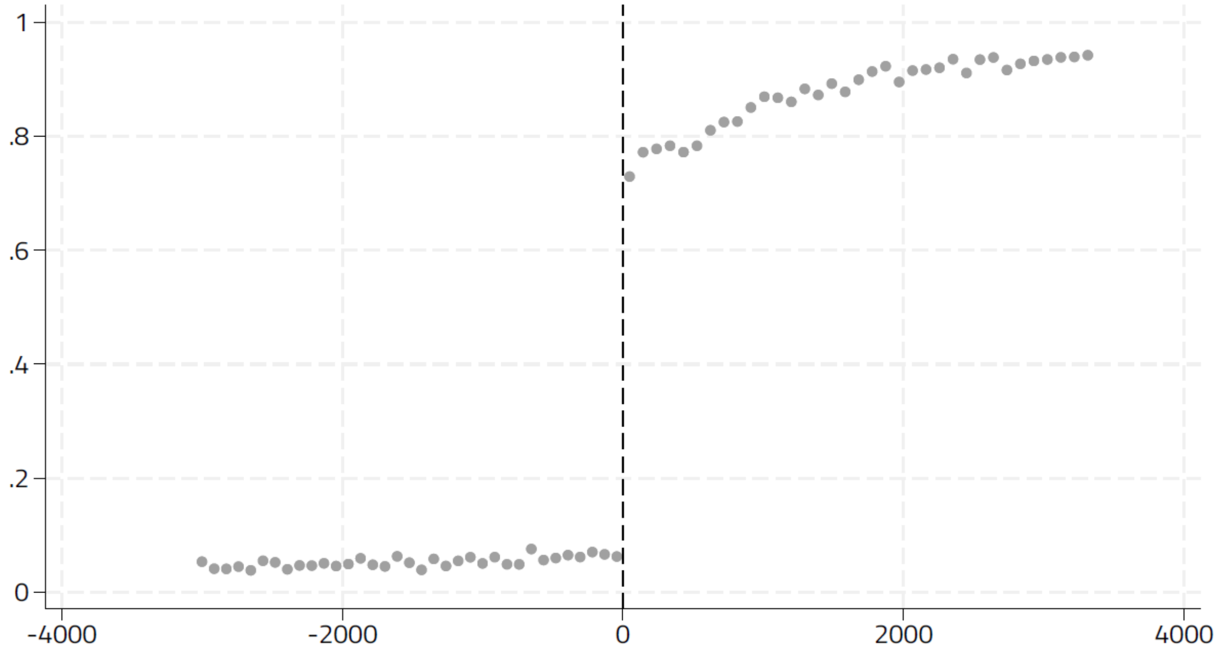
Table 6: First stage estimates.

	(1)	(2)	(3)
		RdC	
Sample:	Overall	Centre-North	South
Below	0.7232***	0.7186***	0.7414***
	(0.0048)	(0.0064)	(0.0062)
Observations	118,464	54,999	74,512

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each column. The dependent variable is *RdC*, a dummy taking value 1 for *RdC* recipients. *Below* is a dummy taking value 1 for individuals who by June 2019 have a household income below the relative threshold. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

This relationship holds across the Overall sample as well as the Centre-North and South sub-samples. individuals meeting the income criterion have a 72-percentage-point higher probability of receiving income support than those with household incomes above the threshold. Figure 4 visually depicts this relationship, showing that the probability of receiving the *RdC* is below 10% for applicants above the threshold, jumps to nearly 80% for those just below it, and increases further to almost 100% for those well below the threshold.

Figure 4: Probability of being an *RdC* recipient against distance from relative income threshold.



Notes: The figure depicts the estimates of the first-stage regression (equation 2). Estimates are from the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. Source: INPS data.

Table 7 presents the main results of our analysis for the Overall sample (panel A), the Centre-North (panel B) and the South sub-samples (panel C). Column 1 shows estimates from a specification without controls, while column 2 incorporates demographic controls, such as age, age squared, a dummy for women residing in the South and an indicator for non-Italian women. Column 3 adds household-related controls, e.g. household size, number of minors, and number of disabled members, and column 4 includes an additional control for living in rented accommodations.

Our findings reveal no significant effect of *RdC* on fertility in the Overall sample or the Centre-North sub-sample. However, we detect a significant positive effect in the South. According to estimates in column 4, our preferred specification, *RdC* recipients in the South are 1.5 percentage points more likely to conceive a child within two years of receiving income support compared to non-recipients—equivalent to a 19% increase in mean fertility. This suggests that income support can influence fertility decisions in poorer households, highlighting a strong responsiveness of reproductive behavior to income changes.

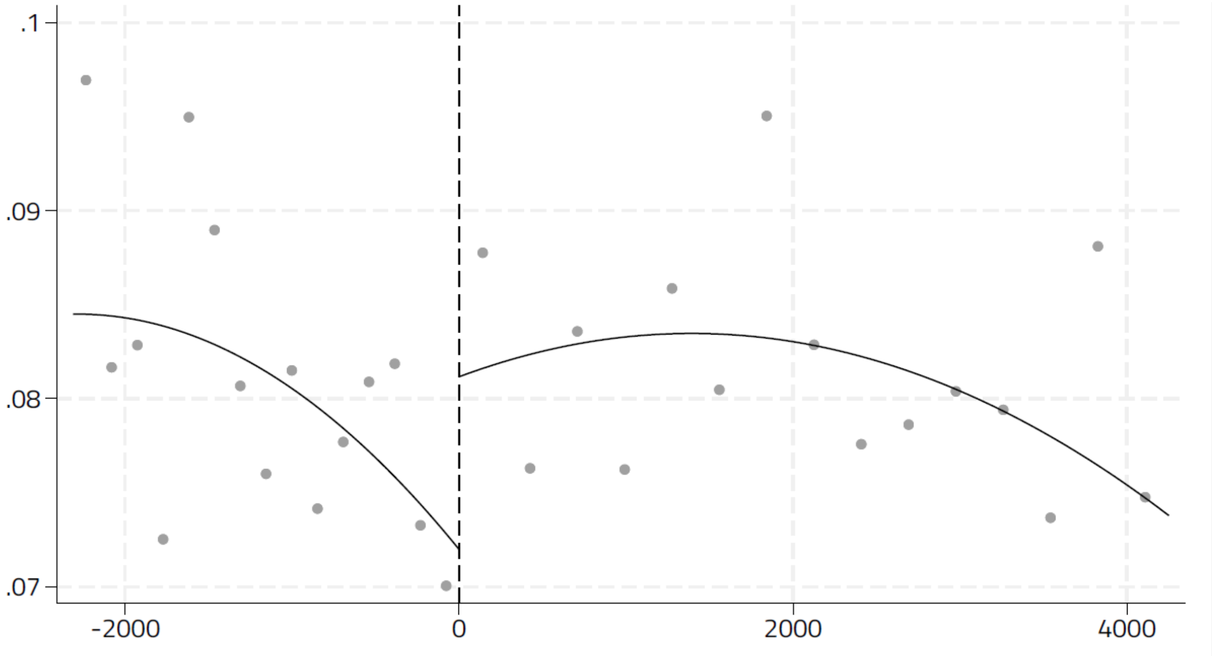
Table 7: Effects on fertility. Second stage estimates.

	(1)	(2)	(3)	(4)
	Birth			
	No Covariates	+Demographic controls	+Household controls	+Rented house
Panel A: Overall sample				
RdC	0.0046	0.0030	0.0029	0.0028
	(0.0045)	(0.0044)	(0.0044)	(0.0044)
Control mean	0.0812	0.0812	0.0812	0.0812
Left bandwidth	-3,044	-3,044	-3,044	-3,044
Right bandwidth	3,362	3,362	3,362	3,362
Observations	118,464	118,464	118,464	118,464
Panel B: Centre-North sub-sample				
RdC	-0.0028	-0.0055	-0.0057	-0.0059
	(0.0066)	(0.0064)	(0.0064)	(0.0064)
Control mean	0.0820	0.0820	0.0820	0.0820
Left bandwidth	-3,002	-3,002	-3,002	-3,002
Right bandwidth	3,606	3,606	3,606	3,606
Observations	54,999	54,999	54,999	54,999
Panel C: South sub-sample				
RdC	0.0167^{***}	0.0152^{**}	0.0149^{**}	0.0148^{**}
	(0.0063)	(0.0061)	(0.0061)	(0.0061)
Control mean	0.0804	0.0804	0.0804	0.0804
Left bandwidth	-2,313	-2,313	-2,313	-2,313
Right bandwidth	4,252	4,252	4,252	4,252
Observations	74,512	74,512	74,512	74,512

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each panel. The dependent variable is *Birth*, a dummy taking value 1 for individuals who conceived a child in the period from June 2019 to June 2021. *RdC* is a dummy taking value 1 for *RdC* recipients. Demographic controls include age, age squared, a dummy for South and a dummy for non-Italian. Household controls include household size, no. of minor and no. of disabled components. Rented house is an indicator for women living in rented houses. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Figure 5 visually illustrates the estimated effect of *RdC* on fertility for women in the South, as shown in Panel C, column 4. Corresponding visualizations for the overall sample and the Centre-North sub-sample are provided in Figures A.5 and A.6 in the Appendix.

