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ABSTRACT

Workplace Peer Effects in Fertility Decisions*

This paper examines the impact of co-workers' fertility on individual fertility decisions. Using matched employer-employee data from Italian social security records (2016–2020), we estimate how fertility among co-workers of similar age and occupation affects the individual likelihood of having a child. We exploit variation introduced by the 2015 Jobs Act, which reduced fertility among workers hired under weaker employment protection. Focusing on workers hired before the reform and using the share of colleagues hired after the reform as an instrument for peer fertility, we find that a one-percentage-point increase in peer fertility raises individual fertility by 0.4 percentage points (a 10% increase). Heterogeneity analysis suggests that while social influence and social norms are key mechanisms, information sharing and career concerns, particularly among women, tend to moderate the response. Our findings highlight how changes in employment protection may have unintended fertility spillovers through workplace social interactions.

JEL Classification: C3, J13, J65, J41, M51

Keywords: career concerns, EPL, fertility, social learning, social norms, workplace

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1. Introduction

Fertility rates have been falling steadily across virtually all high-income countries, with no sign of reversal. In countries like Italy, Spain, and South Korea, birth rates are now so low that populations are projected to shrink rapidly in the coming decades. This trend raises serious concerns, not only about the sustainability of pension and healthcare systems, but also about long-term economic growth, labor supply, and intergenerational balance. As policymakers search for effective ways to support family formation, understanding what drives decisions about when and whether to have children has become more urgent than ever.

While economic factors have long been studied as determinants of fertility (see e.g., Becker, 1981; Francesconi, 2002; Currie and Schwandt, 2014; Cumming and Dettling, 2024),[1] there is increasing recognition that social influences may also play a critical role, particularly in environments where life choices are shaped not only by individual preferences and constraints but also by the behavior of peers. Prior research has documented peer effects in fertility within family, friendship, religious, and neighborhood networks (Evans *et al.*, 1992; Kohler, 2001; Kearney and Levine, 2015; Heissel, 2021; Spolaore and Wacziarg, 2022; Beach and Hanlon, 2023).[2] However, we know relatively little about how the workplace shapes fertility behavior.

This paper contributes to filling this gap in the literature by studying how co-workers affect individual childbearing choices. The workplace is a central social setting, where individuals have daily social interactions and regularly observe others' life choices, potentially updating their own preferences and plans accordingly. It is also an increasingly relevant environment given the growing importance of work-life balance and the potential impact of employer policies on family outcomes. Despite this, peer effects in the workplace remain underexplored, and the existing evidence is sparse and mixed. While Asphjell *et al.* (2013), Pink *et al.* (2014) and Buyukkececi *et al.* (2020) find positive peer effects in Sweden, Germany and the Netherlands, respectively, Ciliberto *et al.* (2016) find overall negative peer effects in Denmark.

Our paper complements the existing literature by providing first causal evidence of peer effects among co-workers in Italy. Importantly, unlike prior studies that rely on random effects (Pink *et al.*, 2014), placebo peer groups (Asphjell *et al.*, 2013) or instruments based on co-workers' siblings' fertility (Ciliberto *et al.*, 2016; Buyukkececi *et al.*, 2020) to identify peer effects, our empirical approach offers two key advantages. First, it applies to the full working population, not just to individuals with siblings. Second, it isolates exogenous variation in peer fertility within actual peer groups in the workplace, defined at the establishment-occupation-age level, rather than relying on proxies or indirectly linked social ties.

We leverage rich administrative data from the Italian Social Security Institute (INPS), covering the universe of private sector employees from 2016 to 2020. Our identification strategy exploits variation in peers' fertility behavior induced by the 2015 Italian Jobs Act, which substantially reduced job security for employees

[1] See also Adsera (2005), Milligan (2005), Lindo (2010), Del Bono *et al.* (2012), Cohen *et al.* (2013); González (2013), Lovenheim and Mumford (2013), Dettling and Kearney (2014), Huttunen and Kellokumpu (2016), De Paola *et al.* (2021), Clark and Lepinteur (2022), and Doepke *et al.* (2023).

[2] See also Bongaarts and Watkins (1996), Montgomery and Casterline (1996), Kuziemko (2006), Munshi and Myaux (2006), Lyngstad and Prskawetz (2010), Kotte and Ludwig (2011), Balbo and Barban (2014), Fletcher and Yakusheva (2016), Cools and Hart (2017), Daudin *et al.* (2019), Buyukkececi *et al.* (2020), Guo *et al.* (2025), and Hu *et al.* (2025).

on open-ended contracts hired after March 7, 2015 in large firms (i.e., those with more than 15 employees). This reform lowered fertility rates among affected workers (De Paola *et al.*, 2021). We therefore focus on workers hired on open-ended contracts in large firms before March 7, 2015, whose job contracts were unaffected, and use the share of their peers hired under the new, less secure regime as an instrument for peer fertility. In effect, our variation comes from comparing over 11 million male and female employees in firms with differing shares of post-reform hires, i.e., co-workers who, due to reduced job security, were less likely to have children.

Our first-stage results confirm the reform's negative effect on peer fertility estimated by De Paola *et al.* (2021): if all co-workers were hired under the Jobs Act, average fertility would be nearly 2% lower. Turning to the second stage estimates, our main findings, we find that a 1-percentage point increase in peer fertility in year t-1 increases an individual's likelihood of having a child in year t by 0.4 percentage points, which corresponds to a 10% increase relative to the average. This suggests that social influence plays a key role in shaping fertility decisions. Importantly, the magnitude of our estimates is in line with prior evidence from other countries: Asphjell *et al.* (2013) report a 10% increase in Sweden, while Buyukkececi *et al.* (2020) find a 5-10% increase in the Netherlands.

To rule out the possibility that our instrument reflects unobservable firm-level factors rather than true peer effects, we restrict the analysis to multi-establishment firms and use the location of each worker's establishment to construct a placebo peer group. Fertility decisions should not be influenced by peers in other establishments of the same firm, where no direct interaction occurs. Consistent with this, we find that the fertility rate of these "false peers" has no effect on individual fertility decisions, strengthening the case for a causal interpretation of our main results.

One potential concern of our identification strategy is that exposure to co-workers hired post-reform, who face reduced job security, might influence individuals' fertility decisions through channels unrelated to peer fertility behavior, thereby violating the exclusion restriction. For instance, working alongside less protected colleagues might heighten awareness of job insecurity more broadly, leading pre-reform workers to worry about their own future career prospects, even if their contractual status remains unchanged. These workers might perceive that the firm is increasingly favoring more "flexible" hires and feel uncertain about their long-term standing or opportunities for advancement. Alternatively, a large influx of newly hired colleagues could signal that the establishment is expanding rapidly, prompting incumbent workers to prioritize career opportunities over family formation.

To address these concerns, we conduct two robustness checks. First, we replicate our main analysis while restricting the sample to firms with stable employment levels over time, thereby holding firm size constant. This helps isolate peer effects from dynamics related to firm expansion or contraction. Second, we construct an alternative instrumental variable based on peers' access to childcare services, using variation in the share of co-workers residing in municipalities with available childcare. This instrument captures peer fertility that is plausibly exogenous to job security concerns. Reassuringly, the results from both exercises

remain consistent with our baseline estimates, lending further credibility to the causal interpretation of our findings.

To explore the mechanisms behind the observed peer effects, we conduct a heterogeneity analysis along several dimensions. We begin by examining differences between men and women, and by considering the gender composition of the peer group. The results reveal that peer effects are smaller for women than for men, consistent with the hypothesis that women, especially early in their careers, may be more concerned with the professional costs of childbearing, which are disproportionately borne by mothers (Adda *et al.,* 2017; Kleven *et al.*, 2019). The effect is even smaller when female workers are exposed to female peers, suggesting that women may be more attuned to, and influenced by, the challenges faced by their colleagues in balancing work and family life.[3] This points to social learning as a moderating mechanism.

Moreover, we show that peer effects are positive for individuals at first childbirth only, consistent with evidence that social learning operates primarily before individuals become parents rather than after they have already experienced parenthood (Lyngstad and Prskawetz, 2010). Interestingly, the impact of peers for first-time parents is significantly smaller for women than for men. Taken together, these findings suggest that information sharing, particularly about the challenges of motherhood, may reduce the positive contagion effect of peers for women, while amplifying it for men, who typically face fewer career and caregiving costs in the transition to parenthood.

Next, we examine how peer effects vary with local gender norms. We find that women are significantly more responsive to peer fertility in regions with more traditional gender role attitudes. This suggests that social norms may amplify peer influences, likely by reinforcing expectations around family formation. As expected, this pattern does not hold for men, whose fertility decisions appear less sensitive to regional variations in gender norms.

Finally, we explore whether career-related concerns shape the strength of peer effects by analyzing variation by tenure and the degree of competition within the firm. We uncover stronger responses among workers with longer tenure, in line with the hypothesis that low-tenure employees face greater competitive pressure and therefore are less inclined to adjust their fertility timing based on peers. Similarly, we find that peer effects are more pronounced in less competitive firms, where wage growth is more compressed. These findings highlight how workplace competition and career concerns can dampen the positive social influence of co-workers' fertility choices.

Beyond the growing literature on peer effects in fertility behavior, our study connects with a wide body of work documenting peer effects across many domains, including consumption (De Giorgi *et al.*, 2020), retirement and saving decisions (Duflo and Saez, 2002, 2003; Brown and Laschever, 2012), financial decisions (Maturana and Nickerson, 2019; McCartney and Shah, 2022), risk aversion (Ahern *et al.*, 2014), educational choices and performance (Sacerdote, 2001; Zimmermann, 2003; Carrell *et al.*, 2009, 2013; Duflo *et al.*, 2011; Feld and Zölitz, 2017; Bertoni and Nisticò, 2023), labor supply, effort and productivity (Falk and Ichino, 2006; Mas and Moretti, 2009; Maurin and Moschion, 2009; Bandiera, Barankay and Rasul, 2010; Waldinger, 2012;

[3] Kuziemko *et al.* (2018) document that, on average, women report that parenthood is harder than they expected.

Nicoletti *et al.*, 2018; Silver, 2021), wages and earnings (Battisti, 2017; Bertoni *et al.* 2021; Hong and Lattanzio, 2022; Cornelissen *et al.*, 2017, 2023); health behavior (Agarwal *et al.* 2021; Fadlon and Nielsen, 2019), criminal behavior (Damn and Dustmann, 2014; Murphy, 2019), household formation (Aparicio-Fenoll and Oppedisano, 2016; Adamopoulou and Kaya, 2018), and parental leave take-up (Dahl *et al.* 2012; Dottori *et al.* 2023, Welteke and Wrohlich, 2019; Casarico *et al.* 2025).

Our findings have important implications for policymakers and employers seeking to promote family-friendly workplaces. By showing that co-workers' fertility decisions significantly influence individual choices, our study highlights the importance of supportive work environments and peer dynamics in shaping reproductive behavior. We also contribute to the growing evidence that job insecurity, such as that introduced by the Jobs Act, can reduce fertility (De Paola *et al.* 2021), and show that peer effects may amplify the impact of such policy changes through social multipliers. In line with the evidence in Li and Zhang (2009) and Rossi and Xiao (2024), who document spillover effects in childbearing decisions using China's family planning policies, our results suggest that social contagion mechanisms can accelerate fertility transitions.

The paper is organized as follows. In Section 2 we introduce the conceptual framework and formulate testable hypotheses. Section 3 describes the institutional setting. In Section 4 we present the data and some descriptive statistics. Section 5 illustrates the identification strategy used in the empirical analysis and presents the main results from our IV approach. Section 6 runs a number of robustness checks, along with a placebo test and reports the results obtained using an alternative instrumental variable. In Section 7 we analyze heterogeneous responses. Section 8 concludes.

2. Conceptual Framework and Hypotheses

We model an individual worker's fertility decision as being influenced by both personal preferences and social interactions within the workplace. Consider a simplified setting in which, in each period *t*, individual *i* chooses whether or not to have a child. The individual's utility from having a child in period *t* is given by:

$$U_i^t\left(Child_i^t = 1\right) = B_i^t + f[SC\left(\bar{F}_{-i}^{t-1}\right), SN\left(\bar{F}_{-i}^{t-1}\right), SL\left(\bar{F}_{-i}^{t-1}\right)] - C_i^t + \varepsilon_i^t$$

where B_i^t denotes the baseline benefit of having a child, reflecting intrinsic preferences and life circumstances, at time t and beyond. The composite peer term, $f\left[SC\left(\bar{F}_{-i}^{t-1}\right), SN\left(\bar{F}_{-i}^{t-1}\right), SL\left(\bar{F}_{-i}^{t-1}\right)\right]$, aggregates three conceptually distinct channels: Social Contagion $SC\left(\bar{F}_{-i}^{t-1}\right)$, Social Norms $SC\left(\bar{F}_{-i}^{t-1}\right)$, and Social Learning $SL\left(\bar{F}_{-i}^{t-1}\right)$, each modeled as a function of the average fertility of individual i's coworkers in the prior period. These components are combined into a single social-influence index, allowing the channels to either reinforce or counteract one another and potentially operate in opposite directions. The overall sign and magnitude of peer influence thus reflect the net effect of these interacting forces. Finally, C_i^t represents the cost of childbearing at time t and beyond, encompassing financial, professional, and time-related considerations.

The worker choses $Child_i^t = 1$ if and only if:

$$B_i^t + f[SC(\bar{F}_{-i}^{t-1}), SN(\bar{F}_{-i}^{t-1}), SL(\bar{F}_{-i}^{t-1})] - C_i^t + \varepsilon_i^t > 0$$

In our framework, the influence of peers' fertility $\bar{F}_{-i}^{t-1}$, operates through three distinct mechanisms: social contagion, social norms and social learning. Each of these channels entails specific behavioral responses and heterogeneity patterns.

Social contagion reflects emotional or behavioral spillovers that lead individuals to imitate the fertility behavior of their peers. The underlying idea is that interacting with colleagues who have newborns can evoke positive feelings, excitement, and trigger an emotional desire to have children or for shared life experiences. This channel can enhance the perceived benefits of parenthood, modelled by the term $SC(\bar{F}_{-i}^{t-1})$, either consciously, through social comparison processes, or unconsciously, by triggering a tendency to synchronize life events with those in one's social circle (Montgomery and Casterline, 1996; Bernardi and Klärner, 2014). According to social comparison theory, individuals tend to adapt their behavior to match those they perceive as similar in social positions or characteristics. In our context, colleagues in the same age group and occupation who become parents can act as positive role models.

Social norms represent shared expectations or implicit pressures within the workplace that shape what is perceived as appropriate or typical behavior within a group (Rindfuss *et al.*, 1988; Fletcher and Yakusheva, 2016). When many co-workers choose to have children, this may reinforce a normative expectation that starting a family at a given career stage or age is "the right thing to do". Conversely, in environments where few peers have children, employees may delay fertility out of concern for appearing deviant or uncommitted. These normative pressures are often gendered: for women, fertility decisions tend to be more closely linked to identity and social validation, making them particularly responsive to social norms. For men, identity-related pressures are typically weaker, implying that peer-induced norm compliance is likely to be stronger among women. Thus, higher peer fertility is expected to raise the probability of childbearing through the norm channel, especially for women.

Social learning operates through an information-sharing channel as individuals update their beliefs about the true costs and benefits of childbearing by observing their peers. In the workplace, colleagues provide valuable signals about how parenthood affects employment trajectories, including experiences with parental leave, reintegration into the workforce, work-life balance, and employer support (Montgomery and Casterline, 1996; Kohler, 2001; Bernardi, 2003; Yakusheva and Fletcher, 2015). Positive experiences, such as peers who return smoothly from leave and successfully balance work and family, may reduce perceived costs and encourage fertility. In contrast, exposure to negative experiences, such as career stagnation, difficulties balancing work and parenting, or even job exit following childbirth, may raise perceived costs and discourage fertility. Thus, the social learning channel can either amplify or dampen peer effects, depending on the nature of observed experiences.