Figure 5: Effects on fertility. RD plot. South sub-sample.



Notes: The figure depicts the estimates of the second-stage regression (equation 1). Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. Source: INPS data.

In Table A.1 in the Appendix, we check the robustness of our main results for the South in several ways. First, we augment our main specification to account for regional differences within the South (column 1). Second, we re-estimate our model using a symmetric bandwidth (column 2). Finally, we estimate the model non parametrically using conventional, bias-corrected, and robust inference in column 3, 4 and 5, respectively. Reassuringly, these robustness checks yield results consistent with those in Table 7, panel C.

We also analyze the effect of the *RdC* excluding children conceived from March 2020 onward, in order to focus on the pre-pandemic period. This approach has the advantage of filtering out potential effects related to the COVID-19 crisis, which may have impacted recipients and non-recipients differently. However, it limits the analysis to a relatively short window, from June 2019 to February 2020. As shown in Table A.2 in the Appendix, the results are very similar to those discussed above. The effect remains concentrated among women residing in the South, with a comparable magnitude.

Furthermore, we assess the robustness of our findings by using progressively smaller bandwidths, comparing women with increasingly similar household incomes. Figure A.7 in the Appendix plots the point estimates as the bandwidth is reduced by €100 increments, up to €1,000. Notably, the estimated effect remains unchanged across all bandwidth sizes, further supporting the validity of our results.

5.1. Heterogeneous fertility responses

In this section we explore the heterogeneous effects of *RdC* on fertility by individual and household characteristics. We focus on the South sub-sample, where a significant effect was detected in the previous section.

In panel A of Table 8, we first test whether our main effect varies across women of different ages and with different number of pre-existing minor children. Reading across the estimates in columns 1-4, our findings suggest that the positive impact of *RdC* on fertility is primarily driven by older women and those with at least one child under the age of 18. This suggests that income support may facilitate higher-order births but does not significantly affect the decision to enter motherhood for younger women.

Table 8: Heterogeneous effects on fertility. South sub-sample.

	(1)	(2)	(3)	(4)
Panel A:	Age<=32	Age>32	No. minors=0	No. minors>=1
RdC	0.0070	0.0188**	0.0046	0.0150**
	(0.0084)	(0.0086)	(0.0108)	(0.0072)
All controls	Yes	Yes	Yes	Yes
Control mean	0.0805	0.0786	0.0795	0.0806
Left bandwidth	-2,593	-1,969	-2,083	-2,567
Right bandwidth	4,786	4,443	3,203	5,514
Observations	42,201	37,955	16,872	68,080
Panel B:	No. disabled=0	No. disabled>=1	Owned house	Rented house
RdC	0.0167**	0.0041	0.0114	0.0253*
	(0.0076)	(0.0120)	(0.0074)	(0.0143)
All controls	Yes	Yes	Yes	Yes
Control mean	0.0801	0.0808	0.0807	0.0792
Left bandwidth	-2,258	-2,928	-2,490	-2,003
Right bandwidth	2,819	5,554	2,951	4,618
Observations	44,933	14,992	43,353	18,318

Notes: Sample includes women aged 16-45 in the South. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

In panel B of Table 8, we further investigate whether the effect varies based on the presence of disabled individuals in the household. Results in columns 1-2 reveal that the fertility effects of the *RdC* program are significant only for individuals with no disabled components in the family. This suggests that the decisions regarding childbearing for individuals with disabled household members might not be directly influenced by income support. These individuals, burdened by the financial, emotional, and logistical challenges of caring for a disabled person, may be more reluctant to expand their family size, requiring more extensive forms of support.

Finally, in columns 3-4 we explore whether the effect is heterogeneous across individuals living in rented versus non-rented accommodations. The results show that the effect is solely observed for those in rented accommodations, indicating that income support plays a particularly crucial role in promoting fertility for those experiencing higher economic uncertainty.

5.2. Effects on labor supply

A fundamental prediction of the classical labor supply model is that, if leisure is a normal good, an increase in unearned income—such as income support or lottery winnings—should lead individuals to reduce their working hours or even exit the labor market entirely, resulting in a proportional decline in earnings. However, this prediction becomes more nuanced in more realistic economic environments. When credit and insurance markets are incomplete or inaccessible, additional factors may come into play, potentially amplifying, mitigating, or even reversing the predicted income effect. Banerjee et al. (2017) and Baird et al. (2018) explore several such mechanisms. First, a self-employment effect: individuals with promising entrepreneurial ideas but limited access to credit may use cash transfers to launch or expand a business, leading to an increase in hours worked rather than a reduction. Second, an insurance effect: cash transfers can function as a safety net, encouraging individuals to take on higher-risk, higher-reward activities they might otherwise avoid due to financial uncertainty. Third, a job search effect: with additional financial resources, individuals may invest more time and effort into finding better employment opportunities, potentially traveling to other locations or upskilling to secure higher-paying jobs. Fourth, a health and productivity effect: financial assistance may enable workers to invest in their health, improving their productivity and ultimately increasing their labor supply.

Additionally, when labor market frictions such as adjustment costs are present, responses to cash transfers may be limited. Individuals will only alter their work hours if the benefits of doing so outweigh the costs of adjustment. The higher these costs, the smaller the expected change in labor supply, meaning that only substantial income shocks are likely to prompt significant shifts in working hours. This explains why most of the existing studies find no significant effects of cash transfers on labor supply (Jones and Marinescu, 2022; Verho et al., 2022; Bibler et al., 2023). However, Vivalt et al. (2024) document negative effects from a large unconditional cash transfer program in the U.S., where two non-profit organizations provided $1,000 per month for three years to 1,000 low-income individuals randomized into the treatment group. Their findings indicate a 3.9 percentage point reduction in the extensive margin of labor supply and a 1-2 hours/week reduction in work hours (a 5-6% drop relative to the control group mean). Comparable negative effects have also been observed in studies examining large income shocks, such as lottery winnings (Cesarini et al., 2017; Imbens et al., 2021; Georgarakos et al., 2023; Golosov et al., 2024).

In this subsection we estimate the short-term impact of the *RdC* program on individual labor supply using our empirical model described in Section 4. We consider both women of childbearing age (16 to 45 years old) and men aged 16 to 56 who live in the same household. In this analysis, we focus exclusively on the period from June 2019 to February 2020 to avoid the confounding effects of the COVID-19 pandemic. The pandemic brought about drastic changes to the economic and social environment, which may have affected labor supply of recipients and non-recipients in different ways, potentially biasing our estimates. Table 9 presents estimates when using as dependent variable i) the probability of being employed for at least one month, ii) the number of months worked. In Table 10 we focus on iii) the earnings obtained between June 2019 and February 2020 for individuals who have been employed for at least one month during this period, iv) daily wages. We separately estimate these effects (for women and men) in the Overall sample (panel A) as well as in the Centre-North (panel B) and South (panel C) sub-samples.

The results in panel A of Table 9 suggest no overall impact of the *RdC* program on labor supply, neither for women nor for men, aligning with recent studies that find no evidence of cash transfers discouraging work. For instance, Maitino et al. (2024) investigate the employment effects of *RdC* in the Italian region of Tuscany using a DiD approach. They find that while the program failed to create employment opportunities through its ALMP, it did not discourage labor supply. Verho et al. (2022) examine Finland's Basic Income Experiment, providing a monthly income transfer of $560 to randomly selected unemployed jobseekers, and report no statistically significant change in employment days during the first year of the experiment. Jones and Marinescu (2022) and Bibler et al. (2023) assess the $2,000 annual income transfer in the Alaska Permanent Fund Dividend, concluding that it had no significant effect on employment.

However, the estimates in panels B and C highlight heterogeneous effects across the Centre-North and South sub-samples. While no significant effects are found on either the extensive margin (probability of being employed) or the intensive margin (months worked) of labor supply for individuals in the South, *RdC* recipients—both women and men—in the Centre-North exhibit a reduction in months worked. More specifically, we observe a decrease of 0.13 months (roughly 4 days) for women and 0.11 months (roughly 3 days) for men over the nine-month period from June

2019 to February 2020. These reductions correspond to a decrease in months worked relative to the control group mean by 10% for women and 8% for men, respectively.

Table 9: Effects on labor supply. Overall sample and Center-North and South sub-samples

	(1)	(2)	(3)	(4)
	Worked at least one month		No. of months worked	
Panel A: Overall sample	Females	Males	Females	Males
RdC	-0.0011	-0.0016	-0.0318	-0.0218
	(0.0056)	-0.0075	-0.037	-0.0404
All controls	Yes	Yes	Yes	Yes
Control mean	0.2054	0.2143	1.224	1.274
Left bandwidth	-4,357	-3,519	-3,663	-4,360
Right bandwidth	3,416	3,113	3,895	4,865
Observations	101,695	62,794	103,703	89,837
Panel B: Centre-North sub-sample	Females	Males	Females	Males
RdC	-0.0176^{*}	-0.0184^{*}	-0.1512^{**}	-0.1459^{**}
	(0.0093)	-0.0099	-0.0627	-0.071
All controls	Yes	Yes	Yes	Yes
Control mean	0.2362	0.2473	1.445	1.4808
Left bandwidth	-3,509	-4,609	-3,675	-3,973
Right bandwidth	2,971	3,656	2,809	3,318
Observations	42,115	37,413	41,990	33,305
Panel C: South sub-sample	Females	Males	Females	Males
RdC	0.0055	0.0035	0.0731	0.0413
	(0.0089)	-0.0109	-0.0491	-0.062
All controls	Yes	Yes	Yes	Yes
Control mean	0.1625	0.17	0.9496	0.9868
Left bandwidth	-2,440	-2,382	-3,168	-2,854
Right bandwidth	3,699	3,664	4,394	4,844
Observations	47,343	32,849	58,039	43,444

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each column. The dependent variable in columns 1 and 2, *Worked at least one month*, is a dummy taking value 1 for individuals who worked at least one month between June 2019 and February 2020, and 0 otherwise. In columns 3 and 4, the dependent variable measures the number of months worked between June 2019 and February 2020. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Additionally, as shown in columns 1 and 2 of Table 10, we find that among those who worked at least one month during the nine-month period under analysis, labor earnings declined by €610 for women and €628 for men, which translate into a decline of approximately 10% for women and around 11% for men, respectively. Although not directly comparable due to differences in benefit amounts, these effects are relatively smaller in magnitude to the 20% decline in total individual income reported by Vivalt et al. (2024) and to the 50% drop in household labor earnings documented by Golosov et al. (2024), but larger than the 5-6% decrease in annual earnings estimated by Cesarini et al. (2017).

The observed reduction in earnings may be driven by a decline in the number of days worked, as previously discussed, or by a potential decrease in daily wages. The latter could reflect a strategic adjustment by recipients seeking to maintain eligibility for the *RdC* program. To test this hypothesis, we compute daily wages by dividing total earnings over the nine-month period by the total number of days worked. As reported in Columns 3 and 4 of Table 10, we find no statistically significant effects on daily wages. This indicates that the decline in earnings is attributable to fewer days worked, rather than reductions in daily wage rates.

Table 10: Effects on earnings and wages. Overall sample and Center-North and South sub-samples

	(1)	(2)	(3)	(4)
	Labor earnings		Daily wages	
Panel A: Overall sample	Females	Males	Females	Males
RdC	-287.7836*	-247.47	-0.9717	-2.5193
	(174.02)	(193.09)	(1.5434)	(1.9392)
All controls	Yes	Yes	Yes	Yes
Control mean	6003.7	5940.88	47.3745	47.4291
Left bandwidth	-3,522	-4,223	-4,375	-4,253
Right bandwidth	3,369	3,491	4,611	4,304
Observations	18,113	14,682	23,712	16,553
Panel B: Centre-North sub-sample	Females	Males	Females	Males
RdC	-692.4734***	-651.2681**	-1.1115	-3.0815
	(225.79)	(268.18)	(2.0008)	(2.428)
All controls	Yes	Yes	Yes	Yes
Control mean	6418.29	6239.72	49.2865	49.0523
Left bandwidth	-3,744	-3,769	-3,707	-3,729
Right bandwidth	3,948	3,719	5,609	3,840
Observations	11,813	8,488	14,355	8,590
Panel C: South sub-sample	Females	Males	Females	Males
RdC	76.846	133.844	-0.8976	-2.6394
	(250.91)	(288.91)	(2.3455)	(2.3464)
All controls	Yes	Yes	Yes	Yes
Control mean	5208.94	5309.45	43.5271	43.9619
Left bandwidth	-2,932	-3,178	-4,071	-5,393
Right bandwidth	3,983	4,067	4,153	6,731
Observations	8,021	6,123	9,097	10,031

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each column. The dependent variable in columns 1 and 2 measures individual labor earnings for those who worked at least one month between June 2019 and February 2020. In columns 3 and 4, the dependent variable measures the daily wage. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

5.3. Mechanisms

The finding that the *RdC* impacts fertility only in Southern Italy may stem from several factors. Firstly, the South has historically been associated with conservative social norms, where family formation and childbearing are highly valued. In this context, income support programs like the *RdC* can alleviate financial constraints, potentially encouraging families to have more children. Secondly, the program likely represents a more substantial boost to household disposable income in the South compared to the Centre-North, where average income levels and employment opportunities are higher. Moreover, since living costs are lower in the South, the support was higher in real terms in the South. Additionally, women in the South often face lower opportunity costs for childbearing due to lower labor market participation rates and fewer employment prospects, making the decision to have children less economically restrictive.

To explore these factors, we examine a range of municipal-level data capturing social norms, income levels, employment opportunities, and childcare services. Social norms are analyzed using two indicators: the take-up of paternity leave at municipality level in years 2016-2018, and a dummy variable for municipalities that had a female mayor at least once during that period.[13] Given that social norms are deeply rooted in cultural contexts and often transmitted across generations, we focus on the social norms prevailing in the municipality where the recipient was born, as these are likely to have influenced their formative environment. These indicators capture different dimensions of gender dynamics within the community. The use of paternity leave by fathers indicates an environment where men are more inclined to share childcare responsibilities, reflecting less traditional gender norms. Similarly, having a female mayor serves as a proxy for female political representation and gender equality in decision-making.

Using these indicators, we classify municipalities into three terciles (lower, middle, and upper) based on paternity leave take-up and into two groups depending on whether a municipality was administered by a female mayor during 2016–2018. Although regions in the Center-North are typically associated with less traditional gender norms, and southern regions with more traditional ones, significant variability exists within each macro-area. For instance, in the South the take-up for the paternity leave is on average 30% (s.d.=0.16), while in the Center-North this figure rises to 55% (s.d.=0.21), with about 10% of Centre-North municipalities showing a take-up rate below 30%.

In Table 11 we report heterogeneous results for all Italian municipalities. Examining columns 1-3, we find that the effect of *RdC* on the probability of conceiving a child within two years is primarily driven by women born in municipalities characterized by low paternity leave take-up, indicating

[13] Paternity leave was introduced in Italy in 2013 with a single day of leave that fathers could take off work during the first 5 month following the birth of their child. The length of the leave was gradually extended to the current 10 days. The leave is fully compensated at 100% of the salary. Despite full coverage, only about 65% of eligible fathers utilized it in 2025. We use municipal-level paternity leave take-up rates from 2015-2018. During this period, the duration of the leave was limited to 2–3 days, and the average take-up rate was around 40%. Considering multiple years to build our proxy of gender norms reduces the impact of missing values, which are likely to occur in smaller municipalities where eligible fathers may not be present in a given year. We exclude the first two years following the introduction of the policy, as take-up was very low—likely due to limited awareness of the measure during its initial implementation.

exposure to more traditional gender roles. Similar results are observed when we split the sample based on whether the RdC recipient was born in a municipality with a female mayor.[14]

These results hold true also when we consider northern and southern municipalities separately and rank them within their respective areas based on our gender norms measures. As illustrated in Table A.3 in the Appendix, women residing in the South who were born in municipalities with more traditional gender norms exhibit a stronger response to *RdC* compared to those born in less traditional municipalities. Conversely, in northern regions, we observe either no effect or a negative effect in areas with more progressive gender norms (see Appendix Table A.4).

Table 11: The role of social norms. Overall sample.

	(1)	(2)	(3)	(4)	(5)
	Paternity leave take-up			Municipality mayor	
	Lower tercile	Middle tercile	Upper tercile	Male	Female
RdC	0.0190***	0.0024	-0.0017	0.0090*	-0.0241**
	(0.0084)	(0.0086)	(0.0062)	(0.005)2	(0.0119)
All controls	Yes	Yes	Yes	Yes	Yes
Control mean	0.0810	0.0808	0.0824	0.0799	0.0828
Left bandwidth	-2,357	-2,711	-3,551	-2,167	-4,124
Right bandwidth	4,820	5,680	4,255	5,826	4,460
Observations	39,965	40,589	40,493	110,621	11,713

Notes: Sample includes women aged 16-45. Estimates are from the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

An additional mechanism could be the different economic conditions between the two geographical areas. To explore this, we examine whether the stronger fertility response in the South might be due to the relatively larger financial impact of the *RdC* in low-income areas. Thus, we group Italian municipalities into three terciles based on the average wages earned by private-sector employees residing there in 2018. As shown in the first three columns of Table 12, we find a positive effect only for recipients living in poorer municipalities.

However, when we rank municipalities within each macro-area (see columns 1-3 of Appendix Tables A.5 and A.6), we find that while in the South the effect is mainly driven by recipients living in

[14] Similar results are found when using as a proxy of gender norms the gender gap in voter turnout at the 2014 European Elections (the difference between male and female turnout rates, where a smaller gap suggests more egalitarian norms, with women more actively participating in public life). We find no effect for women born in municipalities where the difference in turnout is high and a positive effect in those where this difference is smaller.

municipalities with higher average wages, in Centre-Northern municipalities with low average wages, the effect is even negative. This suggests that in very poor areas, the financial support offered by the *RdC* may not be sufficient to generate an impact on fertility.