These channels give rise to a set of testable hypotheses, stated below and followed by their theoretical rationale.

H1: Higher peer fertility increases the individual likelihood of having a child.

This overall positive effect arises because social contagion and social norms shift the utility of childbearing upward, while social learning, though theoretically ambiguous, likely reduces perceived childbearing costs in our specific setting. Indeed, stable workplaces—such as those in our pre-reform sample, composed predominantly of male (67.5%) workers on permanent contracts—are more likely to offer formal leave policies and institutional support, making peer learning more conducive to lowering perceived costs.

H2: Peer effects are weaker for women (higher C_i^t), especially when exposed to female peers.

While women experience greater social pressure due to biological reasons, they also face higher expected costs of childbearing, especially early in their careers (Adda *et al.,* 2017; Kleven *et al.*, 2019). This implies that they may be less affected by the experiences of their peers. In addition, when exposed to female colleagues who experience career penalties following childbirth, women may internalize these costs through the learning channel, dampening the overall peer effect.

H3: Peer fertility is more likely to increase own fertility for individuals who have not yet had children.

Social learning is most relevant for decisions regarding the first childbirth, when individuals face greater uncertainty about the implications of parenthood (Lyngstad and Prskawetz, 2010). Observing peers helps individuals form more accurate beliefs about childbearing, reducing uncertainty and increasing the likelihood of entering parenthood.

H4: Peer effects are larger in societies with more traditional gender norms, especially for women.

Higher peer fertility is more likely to strengthen perceived expectations to have children in contexts with more traditional social norms, particularly among individuals more sensitive to social approval, such as women (Fletcher and Yakusheva, 2016).

H5: Peer effects are larger for higher-tenure workers and those in less competitive firms (lower C_i^t).

Tenure reduces vulnerability to internal labor market competition, making individuals more open to peer influence. Likewise, peer effects are expected to be more pronounced in less competitive settings and in more family-friendly environments (Ciliberto *et al.,* 2016).

3. Institutional Setting

Italy, like many other advanced countries, is plagued by very low fertility, which has become a significant demographic concern. The fertility rate has been declining for decades and has now reached historically low levels. This trend reflects a combination of factors, including increased female labor force participation, societal changes, cultural shifts, poor support for work-life balance, and economic uncertainty. Italian traditions and cultural values make stability and financial security a priority for starting a family, but the labor market has become increasingly insecure compared to the past.

Historically, the Italian labor market has been characterized by strict employment protection legislation (EPL). Initially, the EPL provisions applied mainly to firms with more than 15 employees, while smaller firms were largely exempt. Although a 1990 law introduced some restrictions on dismissals for small firms, employees in larger firms continued to enjoy stronger protection. The first attempt to reduce dismissal costs for firms above the 15-employee cut-off was made through the Fornero reform of 2012, which limited reinstatement in the case of unjustified dismissal and reduced severance compensation. The obligation of reinstatement was still present in many situations, however.

In 2015, the government led by Matteo Renzi implemented the "Jobs Act" as a second attempt to address labor market segmentation in Italy. These reforms greatly restricted the possibility of reinstatement, making it applicable only in cases of discriminatory or specific disciplinary dismissal. Unfair dismissals were now to be compensated by a predetermined monetary payment based on seniority. The reduction in employment protection applied only to firms above the 15-employee threshold: specifically, to all new permanent hires in these firms after 7 March 2015, when the Law went into force, and not to workers hired previously, who are still covered by the reinstatement clause. Firms with a workforce below the 15-employee threshold remained largely unaffected by the reform, as the reinstatement clause did not apply to them even before.

The introduction of the Jobs Act, with its reduced employment protection for new hires, constitutes the basis for our identification strategy that we discuss in Section 5.

4. Data and Descriptive Statistics

Our analysis relies on a matched employee-employer dataset, provided by the Italian Social Security Institute (INPS), which encompasses the universe of private-sector, non-agricultural firms with at least one employee.[4] In the cases in which the worker has multiple job contracts in a year, we retain only the primary job, defined as the one with the highest annual earnings.[5] For each worker-firm record, we have access to detailed information on contract start and end dates, contract type (permanent vs. temporary, full-time vs. part-time), occupation type (blue-collar, white-collar, managerial), annual earnings, number of days worked, reasons for termination (e.g. layoff, resignation), and unique identifiers for both the worker and the firm, thanks to which we can link these records to others containing essential details such as workers' gender, date of birth, citizenship, municipality of residence, ATECO-07 sector, and business location. Additionally, we observe a measure of the company workforce ("*forza aziendale*"), presented as full-time equivalent, on a yearly basis, which we use to identify the 15-employee threshold.[6]

[4] These data cover the universe of labor contracts from the UNIEMENS modules, which all Italian firms must file with INPS.

[5] The few ties are solved by picking the primary job at random.

[6] As noted by Boeri and Garibaldi (2019), this measure is a good proxy of the measure adopted by the Italian labor courts, which considers the average number of full-time open-ended contracts in the last 6 months, the full time equivalent of the number of part-time open-ended contracts in the last 6 months, and the average number of fixed-term employees hired in the last 24 months weighted by their effective job duration.

To measure fertility, we rely on data from the Universal Child Allowance (*Assegno Unico e Universale*), introduced in 2022, which provides benefits to all families with children under the age of 21. This administrative register includes identification codes for both parents, and the child's date of birth. The high take-up rate (approximately 95%) for children born between 2015 and 2020 implies that applications for this benefit can be taken as a reliable indicator of births at the individual level. We utilize this information to determine, in our yearly panel, the decision to have a child for each individual as the child's birth date minus 9 months. Our outcome variable "*Child*" is an indicator for individuals who had a child within a specific year during the period 2016-2020. We focus on fertility decisions by workers of reproductive age (women aged 16-46, men aged 16-56) hired in large firms before the Jobs Act and so not directly affected by the reform.

For each worker we can observe – using the unique firm identifier – every co-worker on an annual basis. This allows us to construct the worker's peer group at time *t*. In our main analysis, the peer group is defined as all workers of the same five-year age group employed in the same firm establishment (i.e. workplace), and in the same type of occupation (blue-collar, white-collar, manager) in a given year. Considering these specific characteristics, we can analyze the impact of peer fertility on individual fertility decisions within a well-defined and comparable group. Our main explanatory variable is the fertility rate of each worker's peer group at time *t-1* (lagged), which we build considering births among co-workers in the period 2015-2019.

Table A.1 presents descriptive statistics of the sample. We observe 11,008,833 individual-year observations, across 111,521 firms and 134,571 distinct workplaces. Our peer group definition yields 1,458,812 peer groups. During the period considered, 3.7% of the workers in our sample had a child. The percentage of female workers is 32.5%, the fraction of immigrant workers around 10.7%. On average, workers are 41 years old, have 7.6 years of tenure and 19.1 years of work experience. In our sample, 47% are blue-collar, 45% white collar, 6% managers. Only 15% work part-time. A large majority of our individuals (63.5%) work in the North of Italy, 19.4% in the Centre, and 17% in the South. The median size of the peer group (the number of co-workers in the same workplace, occupation, and age group) is 23, 16.7% of them were hired after the implementation of the Jobs Act.

5. Identification Strategy and Main Results

Our analysis offers empirical evidence on how the fertility decisions of an individual are influenced by the fertility of his or her co-workers (peers). Since the aim is to identify peer effects, we need to tackle the common econometric challenges associated with this issue, as described by Manski (1993) and Lyle (2007). The first challenge is the "reflection" problem, that is, the fact that fertility among peers is typically determined simultaneously, making it difficult to distinguish the influence of peers on the subject's fertility decisions from the influence of the subject's decisions on peers. The second challenge involves "correlated effects," wherein common unobservable characteristics at the group level (those specific to the workplace, say) may affect the fertility decisions of each individual in the group and potentially confound the relationship between peer

fertility and individual fertility outcomes. The third challenge relates to the issue of selection. Peer groups are typically formed endogenously, individuals tending to associate with others who have similar characteristics. If these characteristics are not observable but affect the fertility outcome, the estimation of the peer effect might suffer from selection bias.