Table 12: The role of local economic conditions. Overall sample.

	(1)	(2)	(3)	(4)	(5)	(6)
		Average wage			Employment rate	
	Lower tercile	Middle tercile	Upper tercile	Lower tercile	Middle tercile	Upper tercile
RdC	0.0150*	0.0014	0.0052	0.0198*	0.0035	0.0062
	(0.0081)	(0.0070)	(0.0065)	(0.0018)	(0.0093)	(0.0102)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.0806	0.0816	0.0823	0.0806	0.0829	0.0832
Left bandwidth	-2,239	-3,175	-3,320	-2,293	-3,425	-3,316
Right bandwidth	4,305	3,175	3,320	4,150	6,442	3,755
Observations	43,515	49,503	52,688	17,729	28,048	19,889

Notes: Sample includes women aged 16-45. Estimates are from the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

We also consider the employment rate as an indicator of local economic conditions.[15] A lower employment rate may reflect a lower opportunity cost of having a child, potentially resulting in a greater impact of the *RdC*. As shown in columns 4-6 of Table 12, when municipalities across the Overall sample are ranked by employment rate, we observe a positive effect only in municipalities with lower employment rates, consistent with our hypothesis. Similar results are presented in columns 4-6 of Appendix Table A.5, for the South sub-sample, where we detect an effect among individuals residing in municipalities with employment rates in the middle of the distribution. For women in the Center-North, however, we find no effect across all sub-samples, likely because in these regions, the unemployment rate remains relatively high even in lower tiers (see columns 4-6 of Table A.6 in the Appendix).

Finally, we investigate how the effect varies based on the cost of having children, measured by the availability of childcare in the municipality of residence. Childcare availability reduces the costs associated with childbearing, particularly for women. We divide municipalities into two groups: those below and those above the median value of childcare availability. As shown in Table 13, we do not find any effect on either group for the Overall sample or individuals residing in the Centre-North. However, for individuals residing in the South, we find that the change in income due to *RdC* is

[15] We consider the employment rate for 2011, as it is the most recent year for which this information is available at the municipal level.

associated with an increase in fertility only for women in municipalities with above-median childcare availability. This suggests that complementary services, which mitigate the burdens of motherhood, enhance the effectiveness of income support in encouraging childbearing.

Table 13: The role of childcare availability. Overall sample and Center-North and South sub-samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	Childcare availability					
	Below median	Above median	Below median	Above median	Below median	Above median
Sample:	Overall		Center-North		South	
RdC	0.0035	0.0003	-0.0039	-0.0037	0.0136	0.0167**
	(0.0060)	(0.0054)	(0.0049)	(0.0097)	(0.0085)	(0.0082)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.0813	0.0831	0.0830	0.0809	0.0804	0.0802
Left bandwidth	-2,967	-4,236	-3,564	-2,819	-2,451	-2,296
Right bandwidth	3,969	3,801	4,169	4,819	4,879	5,486
Observations	61,579	74,599	46,927	14,473	39,948	47,818

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each column. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Taken together, the findings reported in this section suggest that income support can play a significant role in boosting fertility, but its effectiveness is influenced by local economic and social conditions. The impact of the *RdC* on fertility is primarily observed in Southern Italy, where conservative social norms, lower opportunity costs for childbearing, and relatively higher financial benefits from the program may create a more favorable environment for increasing fertility. In contrast, no such effect is observed in the Center-North, where the *RdC*'s impact is diminished by higher average income levels, more progressive gender norms, and lower unemployment rates.

5.4. Additional results from survey data

In this section we complement our main RDD analysis with additional results obtained when utilizing the “Participation, Labor, Unemployment, Survey” (PLUS) data of the Italian National Institute for Public Policy Analysis (INAPP). The survey, designed to provide a comprehensive overview of the Italian population, focuses on specific target groups in the labor market, including women, youth, and individuals over 50. In particular, it examines key labor market aspects, such as youth entry, longer employment duration for older workers, female labor force participation, and job search patterns. We use the 2021 wave of the survey, which also asks respondents whether they applied to the *RdC* program and whether they received or not the benefit over the last 12 months. This allows for the possibility to link indicators for *RdC* recipients and non-recipients among applicants to information on fertility intentions, labor supply, health, income, education, family background, services in the area, trust, wellbeing, etc.

The 2021 wave interviews 46,282 individuals aged 18 to 74 across Italy. We restrict the sample of analysis to respondents of childbearing age (18-46 for women and 18-56 for men), who have applied to the *RdC* program. This leads to a final sample of 2,380 observations. The empirical analysis compares the outcomes of individuals who received the benefit with the outcomes of those who applied to the program but did not receive the benefit. Figure A.8 in the Appendix shows the balance tests for key individual characteristics. The estimates in the figure show that *RdC* recipients are observationally similar to non-recipients, except for a few variables, such as never married, pre-existing children, household income, and residence in the South. This is in line with the evidence from the analysis of INPS administrative records reported in previous sections.

We then regress several outcome variables on the treatment indicator, *RdC* recipient, while controlling for the set of covariates described in Figure A.8. To complement the evidence on the fertility effects of the *RdC* obtained through the RDD analysis, we first focus on child intention, defined as a dummy that takes value 1 for respondents who intend to have a child within three years. Results in Table A.7 in the Appendix reveal that fertility intentions are 7.5 percentage points higher for *RdC* recipients compared to non-recipients (column 1). Notably, we find that this trend is entirely driven by individuals in the South (column 2), in line with the findings from INPS administrative data. Moreover, the estimates in columns 3 to 7 suggest further heterogeneous effects by citizenship and education.

Second, we explore whether *RdC* impacts on financial conditions, health, employment and job search. Results, presented in Appendix Table A.8, indicate that income support significantly alleviates financial constraints and improves health outcomes, supporting the health effect hypothesis proposed by Banerjee et al. (2017). Additionally, the estimate in column 3 suggests no significant effect of *RdC* on the likelihood of being employed, in line with the RDD estimates presented in Table 9. Importantly, results in column 4 indicate that participation in the *RdC* program significantly increases job search activities, consistent with Banerjee et al. (2017)'s hypothesis that cash transfers may allow recipients to search longer and secure better-fitting or higher-quality jobs.

Finally, Figure A.9 in the Appendix shows the percentages of *RdC* recipients who report increased levels of trust or wellbeing following the receipt of the income support. In particular, the evidence in the figure not only confirms that receiving the benefit is strongly associated with an improvement in financial conditions and health, but it also suggests that recipients experience increased trust, especially in institutions, with the inclusion in the minimum income program. This reinforces the idea that the impact of *RdC* on fertility might also be attributable to increased sense of stability and self-confidence perceived by participants in the program.

6. Conclusions

In this paper, we investigate the effect of a minimum income scheme introduced in Italy in 2019 on a woman's likelihood of having a child within two years of receiving the benefit. We use administrative data on the universe of applicants to the program and compare the fertility decisions of women with household income just below the relative threshold (i.e. recipients) with those just above the threshold (i.e. non recipients) in a Fuzzy RDD strategy.

Our results reveal a clear North-South divide: while income support has no impact on fertility among women in the Centre-North, it significantly encourages fertility among women in the South. Specifically, recipients in the South experience a 1.5 percentage point increase in the probability of conceiving within two years, representing an 18% rise in mean fertility between June 2019 and June 2021. Additionally, our analysis highlights heterogenous labor supply responses across the two regions. While the *RdC* has no significant effect on labor supply in the South, beneficiaries in the Centre-North work 3 to 4 fewer days and reduce earnings of approximately 10 to 11% over the nine-month period between June 2019 and February 2020. Taken together, these findings suggest that income support led to increased consumption in the South (considering children as normal goods), but an increase in leisure in the Centre-North. As we further show in the analysis of the mechanisms, these differing responses appear to be driven by more traditional gender norms, greater financial constraints, and lower opportunity costs of childbearing in the South relative to the Centre-North.

These findings contribute to a deeper understanding of the general equilibrium effects of minimum income schemes. They indicate that, although primarily designed to provide financial support to impoverished families, such policies may have substantial positive spillover effects on fertility rates. This is particularly relevant for policymakers of many wealthy countries like Italy, where fertility rates are are persistently low and require innovative approaches to address population aging and demographic challenges.

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Appendix

Table A.1: Effects on fertility. Robustness checks. South sub-sample.

	(1) + Region dummies	(2) Using MSE symmetric bandwidth	(3) Non-parametric conventional	(4) Non-parametric bias-corrected	(5) Non-parametric robust
RdC	0.0160**	0.0115*	0.0124**	0.0121**	0.0121
	(0.0062)	(0.0069)	(0.0058)	(0.0058)	(0.0086)
All controls	Yes	Yes	Yes	Yes	Yes
Control mean	0.0802	0.0807	0.0883	0.0883	0.0883
Left bandwidth	-2,247	-2,386	-2,241	-2,241	-2,241
Right bandwidth	4,061	2,386	4,868	4,868	4,868
Observations	71,046	47,547	326,622	326,622	326,622

Notes: Sample includes women aged 16-45 in the South. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. The dependent variable is *Birth*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are age, age squared, household size, n. of minor components, n. of disabled components, rented house, non-Italian, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A2: Effects on fertility. Second stage estimates.