Analytically, we regress an individual's probability of having a child on the average fertility of the group of peers in the workplace using the following Linear Probability Model:

$$Child_i^t = \beta_0 + \beta_1 \bar{F}_{-i}^{t-1} + \beta_2 X_i^t + u_i^t \quad (1)$$

where the dependent variable $Child_i^t$ is a binary indicator that takes the value 1 if individual *i* in year *t* has conceived a child and value 0 otherwise, and $\bar{F}_{-i}^{t-1}$ is the average fertility rate in year *t-1* among all *i*'s co-workers in the same workplace (i.e. establishment), occupation (blue collar, white collar, manager) and age group (<=20, 21-25, 26-30, 31-35, 36-40, >40). X_i^t is a vector of individual characteristics (female, age, age squared, tenure, experience, immigrant, type of occupation, region of residence, industrial sector dummies, etc.) and peer characteristics (% of female peers, % immigrant peers, % part-time peers, average peer tenure, and average peer experience), and u_i^t is an error term. We cluster standard errors at the firm level to account for potential within-firm correlations.

The OLS estimate of β_1 may not capture the causal impact of peers because of the correlation between the peer fertility rate and the error term. Our identification strategy, therefore, relies on an instrumental variable approach. To this end, we leverage the 2015 Jobs Act reform, which has been shown to have reduced fertility rates by weakening employment protection for newly hired employees (De Paola *et al.*, 2021). More specifically, we investigate how the fertility of workers who were not directly affected by the Jobs Act and were employed in large firms during the period 2016-2020 responded to the lower average fertility among their peers hired after the reform. We thus estimate equation (1) using a Two-Stage-Least-Squares (2SLS) estimator.

In the First Stage equation we assume that the peer fertility rate, $\bar{F}_{-i}^{t-1}$, is affected by the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act, JA_{-i}^{t-1}, hence exposed to lower job security, and estimate the following equation:

$$\bar{F}_{-i}^{t-1} = \pi_0 + \pi_1 JA_{-i}^{t-1} + \pi_2 X_{-i}^{t-1} + e_{-i}^{t-1} \quad (2)$$

Our hypothesis is that the greater the fraction of co-workers hired under the Jobs Act in a firm, the lower the fertility rate among *i*'s colleagues; that is, π_1 is negative. To account for other possible determinants of peers' fertility rate, in the equation we control for several characteristics of the peer group (the vector *X*), such as average age, average tenure, average experience, % of female, % of immigrant, and % of part-time workers.

We first verify the relevance of our instrument estimating the First Stage equation (results in Table 1). In column 1 of the Table, we run a specification with only controls at the individual and at the peer group level. In columns 2, 3 and 4 we progressively add year, region, and sector dummies. The estimate in column 4 indicates that if the share of peers hired under the Jobs Act were 100%, the average fertility rate in the group would be 1.9% lower. This effect, obtained with administrative data, is in line with the findings of De Paola *et al.* (2021); using Labor Force Survey data, they estimate a 2-percentage-point reduction in the probability of having a child for women affected by the Jobs Act. The effect is highly significant statistically, and the corresponding F-stat of the First Stage is above 1,000.

Since we focus on employees hired before the Jobs Act, we are confident that the instrument is exogenous. The exclusion restriction assumption requires that the share of colleagues hired under the Jobs Act has no direct influence on the decision of individual *i* to have a child or on its determinants. To validate this assumption, we conduct a battery of robustness checks and a placebo test in Section 6. Therefore, the 2SLS estimate of β_1 captures the causal impact of the peer fertility rate on the probability of having a child for an individual not directly affected by the Jobs Act.[7]

Table 1. First Stage Estimates. Peer Fertility and Fraction of Peers Hired under Jobs Act

	(1)	(2)	(3)	(4)
	Peer Fertility Rate			
Fraction Jobs Act Peers	-0.0142***	-0.0189***	-0.0191***	-0.0188***
	(0.00041)	(0.00056)	(0.00055)	(0.00054)
Individual controls	YES	YES	YES	YES
Peer group controls	YES	YES	YES	YES
Year dummies	NO	YES	YES	YES
Region dummies	NO	NO	YES	YES
Sector dummies (90)	NO	NO	NO	YES
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	1182.13	1139.43	1218.67	1195.91
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.00000	0.00000	0.00000	0.00000
Observations	11,008,833	11,008,833	11,008,833	11,008,833

Notes: Each column reports estimates from OLS regression. The dependent variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers hired under the Jobs Act. Individual controls: Female, Age, Age Squared, Immigrant, Tenure, Experience, Part time. Peer group controls: % Females, % Immigrants, Avg. Tenure, Avg. Experience, % Part time. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table 2 reports the main results concerning the effect of co-workers on individual fertility, obtained by estimating equation (1) with 2SLS.[8] In column 1 we control for individual and peer characteristics. The peer fertility rate has a positive and strongly significant effect on an individual's probability of having a child. The estimated coefficient indicates that a 1-percentage-point increase in average peer fertility leads to a 0.45 percentage point increase in the individual probability of having a child.

[7] Reduced-form estimates, reported in Table A.2 in the Appendix, show a significant negative effect of the fraction of co-workers hired under the Jobs Act on the probability of conceiving a child for workers hired before the Jobs Act.
[8] The OLS estimates of equation (1) are reported in Table A.3 in the Appendix.

Table 2. Individual Fertility and Fertility of Peers. 2SLS Estimates

	(1)	(2)	(3)	(4)
Second-stage regressions				
Peer Fertility Rate	0.4538***	0.4044***	0.4088***	0.4023***
	(0.0299)	(0.0276)	(0.0273)	(0.0276)
Female	-0.0049***	-0.0052***	-0.0050***	-0.0049***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Age	0.0041***	0.0042***	0.0041***	0.0041***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age Squared	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Immigrant	0.0081***	0.0081***	0.0086***	0.0088***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Tenure	-0.0003***	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Part-Time	-0.0082***	-0.0083***	-0.0084***	-0.0083***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Blue-Collar	-0.0021***	-0.0022***	-0.0028***	-0.0023***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
White-Collar	0.0010***	0.0012***	0.0009**	0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Peer Fraction of Female	0.0039***	0.0044***	0.0049***	0.0056***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Peer Fraction of Immigrants	-0.0064***	-0.0063***	-0.0050***	-0.0043***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Peer Tenure	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Peer Experience	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Peer Fraction of Part-Time	0.0023***	0.0019***	0.0011*	0.0012*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
First-stage regressions				
Fraction Jobs Act Peers	-0.0142***	-0.0189***	-0.0191***	-0.0188***
	(0.0004)	(0.0006)	(0.0005)	(0.0005)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	1182.13	1139.43	1218.67	1195.91
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Year dummies	NO	YES	YES	YES
Region dummies	NO	NO	YES	YES
Sector dummies (90)	NO	NO	NO	YES
Mean of dependent variable	0.037	0.037	0.037	0.037
SD of dependent variable	0.189	0.189	0.189	0.189
Median peer group size	23	23	23	23
Observations	11,008,833	11,008,833	11,008,833	11,008,833

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Standard errors in parentheses are clustered at the firm level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$. *Sources*: INPS Archives and *Assegno Unico e Universale* records.

As for the control variables, our results are in line with previous studies: age and fertility show a concave relationship (with a maximum at age 32.8), immigrants have a higher probability of having a child, and workers with more years of labor market experience and on part-time jobs have a lower probability.

In columns 2, 3 and 4 we progressively add year, region, and industry dummies to control for time-specific shocks and unobserved heterogeneities across regions and industries. Reassuringly, our main estimate remains not only strongly significant but also stable in magnitude at around 0.40 percentage points. The results from our preferred specification in column 4 indicate a 10% increase in fertility following a 1-percentage point increase in co-workers' fertility. This positive peer effect is consistent with our first hypothesis (*H1*) outlined in Section 2 and mirrors findings of Asphjell *et al.* (2013) and Buyukkececi *et al.* (2020), who report similarly sized effects for Sweden and the Netherlands, respectively.