	(1)	(2)	(3)	(4)
	Birth			
	No Covariates	+Demographic controls	+Household controls	+Rented house
Panel A: Overall sample				
RdC	0.0029	0.0026	0.0025	0.0025
	(0.0024)	(0.0023)	(0.0023)	(0.0023)
Control mean	0.0314	0.0314	0.0314	0.0314
Left bandwidth	-3,607	-3,607	-3,607	-3,607
Right bandwidth	5,654	5,654	5,654	5,654
Observations	182,485	182,485	182,485	182,485
Panel B: Centre-North sub-sample				
RdC	0.0023	0.0013	0.0012	0.0011
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Control mean	0.0316	0.0316	0.0316	0.0316
Left bandwidth	-3,080	-3,080	-3,080	-3,080
Right bandwidth	3,763	3,763	3,763	3,763
Observations	54,999	54,999	54,999	54,999
Panel C: South sub-sample				
RdC	0.0072*	0.0068*	0.0068*	0.0068*
	(0.0039)	(0.0038)	(0.0038)	(0.0038)
Control mean	0.0303	0.0303	0.0303	0.0303
Left bandwidth	-2598	-2598	-2598	-2598
Right bandwidth	3781	3781	3781	3781
Observations	69085	69085	69085	69085

Notes: Sample includes women aged 16-45. The Mean Squared Error (MSE) optimization criterion with asymmetric bandwidth is used to select the optimal-bandwidth sample in each panel. The dependent variable is *Birth*, a dummy taking value 1 for individuals who conceived a child in the period from June 2019 to June 2021. *RdC* is a dummy taking value 1 for *RdC* recipients. Demographic controls include age, age squared, a dummy for South and a dummy for non-Italian. Household controls include household size, no. of minor and no. of disabled components. Rented house is an indicator for women living in rented houses. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A.3: The role of social norms. South sub-sample.

	(1)	(2)	(3)	(4)	(5)
	Paternity leave take-up			Municipality mayor	
	Lower tercile	Middle tercile	Upper tercile	Male	Female
RdC	0.0291***	0.0090	0.0012	0.0128**	-0.0130
	(0.0104)	(0.0108)	(0.0101)	(0.0064)	(0.0229)
All controls	Yes	Yes	Yes	Yes	Yes
Control mean	0.0791	0.0808	0.0815	0.0793	0.0830
Left bandwidth	-2,114	-2,328	-3,539	-4,057	-2,127
Right bandwidth	4,331	4,842	4,392	6,112	5,773
Observations	25,258	42,856	49,358	83,230	4,963

Notes: Sample includes women aged 16-45 in the South. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. RdC is a dummy taking value 1 for RdC recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with RdC. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A.4: The role of social norms. Center-North sub-sample.

	(1)	(2)	(3)	(4)	(5)
	Paternity leave take-up			Municipality mayor	
	Lower tercile	Middle tercile	Upper tercile	Male	Female
RdC	-0.0155	-0.0026	0.0038	0.0090	-0.0296**
	(0.0118)	(0.0113)	(0.0105)	(0.0078)	(0.0136)
All controls	Yes	Yes	Yes	Yes	Yes
Control mean	0.0821	0.0831	0.0825	0.0832	0.0829
Left bandwidth	-3,055	-3,341	-4,134	-3,661	-3,931
Right bandwidth	3,852	3,929	3,617	4,372	4,370
Observations	12,720	10,135	10,968	24,976	7,941

Notes: Sample includes women aged 16-45. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A.5: The role of local economic conditions. South sub-sample.

	(1)	(2)	(3)	(4)	(5)	(6)
	Average wage			Employment rate		
	Lower tercile	Middle tercile	Upper tercile	Lower tercile	Middle tercile	Upper tercile
RdC	0.0110	0.0052	0.0174*	0.0164	0.0224*	0.0056
	(0.0094)	(0.0099)	(0.0099)	(0.0114)	(0.0118)	(0.0100)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.0805	0.0805	0.0808	0.0792	0.0798	0.0807
Left bandwidth	-2,548	-2,318	-2,370	-2,096	-2,208	-2,344
Right bandwidth	5,606	5,764	5,779	5,938	4,052	4,610
Observations	36,457	32,118	30,615	27,998	21,113	25,877

Notes: Sample includes women aged 16-45 in the South. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A.6: The role of local economic conditions. Center-North sub-sample.

	(1)	(2)	(3)	(1)	(2)	(3)
	Average wage			Employment rate		
	Lower tercile	Middle tercile	Upper tercile	Lower tercile	Middle tercile	Upper tercile
RdC	-0.0198*	0.0035	0.0062	0.0031	-0.0117	-0.0087
	(0.0118)	(0.0093)	(0.0102)	(0.0132)	(0.0126)	(0.0102)
All controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.0806	0.0829	0.0832	0.0831	0.0824	0.0824
Left bandwidth	-2,293	-3,425	-3,316	-3,312	-3,212	-4,543
Right bandwidth	4,150	6,422	3,755	4,622	3,800	4,076
Observations	17,729	28,048	19,889	11,052	9,433	11,473

Notes: Sample includes women aged 16-45. The dependent variable is *Child*, a dummy taking value 1 for individuals who conceived a child from June 2019 to June 2021, and 0 otherwise. *RdC* is a dummy taking value 1 for *RdC* recipients. Controls are 2nd order polynomial for age, household size, n. of minor components, n. of disabled components, rented house, migration status, 1st order polynomial of the running variable and its interaction with *RdC*. Standard errors in parentheses are clustered at the running variable level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: INPS data.

Table A.7: Effects on fertility intentions. Survey data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Intend to have a child within 3 years						
RdC	0.075***	0.037	0.061**	0.083***	0.061***	0.043**	0.088***
	(0.019)	(0.025)	(0.026)	(0.019)	(0.023)	(0.021)	(0.026)
RdC * South		0.082**					
		(0.037)					
RdC * Age>30			0.026				
			(0.037)				
RdC * Non Italian				-0.129*			
				(0.071)			
RdC * Pre-existing children					0.031		
					(0.038)		
RdC * Tertiary education						0.116***	
						(0.044)	
RdC * Home owner							-0.027
							(0.037)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,380	2,380	2,380	2,380	2,380	2,380	2,380
Control mean				0.260			

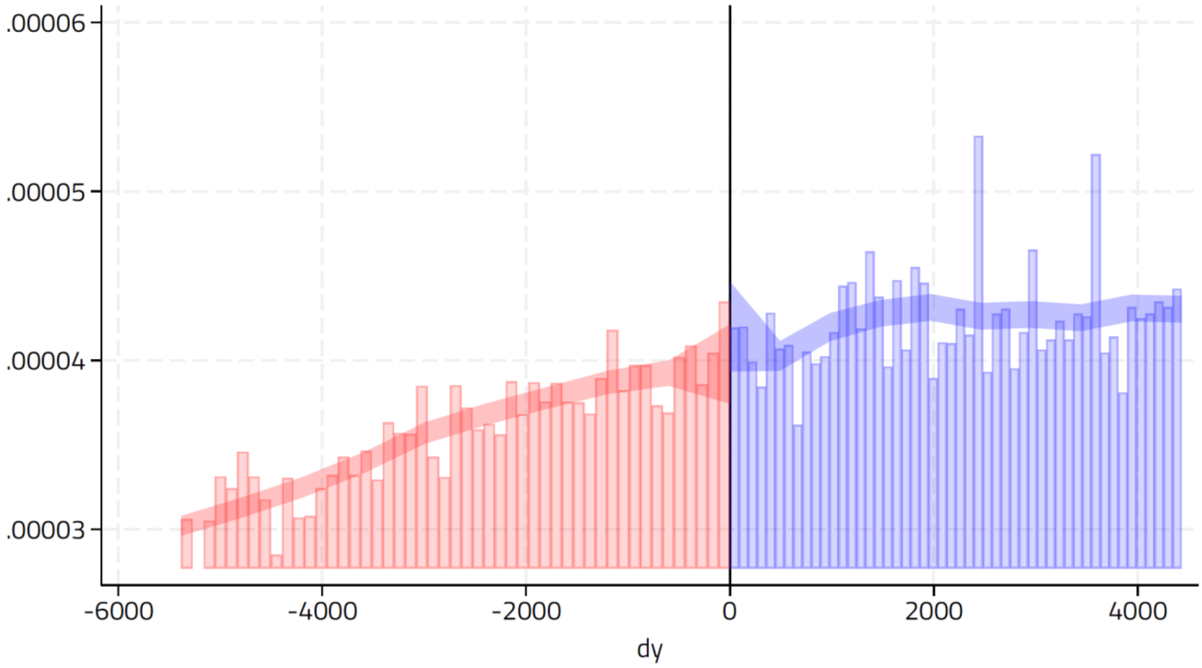
Notes: OLS estimates are reported in each column. The sample consists of individuals who have applied to the *RdC* and were either accepted or rejected. The dependent variable is a dummy that takes value of 1 for respondents who have intention to have children within 3 years, and 0 otherwise. *RdC* recipient, our treatment variable, is a dummy that takes value of 1 for respondents who received income support in 2020, and 0 otherwise. Baseline controls include: Female, Age, Non Italian, Never married, Have children, Tertiary education, Father has tertiary education, Partner has tertiary education, Home owner, Household income below €1,000/month, Residence in the South. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Sources*: INAPP Survey PLUS 2021.