6. Robustness Checks

In Table 3, we assess the robustness of our main estimates along several dimensions. First, in column 1 we augment our main specification with the inclusion of firm fixed effects so as to account for unobserved firm-level heterogeneity. Reassuringly, the main estimate remains positive and strongly significant, although somewhat smaller in magnitude.

Second, in column 2 we replicate our main analysis in a sample of firms that did not change their size during the period of analysis. The concern is that the workers in firms with larger shares of newly hired colleagues might interpret this as a signal that the firm is expanding or is favoring more flexible hires, which might directly induce them to prioritize career opportunities over family formation, regardless of peer fertility. By keeping firm size fixed, we block the potential path from exposure to newly hired colleagues to individual fertility via those unmeasured confounding factors. The estimate in column 2 is still strongly significant, and become larger in magnitude, likely due to the very small sample size. To ensure that this latter result is not driven by a few firms, we run this test on a sample of firms that experienced just a minor change in size over the period under scrutiny, i.e., those with a change in size between the 25th and the 75th percentile. This allows us to have a much larger sample size compared to column 2. Notably, the estimate in column 3 remains significant and positive, but with a relatively smaller magnitude relative to column 2.

Third, in columns 4 and 5, we check whether our main results change when peer fertility is measured two years prior (at year t-2 rather than at t-1) or as the average between t-1 and t-2, both of which imply losing the first year of observation. The results obtained from these two exercises are remarkably similar to our main results in Table 2, column 4.

In Table A.4 in the Appendix we also show that our main results are robust to alternative thresholds to define large firms, namely 20 or 50 employees (columns 1 and 2, respectively). Furthermore, in columns 3-5 we re-run the analysis excluding firms with more than one establishment (where large firm size could mask several smaller establishments) and progressively reducing their size. We also find that the magnitude of the effect increases when moving from relatively larger (<=250 employees) to relatively smaller firms (<=50 employees), in line with the thesis that social interactions tend to be more salient in smaller firms.

Table 3. Further Robustness Checks

	(1) Firm FEs	(2) Firm size fixed over sample period	(3) Firm size change in [p25, p75] over sample period	(4) Peer fertility at year t-2	(5) Average peer fertility between t-1 and t-2 (year>2016)
Second-stage regressions					
Peer Fertility Rate	0.3562***	0.5321***	0.3601***	0.4049***	0.4346***
	(0.0355)	(0.1477)	(0.0635)	(0.0312)	(0.0288)
First-stage regressions					
Fraction Jobs Act Peers	-0.0174***	-0.0187***	-0.0195***	-0.0189***	-0.0218***
	(0.0006)	(0.0027)	(0.0012)	(0.0006)	(0.0006)
Weak identification test					
Kleibergen-Paap rk Wald F-stat	793.35	46.08	270.51	882.20	1214.23
Weak-instrument-robust inference					
Anderson-Rubin Wald test p-val	0.0000	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.037	0.037	0.035	0.035	0.035
SD of dependent variable	0.188	0.189	0.183	0.184	0.183
Median peer group size	23	10	21	23	24
Observations	11,008,833	224,666	1,836,445	7,534,282	7,436,473

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

We further prove the robustness of our main results to alternative definitions of the peer group. In our main analysis, the peer group consists of employees in the same workplace, age group, and occupation. Here we introduce two alternative definitions: the first includes employees from the same workplace and age group, regardless of occupation, while the second includes co-workers in the same workplace, occupation, age group, and gender. The estimates reported in Appendix Table A.5 demonstrate that our main findings do not hinge on the way we define the peer group.

We also consider the following alternative instruments: (i) a dummy equal to one if this share exceeds the 75th percentile; and (ii) two dummy variables indicating medium exposure (share between the 25th and 75th percentiles) and high exposure (share above the 75th percentile) to pre–Jobs Act peers. The results, reported in Appendix Table A.6, indicate that our main findings remain qualitatively unchanged.

6.1. Placebo Test

One concern with our estimation strategy is that our instrument might be capturing unobservable firm characteristics that affect the fertility rates of newly hired and incumbent workers alike. To investigate this issue, we focus on firms with multiple workplaces (about 1 million workers in our sample are employed in such firms) and conduct a placebo test using workers in other plants of the same firm to construct an artificial,

fake peer fertility rate. The idea is that workers' fertility decisions should not respond to changes in the fertility rate of peers of the same firm with whom they do not actually interact, i.e. those in other workplaces.

In Table 4, column 1, we check whether the impact of peer fertility on individual fertility is driven by the average fertility rate in other workplaces of the same firm. Importantly, the coefficient of the average fertility rate of workers in other plants of the same firm is now much smaller (almost close to zero) and indeed has no significant effect on the individual probability of having a child. This reassures us that our main effect does not represent a spurious correlation.

In addition, to ensure that the sample of multi-plant firms is not driving our results, in column 2 of Table 4 we replicate our main regression using the placebo sample (but with the actual peers) and find comparable results to those in Table 2, column 4.

Table 4. Placebo Test: Using Peer Fertility Rate in Other Establishments of the Same Firm

	(1) Placebo test	(2) Main effect in the placebo sample
Second-stage regressions		
Peer Fertility Rate	0.0645	0.3449***
	(0.0415)	(0.0537)
First-stage regressions		
Fraction Jobs Act Peers	-0.0171***	-0.0190***
	(0.0020)	(0.0013)
Weak identification test		
Kleibergen-Paap rk Wald F-statistic	76.17	227.12
Weak-instrument-robust inference		
Anderson-Rubin Wald test p-value	0.0000	0.0000
Year dummies	YES	YES
Region dummies	YES	YES
Sector dummies (90)	YES	YES
Mean of dependent variable	0.036	0.036
SD of dependent variable	0.186	0.187
Median peer group size	29	32
Observations	2,720,667	2,679,680

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. In column 1, the treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same occupation and age group but in a different workplace of the same firm, while the instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same occupation and age group but in a different workplace of the same firm, hired after the Jobs Act. In column 2, the treatment and instrumental variables are measured as described in Table 2. Each specification includes individual controls, peer group as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

6.2. Alternative Instrumental Variable

Another potential concern with our estimation strategy, which might not be alleviated by the placebo test, is that exposure to co-workers hired after the Jobs Act (as captured by our instrumental variable) might influence individuals' fertility decisions through channels that are unrelated to co-workers' fertility choices. Most notably, such exposure could increase the salience of job insecurity, and make individual workers worry about their future career prospects, thus violating the exclusion restriction.

In Table 5, we address this concern by using an alternative instrument that relies on differences in access to childcare services among co-workers. Specifically, using data on childcare availability at the municipal level provided by ISTAT,[9] we exploit differences in the proportion of peers who live in municipalities where public childcare is available. This availability is expected to influence peers' fertility choices but it is unlikely to be correlated with job security perceptions within the firm. This approach offers a way to isolate peer effects driven by external family-support policies rather than internal labor market dynamics. Encouragingly, the results obtained using this alternative instrument closely mirrors our main findings, even when firm fixed-effects are included in column 5. This evidence further reinforces the credibility of our causal interpretation.

Table 5. Additional Robustness Check: Using IV Based on Peers' Childcare Exposure

	(1)	(2)	(3)	(4)	(5)
Second-stage regressions					
Peer Fertility Rate	0.5220***	0.4735***	0.4721***	0.4683***	0.4400***
	(0.0353)	(0.0346)	(0.0336)	(0.0338)	(0.0461)
First-stage regressions					
Fraction Peers with Childcare	0.0089***	0.0099***	0.0105***	0.0104***	0.0113***
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Weak identification test					
Kleibergen-Paap rk Wald F-statistic	710.70	595.91	692.61	719.16	460.38
Weak-instrument-robust inference					
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Year dummies	NO	YES	YES	YES	YES
Region dummies	NO	NO	YES	YES	NO
Sector dummies (90)	NO	NO	NO	YES	NO
Firm dummies	NO	NO	NO	NO	YES
Mean of dependent variable	0.037	0.037	0.037	0.037	0.037
SD of dependent variable	0.189	0.189	0.189	0.188	0.189
Median peer group size	23	23	23	23	23
Observations	10,845,350	10,845,350	10,845,350	10,845,350	10,845,350

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Peers with Childcare*, measures the fraction of co-workers residing in municipalities covered by childcare services. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

7. Heterogeneous Responses

This Section elaborates on the mechanisms through which peer fertility may shape individual fertility decisions, investigating how the estimated peer effects vary with individual and peer group characteristics as well as with local and firm-level factors. As noted in Section 2, peer influence in the workplace may operate through social influence, social norms, and social learning, and may be attenuated by career concerns.

[9] Indagine su nidi e servizi integrativi per la prima infanzia 2019-2020.

We begin by examining gender differences in peer effects on fertility in Table 6. The results reveal that the magnitude of the response differs substantially between men and women. As shown in columns 1 and 2, a 1-percentage-point increase in peer fertility is associated with a 7% (=0.003235/0.044) increase in own probability of having a child for women, compared to a 15% (=0.004882/0.033) increase for men. This finding provides empirical support to our hypothesis *H2* in Section 2. This disparity likely reflects the disproportionate burden that women continue to bear in balancing work and family responsibilities, particularly with regard to childcare. While social influence appears to affect both genders (the estimated peer effect is positive for both women and men), the smaller effect for women suggests that career-related concerns may dampen the extent to which they adjust their fertility behavior in response to their colleagues.

Table A.7 in the Appendix further explores gender-specific responses to peer fertility by distinguishing between the influence of female and male co-workers. Columns 1–2 report the effects of female peer fertility, while columns 3–4 examine the influence of male peers. The findings reveal that both men and women are more responsive to the fertility behavior of male colleagues. This pattern supports the idea that when female co-workers have children, the associated challenges of parenthood, especially for women, are more visible, potentially tempering the influence of peer behavior. In contrast, when male peers become fathers, the costs and consequences are less salient, leading to a stronger social influence effect on both genders.

Table 6. Heterogeneous Responses: by Gender

	(1) Female	(2) Male
Second-stage regressions		
Peer Fertility Rate	0.3235***	0.4882***
	(0.0372)	(0.0398)
First-stage regressions		
Fraction Jobs Act Peers	-0.0235***	-0.0148***
	(0.0007)	(0.0006)
Weak identification test		
Kleibergen-Paap rk Wald F-statistic	995.97	674.27
Weak-instrument-robust inference		
Anderson-Rubin Wald test p-value	0.0000	0.0000
Mean of dependent variable	0.044	0.033
SD of dependent variable	0.205	0.180
Observations	3,583,868	7,424,965

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Taken together, these findings provide suggestive evidence that social learning might also mediate the relationship between peer and individual fertility decisions. This mechanism is particularly plausible in the Italian context, where the estimated child penalty (approximately 33% according to Kleven *et al.,* 2024) is notably higher than the European average (29%) and the United States (25%). In such an environment, female

workers are likely to be especially sensitive to the challenges their female colleagues face in reconciling work and family life. These experiences can shape expectations and choices, particularly if the peer experiences are perceived as negative. It is perhaps not surprising that many women report finding parenthood more difficult than anticipated (Kuziemko *et al.*, 2018).

Consistent with prior evidence that social learning plays a greater role before individuals become parents (Lyngstad and Prskawetz, 2010) and with our hypothesis *H3* in Section 2, our results in Table 7 show that peer effects are positive for workers at first childbirth but turn negative for those who already have children. When it comes to higher order births, both social learning and peer pressure mechanisms are likely to have weaker effects, as individuals have already gained relevant information and responded to social expectations with their first child. This may allow other factors, such as dynamics related to the internal labour market, to play a more prominent role. In particular, the presence of peers with young children might generate a negative peer effect if it is perceived as an opportunity for career advancement (e.g., filling in for colleagues on leave), or if employers exert implicit or explicit pressure to limit additional parental leaves, especially in contexts where managing multiple employees with young children poses organizational challenges. While this pattern holds for both female and male workers, the gender differences in the coefficients for first-time parents (columns 1 and 3) suggest a gender asymmetry in how social learning operates: for women, the peer effect appears attenuated, possibly due to increased awareness of the challenges associated with motherhood; for men, by contrast, peer influence may be reinforced, as the perceived costs of parenthood are less immediate or visible.

Table 7. Heterogeneous Responses: by Gender and Birth Order

	(1)	(2)	(3)	(4)
	Female		Male	
	N. pre-existing children=0	N. pre-existing children>=1	N. pre-existing children=0	N. pre-existing children>=1
Second-stage regressions				
Peer Fertility Rate	0.2075***	-0.4376***	0.8791***	-0.0854
	(0.0375)	(0.1044)	(0.0732)	(0.0533)
First-stage regressions				
Fraction Jobs Act Peers	-0.0204***	-0.0404***	-0.0088***	-0.0245***
	(0.0007)	(0.0016)	(0.0005)	(0.0009)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	794.08	610.90	268.93	749.23
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.11
Mean of dependent variable	0.028	0.150	0.023	0.060
SD of dependent variable	0.166	0.356	0.149	0.237
Observations	3,126,891	456,977	5,250,641	2,174,324

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sources: INPS Archives and *Assegno Unico e Universale* records.

Next, in Table 8 we examine the role of social norms in shaping peer effects by testing whether the impact of peer fertility varies with prevailing gender norms in a worker's region. Specifically, we assess whether the effect differs between areas characterized by more traditional versus more egalitarian gender roles. In regions with more traditional gender norms (i.e., where women are primarily expected to look after home and family) observing peers who have children may generate stronger social pressure. Since women's fertility decisions are often more closely tied to identity and social validation than men's, who typically face less identity-based pressure in this domain, we expect women to be more responsive to such peer influences.

Using data from the fourth wave of the European Values Study, we classify Italian regions into two groups based on whether the share of respondents agreeing with the statement "A man's job is to earn money; a woman's job is to look after home and family" is above or below the median. Regions above the median are classified as having more traditional gender norms. We then run separate regressions by gender and social norm group.

Table 8. Heterogeneous Responses: by Gender and Type of Gender Norms

	(1)	(2)	(3)	(4)
	Female		Male	
	More traditional gender norms	Less traditional gender norms	More traditional gender norms	Less traditional gender norms
Second-stage regressions				
Peer Fertility Rate	0.4020***	0.1767**	0.4582***	0.5259***
	(0.0474)	(0.0561)	(0.0492)	(0.0624)
First-stage regressions				
Fraction Jobs Act Peers	-0.0237***	-0.0230***	-0.0153***	-0.0139***
	(0.0009)	(0.0010)	(0.0007)	(0.0008)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	624.34	506.92	472.77	310.58
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.045	0.043	0.034	0.033
SD of dependent variable	0.206	0.203	0.181	0.180
Observations	2,156,635	1,531,824	4,512,423	3,161,530

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Regions with more traditional gender norms are those with above-median answers to the question "A man's job is to earn money; a woman's job is to look after home and family" (from the fourth European Value Survey). Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archive*, Assegno Unico e Universale* records, and European Value Surveys.

Consistent with our hypothesis *H4* in Section 2, the estimates in Table 8 show that female workers in more traditional regions exhibit a substantially stronger response to peer fertility (coefficient = 0.4020) than those in more egalitarian regions (0.1767). For men the difference in coefficients is less pronounced. Remarkably, we find consistent results in Table A.8 of the Appendix, where we use paternity leave take-up

rates at the municipality level (2016–2018) as a more granular proxy for local gender norms than in Table 8 (see Biasi, De Paola, and Gioia, 2025).[10]

Overall, these findings suggest that in less egalitarian societies, women may face stronger social expectations around motherhood, making them more responsive to the fertility behavior of their colleagues. This interpretation aligns with Fletcher and Yakusheva (2016), who identify social norms as a key mechanism behind peer effects in fertility decisions.