Table A.8: Effects on financial conditions, health and employment. Survey data.

	(1) More than 30% of household income for food expenditure	(2) Self-reported health status is good	(3) Employed	(4) Job search
RdC recipient	-0.034*	0.128***	0.015	0.043**
	(0.019)	(0.020)	(0.019)	(0.019)
Baseline controls	Yes	Yes	Yes	Yes
Observations	2,380	2,380	2,380	2,380
Control mean	0.307	0.466	0.416	0.296

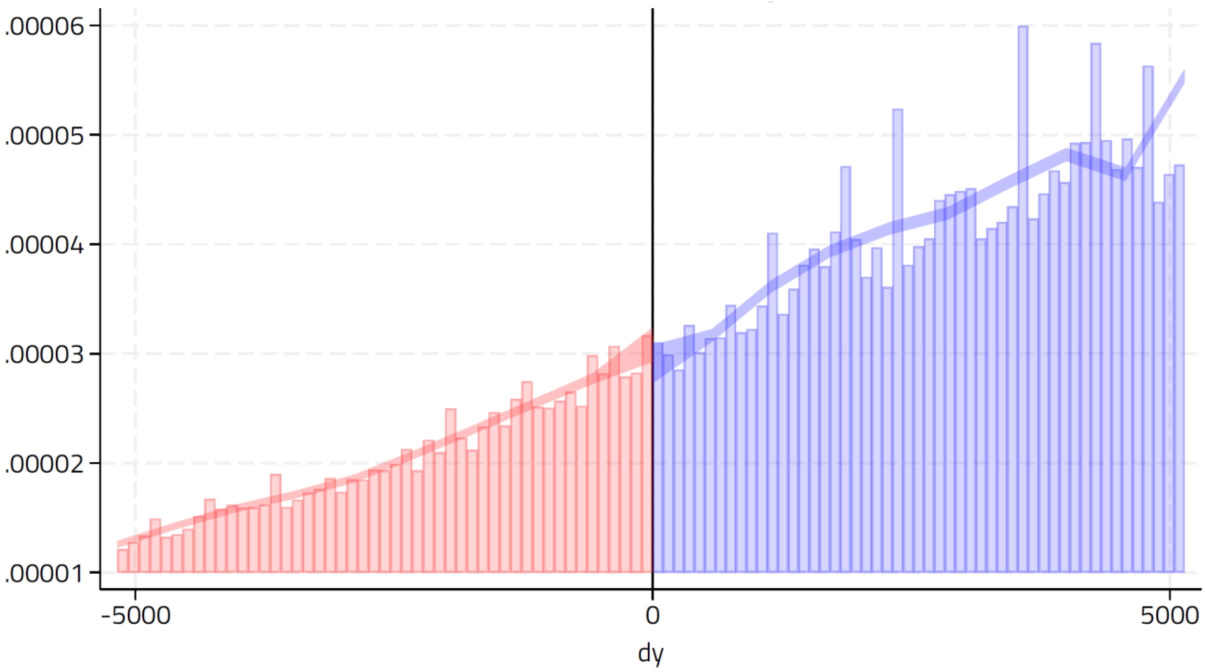
Notes: OLS estimates are reported in each column. The sample consists of individuals who have applied to the *RdC* and their application was either accepted or rejected. The dependent variable changes across columns. In columns 1 and 2, 30% and 20% represent the median value of the relative variable. *RdC* recipient, our treatment variable, is a dummy that takes value of 1 for respondents who received income support in 2020, and 0 otherwise. Baseline controls include: Female, Age, Non Italian, Never married, Pre-existing children, Tertiary education, Father with tertiary education, Partner with tertiary education, Home owner, Household income below €1,000/month, Residence in the South. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Sources: INAPP Survey PLUS 2020.

Figure A.1. McCrary test. Centre-North sub-sample.



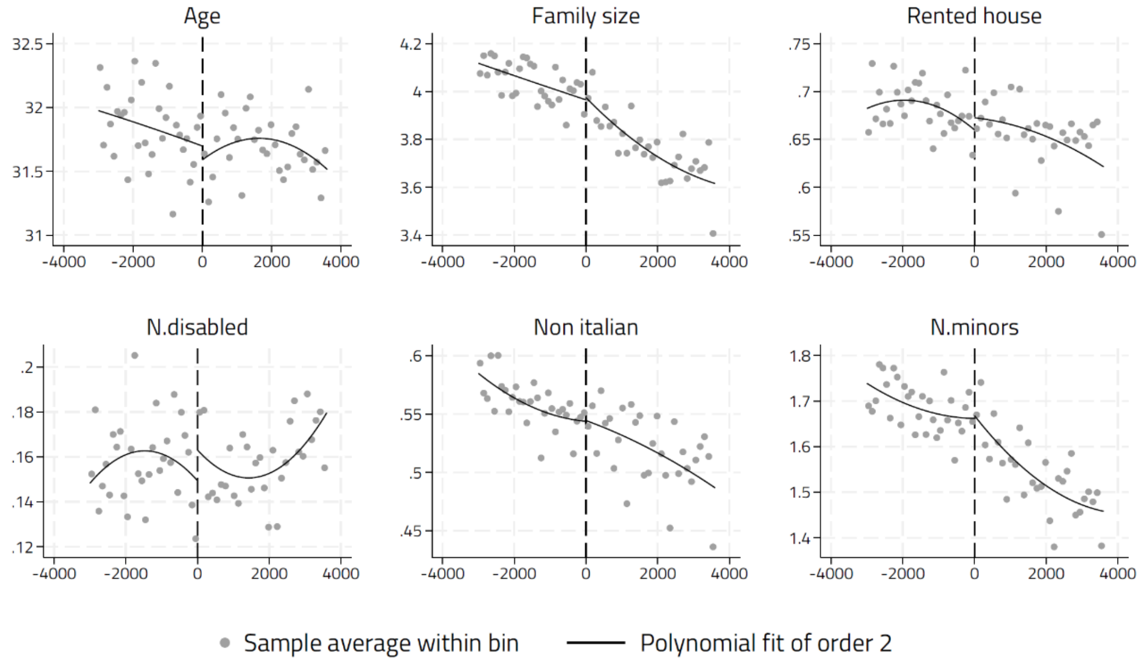
Notes: The figure depicts the estimates of the McCrary test in the Centre-North optimal-bandwidth sample of 54,999 female applicants aged 16-45 in the Centre-North, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 205,808 applicants in the Centre-North. Histograms represent the log density of the running variable, computed as the difference between the threshold and the applicant's household income. Blue histograms on the right refer to *RdC* recipients, while red histograms on the left refer to non-recipients. Source: INPS data.

Figure A.2. McCrary test. South sub-sample.



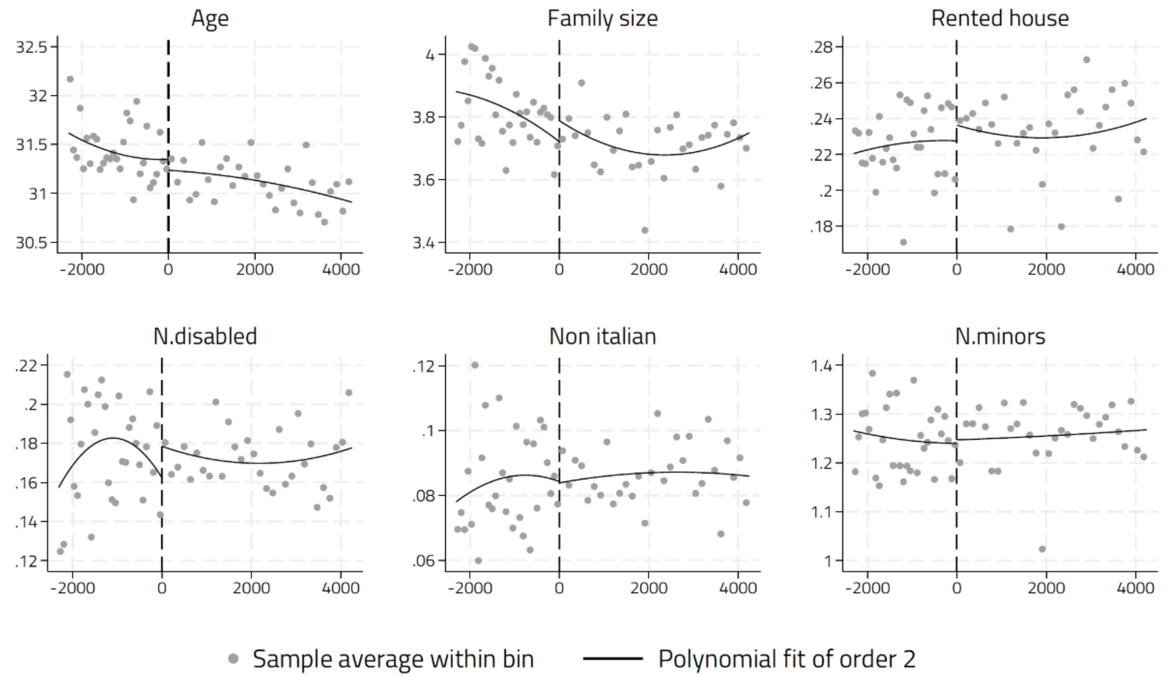
Notes: The figure depicts the estimates of the McCrary test in the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. Histograms represent the log density of the running variable, computed as the difference between the threshold and the applicant's household income. Blue histograms on the right refer to *RdC* recipients, while red histograms on the left refer to non-recipients. Source: INPS data.