Appendix Table A.9 provides additional evidence on the importance of social norms by showing how peer effects differ between native and immigrant workers. Immigrants often originate from countries with more traditional gender norms than those prevalent in Italian society. According to data from the Italian National Statistics Institute (ISTAT), the largest foreign community in Italy are from Romania (21.5% of the foreign population), Morocco (8.4%) and Albania (8.3%). The estimates in columns 1-2 indicate that peer effects are statistically significant for both groups but remarkably stronger among immigrant workers (12% vs. 9%), consistent with the hypothesis that traditional gender norms may amplify the influence of peer fertility. Further analysis in columns 3-4 focuses on immigrant workers and shows that peer effects are significant only when the proportion of immigrants within the peer group is relatively high. This suggests that identification with culturally similar co-workers may intensify social pressure, thereby reinforcing the influence of peers on fertility decisions.

In Table A.10 in the Appendix, we also investigate whether the gender composition of the peer group moderates the impact of peer fertility. Specifically, we examine how the share of female co-workers influences the strength of peer effects. For women, a higher proportion of female peers could enhance social identification and thereby strengthen peer influence. However, greater exposure to the challenges of motherhood (whether through observation or informal conversations) may lower this effect by making the costs of parenthood more salient. For men, by contrast, working in a more female-dominated environment may weaken peer effects, both due to lower social identification and because the downsides of childbearing may become more visible. The results in Table A.10 broadly support these expectations. Among women, peer effects diminish as the share of female co-workers increases (columns 1–2), suggesting that the information-sharing channel may counteract the social contagion and social norms mechanisms. Among men (columns 3–4), peer effects also decline in more female-dominated workplaces, consistent with weaker identification with peers and reduced visibility of the perceived benefits of childbearing.

To further examine the role of career-related concerns, in Table 9 we analyze heterogeneity in peer effects by tenure, separately for women and men. Tenure serves as a proxy for job stability and perceived competition within the workplace, separately for men and women. The results show that both female and male workers with longer tenure (those above the gender-specific median) exhibit significantly stronger responses

[10] Paternity leave was introduced in Italy in 2013 and gradually extended to 10 fully compensated days. Despite full coverage, take-up remained limited. We use municipal-level take-up rates from 2015–2018 (when the leave duration was of 2–3 days and average participation was around 40%) as a proxy for local gender norms. We exclude the initial rollout years (2013–2014) due to low awareness and uptake. Results are robust to including more recent years. Data source: INPS.

to peer fertility. This supports the idea that high-tenure employees may feel less in competition with their co-workers and are thus more influenced by their peers' family choices, as predicted in our hypothesis *H5* in Section 2. In addition, we find that the disparity is more pronounced among women, suggesting that career-related concerns weigh more heavily on their fertility decisions.

Table 9. Heterogeneous Responses: by Gender and Tenure

	(1)	(2)	(3)	(4)
	Female		Male	
	Tenure <=median	Tenure >median	Tenure <=median	Tenure >median
Second-stage regressions				
Peer Fertility Rate	0.3229***	0.5952***	0.4757***	0.5848***
	(0.0406)	(0.0657)	(0.0465)	(0.0603)
First-stage regressions				
Fraction Jobs Act Peers	-0.0266***	-0.0219***	-0.0153***	-0.0174***
	(0.0009)	(0.0010)	(0.0006)	(0.0010)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	909.69	476.61	637.44	310.23
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.053	0.029	0.039	0.026
SD of dependent variable	0.224	0.163	0.194	0.160
Observations	2,193,761	1,390,107	4,152,264	3,272,701

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table 10 provides additional evidence supporting the competition mechanism by exploring how peer effects vary with competitiveness within the firm. We measure firm-level competition using wage growth dispersion: workers in firms with higher dispersion are assumed to face greater internal competition, as large variation in wage growth may signal fewer predictable pathways for advancement. The estimates show that in more competitive environments (i.e., firms with above-median wage growth dispersion), both women (columns 1-2) and men (columns 3-4) are less responsive to peer fertility. This finding is consistent with the hypothesis *H5* in Section 2, which posits that when workers perceive greater competition for career opportunities, they may be less likely to follow peer behavior when it comes to childbearing.

Table 10. Heterogeneous Responses: by Gender and Competition Within Firm

	(1)	(2)	(3)	(4)
	Female		Male	
	Wage growth dispersion <=median	Wage growth dispersion >median	Wage growth dispersion <=median	Wage growth dispersion >median
Second-stage regressions				
Peer Fertility Rate	0.3904***	0.3060***	0.5188***	0.4552***
	(0.0850)	(0.0420)	(0.0884)	(0.0466)
First-stage regressions				
Fraction Jobs Act Peers	-0.0222***	-0.0235***	-0.0127***	-0.0148***
	(0.0014)	(0.0009)	(0.0011)	(0.0006)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	268.41	747.68	130.99	538.30
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.040	0.045	0.031	0.036
SD of dependent variable	0.195	0.208	0.172	0.185
Observations	896,092	2,687,776	3,080,452	4,344,513

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

8. Conclusions

We estimate how colleagues' fertility affects a worker's likelihood of having a child. Using administrative data from the Italian Social Security Institute (INPS) for 2016-2020 and an instrumental variable approach, we provide evidence that co-workers significantly shape individual fertility behavior, an area that has been relatively little explored in the literature on peer effects.

We exploit variation in workplace fertility induced by the 2015 Jobs Act, which reduced employment protection, and consequently fertility, for new hires on open-ended contracts in large firms (more than 15 employees). We focus on similar workers who were hired before the reform, and thus retained unchanged levels of employment protection, and use the fraction of co-workers hired after the reform as an instrument for peer fertility. We document that a 1-percentage-point increase in co-workers' fertility leads to a 0.3. to 0.4 percentage point increase in an individual probability of having a child, representing a 10% rise in average fertility.

Our results are robust to a number of checks, including alternative definitions of peer groups, the use of different samples based on firm size, restricting the sample to firms with relatively constant size, and employing an alternative instrumental variable. Moreover, the results of a placebo test – in which we assign to each worker a fake peer group from a different plant within a multi-plant firm – reassure us that our identification strategy is not capturing spurious effects.

The heterogeneity analysis yields valuable insights into the mechanisms underlying peer effects in fertility decisions. First, peer effects on fertility are weaker for women than men, particularly among women

early in their careers, likely due to greater concern over the professional costs of childbearing. The effect further declines when female peers are the reference group, suggesting that women may be more aware of and influenced by the challenges their female colleagues face in balancing work and family. Second, peer effects turn out to be positive only for first births, consistent with the idea that social learning is more influential before parenthood. Third, women are more responsive to peer fertility in regions with traditional gender norms, highlighting the amplifying role of social expectations, an effect not observed among men. Fourth, career concerns also moderate peer influence: workers with longer tenure and those in less competitive firms are more affected by peer fertility, suggesting that competition and job insecurity reduce social contagion in fertility behavior.

Overall, our findings shed light on how work-related concerns, societal expectations, and information sharing interact to shape peer dynamics around fertility. Understanding these mechanisms is crucial, not only for capturing the complexities of peer effects but also for anticipating how policy interventions could directly or indirectly affect fertility decisions. Since the choice to have children is not made in isolation but is shaped by the behavior of colleagues, workplace social interactions can significantly amplify the effects of policy changes. In particular, our study highlights how labor market reforms designed to enhance flexibility may unintentionally lower fertility rates. These effects are not driven by policy alone but are amplified through social contagion within the workplace. As individuals adjust their family planning in response to peers, the cumulative impact of such reforms can extend well beyond their direct targets. This underscores the importance of a holistic approach to policymaking, one that considers not only the immediate effects but also the broader social dynamics influencing individual decisions.