Figure A.3. Balance checks. Centre-North sub-sample.



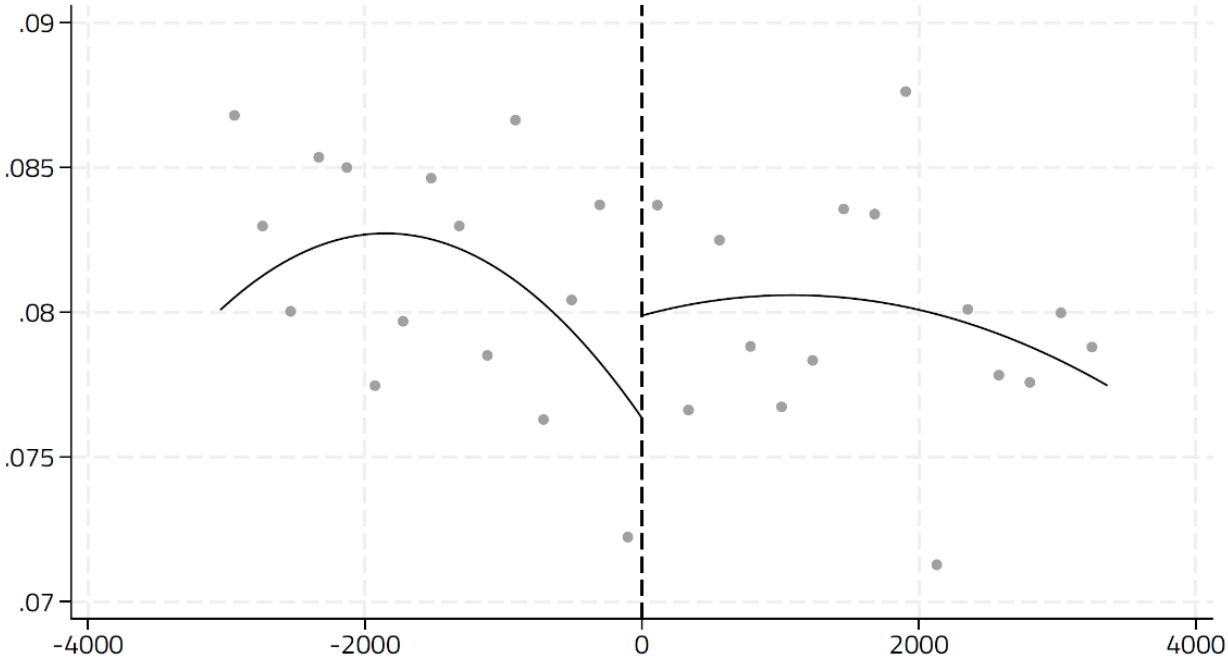
Notes: The figure depicts the values of each individual characteristic plotted against the running variable, computed as the difference between the threshold and the applicant's household income. Estimates are from the Centre-North optimal-bandwidth sample of 54,999 female applicants aged 16-45 in the Centre-North, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 205,808 applicants in the Centre-North. Source: INPS data.

Figure A.4. Balance checks. South sub-sample.



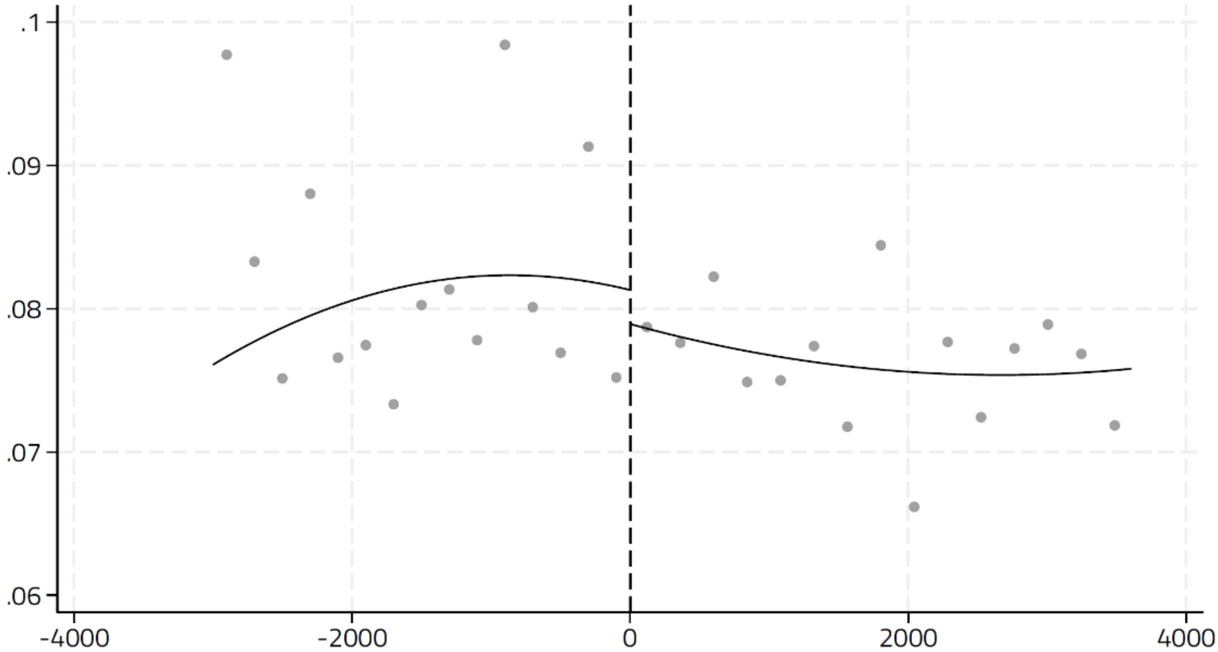
Notes: The figure depicts the values of each individual characteristic plotted against the running variable, computed as the difference between the threshold and the applicant's household income. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. Source: INPS data.

Figure A.5: Effects on fertility. RD plot. Overall sample.



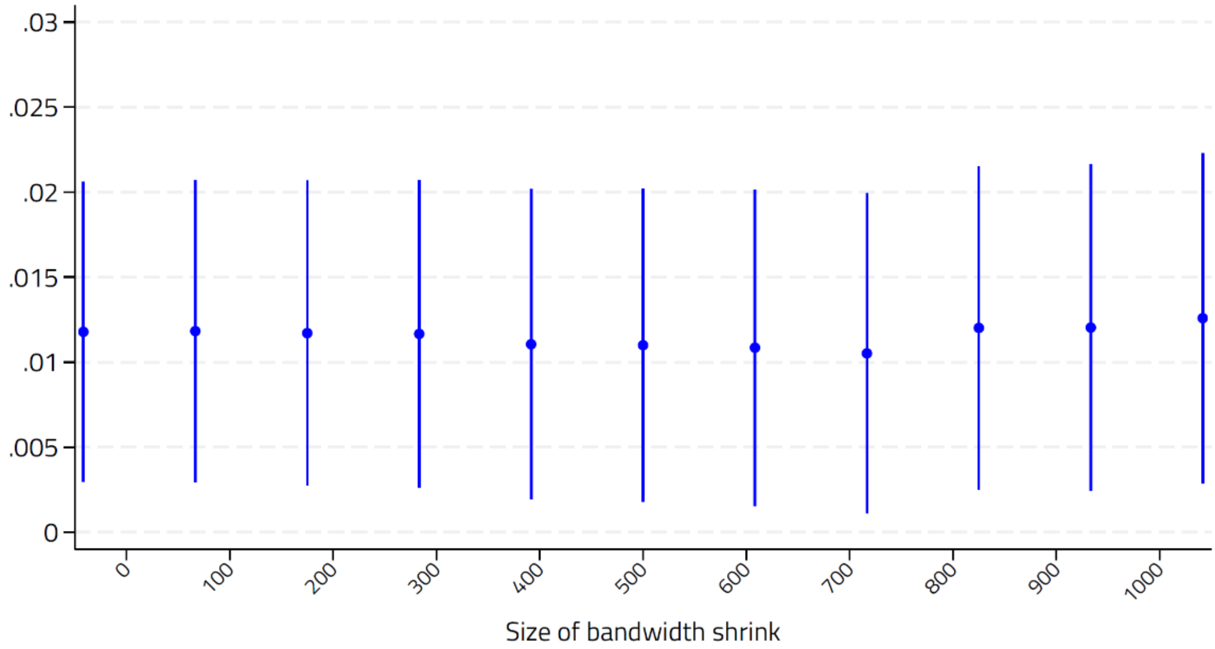
Notes: The figure depicts the estimates of the second-stage regression (equation 1). Estimates are from the Overall optimal-bandwidth sample of 118,464 female applicants aged 16-45, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 532,430 applicants. Source: INPS data.

Figure A.6: : Effects on fertility. RD plot. Centre-North sub-sample.



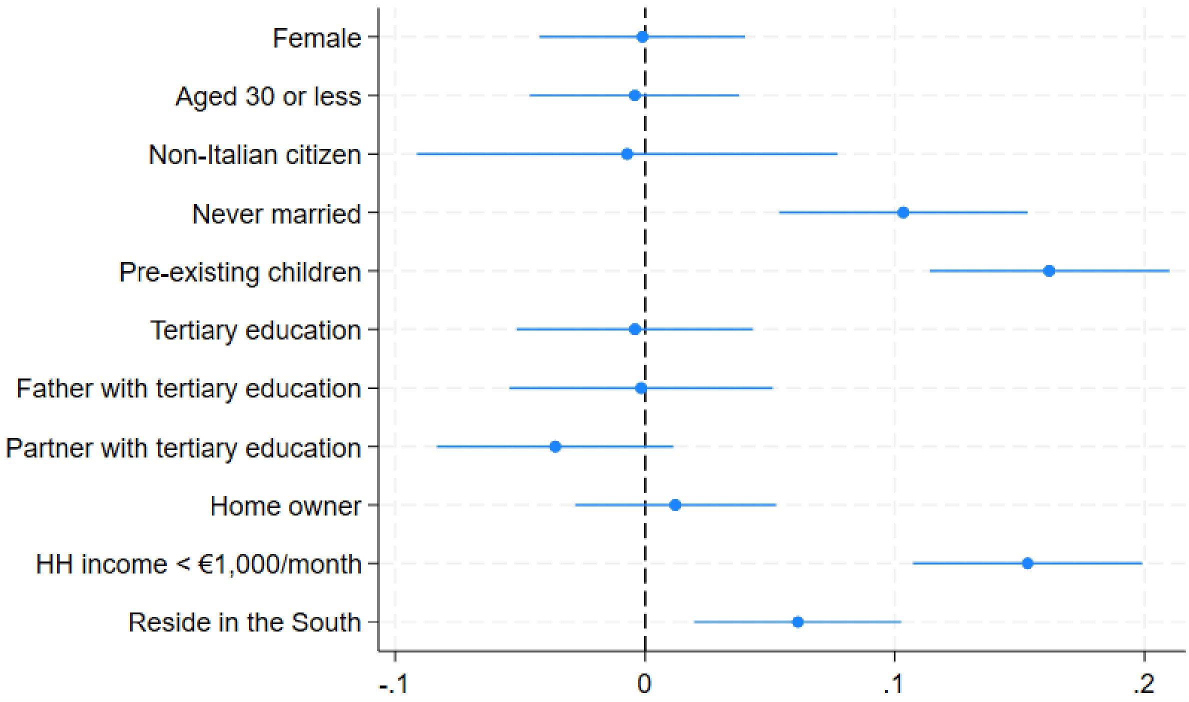
Notes: The figure depicts the estimates of the second-stage regression (equation 1). Estimates are from the Centre-North optimal-bandwidth sample of 54,999 female applicants aged 16-45 in the Centre-North, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 205,808 applicants in the Centre-North. Source: INPS data.

Figure A.7. Effects on fertility. Robustness: shrinking the size of the bandwidth. South sub-sample.



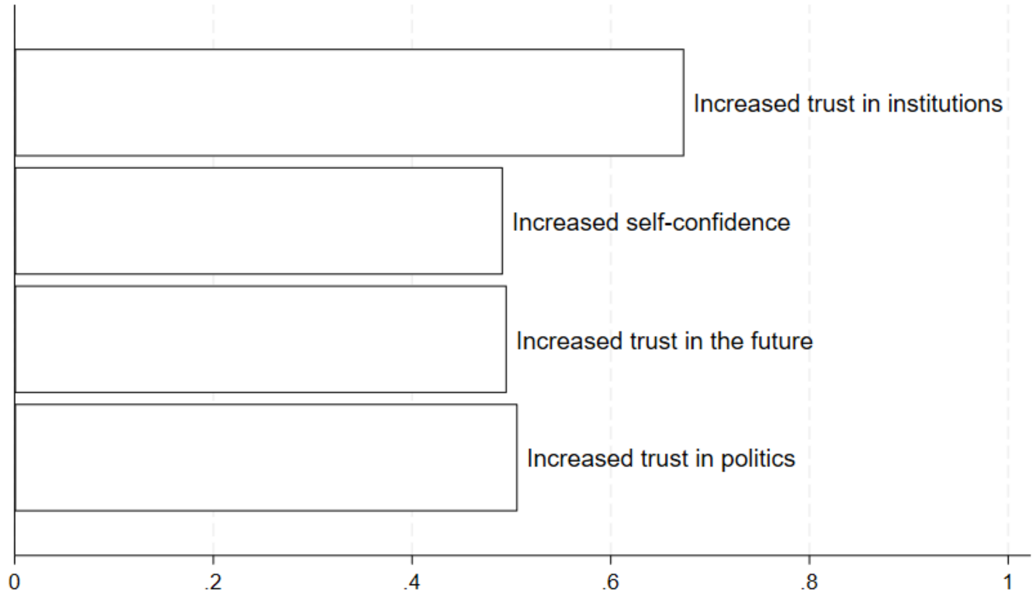
Notes: The figure illustrates the point estimates and the 95% confidence intervals, obtained by estimating our main second-stage regression (equation 2) using an optimal bandwidth that declines by 100 euro at a time, up to 1,000 euro. Estimates are from the South optimal-bandwidth sample of 74,512 female applicants aged 16-45 in the South, obtained after applying the MSE optimization criterion with asymmetric bandwidth to the initial sample of 326,622 applicants in the South. Source: INPS data.

Figure A.8: Balance Checks. Survey data.

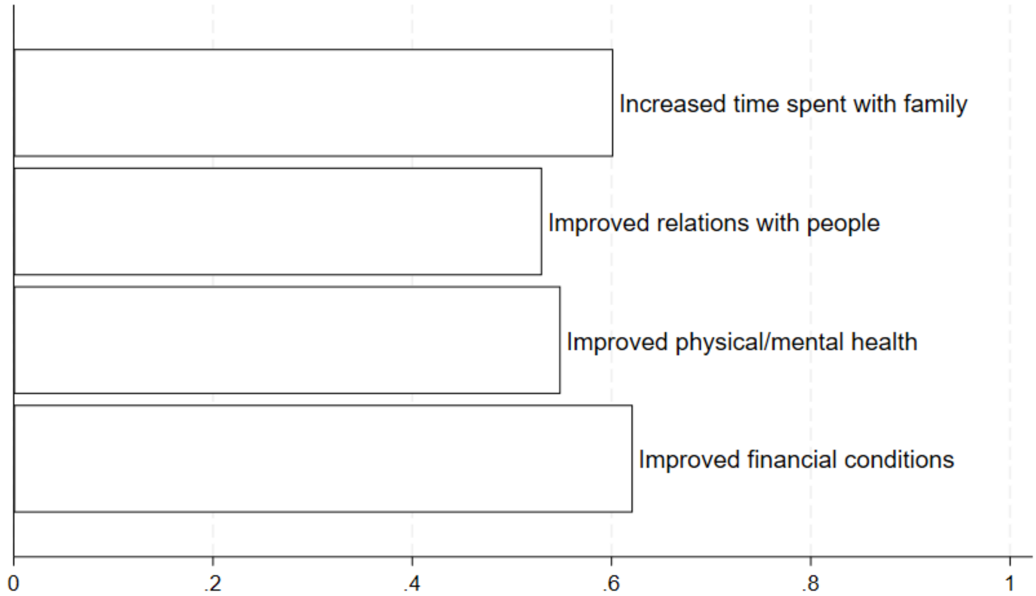


Notes: The figure shows the point estimates and the 95% confidence interval of separate OLS regressions of the effect of each covariate on the treatment indicator for *RdC* recipient. Source: INAPP Survey PLUS 2021.

Figure A.9: Perception Changes for *RdC* recipients.



Panel A: Trust



Panel B: Wellbeing

Notes: The figure shows the percentage of *RdC* recipients reporting an increase in trust or wellbeing after being included in the *RdC* program. Source: INAPP Survey PLUS 2021.