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APPENDIX

Table A.1. Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Outcome variable				
Child	0.037	0.189	0	1
Treatment variable				
Peer Fertility Rate	0.035	0.070	0	1
Instrumental variables				
Fraction Jobs Act Peers (main)	0.167	0.208	0	1
Fraction Peers with Childcare (alternative)	0.676	0.267	0	1
Controls				
Female	0.325	0.469	0	1
Age	40.964	7.004	16	56
Immigrant	0.107	0.310	0	1
Tenure	7.574	2.918	1	12
Experience	19.145	7.327	0	32
Part-Time	0.152	0.359	0	1
Blue-Collar	0.472	0.499	0	1
White-Collar	0.447	0.497	0	1
Manager	0.064	0.245	0	1
North	0.635	0.481	0	1
Centre	0.194	0.396	0	1
South	0.170	0.376	0	1

Notes: Sample: 11,008,833 observations. The sample includes female employees aged 16-46 and male employees aged 16-56, with permanent contracts in private-sector firms.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A.2. Reduced-Form Estimates

	(1)	(2)	(3)	(4)
Fraction Jobs Act Peers	-0.0064***	-0.0077***	-0.0078***	-0.0076***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Individual controls	YES	YES	YES	YES
Peer Group controls	YES	YES	YES	YES
Year dummies	NO	YES	YES	YES
Region dummies	NO	NO	YES	YES
Sector dummies (90)	NO	NO	NO	YES
Observations	11,008,833	11,008,833	11,008,833	11,008,833

Notes: Each column reports estimates from the OLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The variable *Fraction Jobs Act Peers* measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Individual controls: Female, Age, Age Squared, Immigrant, Tenure, Experience, Part time. Peer group controls: % Females, % Immigrants, Avg. Tenure, Avg. Experience, % Part time. Standard errors in parentheses are clustered at the firm level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.
Sources: INPS Archives.

Table A.3. OLS Estimates

	(1)	(2)	(3)	(4)
Peer Fertility Rate	0.0461***	0.0460***	0.0448***	0.0434***
	(0.0014)	(0.0014)	(0.0014)	(0.0013)
Individual controls	YES	YES	YES	YES
Peer Group controls	YES	YES	YES	YES
Year dummies	NO	YES	YES	YES
Region dummies	NO	NO	YES	YES
Sector dummies (90)	NO	NO	NO	YES
Observations	11,008,833	11,008,833	11,008,833	11,008,833

Notes: Each column reports estimates from the OLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The variable *Peer Fertility Rate* measures the average fertility rate among co-workers in the same workplace, occupation, and age group. Individual controls: Female, Age, Age Squared, Immigrant, Tenure, Experience, Part time. Peer group controls: % Females, % Immigrants, Avg. Tenure, Avg. Experience, % Part time. Standard errors in parentheses are clustered at the firm level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.
Sources: INPS Archives.

Table A.4. Robustness Checks: Alternative Firm Size Categories

	(1) Firm size >=20	(2) Firm size >=50	(3) Firm size <=250	(4) Firm size <=150	(5) Firm size <=50
Second-stage regressions					
Peer Fertility Rate	0.4118***	0.4233***	0.3994***	0.4077***	0.4309***
	(0.0287)	(0.0331)	(0.0334)	(0.0363)	(0.0407)
First-stage regressions					
Fraction Jobs Act Peers	-0.0191***	-0.0207***	-0.0179***	-0.0176***	-0.0171***
	(0.0006)	(0.0008)	(0.0005)	(0.0005)	(0.0006)
Weak identification test					
Kleibergen-Paap rk Wald F-stat	1073.64	719.74	1293.57	1141.15	704.85
Weak-instrument-robust inference					
Anderson-Rubin Wald test p-val	0.0000	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.037	0.037	0.037	0.037	0.036
SD of dependent variable	0.189	0.189	0.188	0.188	0.187
Median peer group size	26	42	11	9	6
Observations	10,424,671	8,296,683	5,565,783	4,668,235	2,514,017

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. In columns 3-5 we consider only firms with one establishment. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A.5. Robustness Checks: Alternative Peer Group Definitions

	(1)	(2)
Second-stage regressions		
Peer Fertility Rate (same age group)	0.4197***	
	(0.0341)	
Peer Fertility Rate (same age group, occupation, and gender)		0.3264***
		(0.0397)
First-stage regressions		
Fraction Jobs Act Peers	-0.0120***	-0.0099***
	(0.0004)	(0.0004)
Weak identification test		
Kleibergen-Paap rk Wald F-stat	712.95	522.40
Weak-instrument-robust inference		
Anderson-Rubin Wald test p-val	0.0000	0.0000
Mean of dependent variable	0.037	0.036
SD of dependent variable	0.189	0.188
Median peer group size	23	25
Observations	11,008,833	10,592,914

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate,* measures the average fertility rate among co-workers in the same workplace, occupation, and age group in column 1 (our main definition), in the same workplace and age group in column 2, and in the same workplace, age group, occupation, and gender in column 3. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A.6. Robustness Checks: High a Medium Fraction of Jobs Act Peers

	(1)	(2)
Second-stage regressions		
Peer Fertility Rate	0.2581***	0.2461***
	(0.0586)	(0.0409)
First-stage regressions		
Fraction Jobs Act Peers above 75th perc.	-0.0008***	-0.0014***
	(0.0002)	(0.0003)
Fraction Jobs Act Peers between 25Th and 75th perc.		-0.0006***
		(0.0002)
Weak identification test		
Kleibergen-Paap rk Wald F-stat	278.54	269.687
Weak-instrument-robust inference		
Anderson-Rubin Wald test p-val	0.0000	0.0000
Mean of dependent variable	0.037	0.037
SD of dependent variable	0.189	0.189
Median peer group size	23	23
Observations	11,008,833	11,008,833

Notes: Each column reports first- and second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate,* measures the average fertility rate among co-workers in the same workplace, occupation, and age group in column 1 (our main definition), in the same workplace and age group in column 2, and in the same workplace, age group, occupation, and gender in column 3. The instrumental variables, *Fraction Jobs Act Peers above 75th perc* and *Fraction Jobs Act Peers between 25th and 75th perc* are dummy variables equal to one if the fraction of co-workers in the same workplace, occupation, and age group who were hired after the Jobs Act exceeds the 75th percentile or falls between the 25th and 75th percentiles, respectively, of the corresponding distribution. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A.7. Heterogeneous Responses to Peers of Same and Opposite Gender

	(1) Female	(2) Male	(3) Female	(4) Male
Second-stage regressions				
Peer Fertility Rate (Females)	0.2597***	0.2987***		
	(0.0275)	(0.0329)		
Peer Fertility Rate (Males)			0.4088***	0.5479***
			(0.1048)	(0.0542)
First-stage regressions				
Fraction Jobs Act Peers	-0.0291***	-0.0195***	-0.0090***	-0.0106***
	(0.0008)	(0.0012)	(0.0011)	(0.0006)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	1337.37	268.28	63.14	319.23
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0012	0.0000	0.0000	0.0000
Mean of dependent variable	0.044	0.033	0.041	0.033
SD of dependent variable	0.205	0.179	0.199	0.179
Observations	3,332,142	3,922,425	2,890,585	7,260,772

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A8. Heterogeneous Responses: by Gender and Paternity Leave Take-up Rate

	(1)	(2)	(3)	(4)
	Female		Male	
	Paternity leave take-up rate <=median	Paternity leave take-up rate >median	Paternity leave take-up rate <=median	Paternity leave take-up rate >median
Second-stage regressions				
Peer Fertility Rate	0.3460***	0.3039***	0.4482***	0.5059***
	(0.0556)	(0.0471)	(0.0580)	(0.0523)
First-stage regressions				
Fraction Jobs Act Peers	-0.0223***	-0.0244***	-0.0142***	-0.0151***
	(0.0010)	(0.0008)	(0.0007)	(0.0006)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	541.46	829.47	356.97	555.47
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.045	0.043	0.034	0.033
SD of dependent variable	0.206	0.203	0.181	0.180
Observations	1,631,258	1,952,610	3,593,726	3,831,239

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Municipalities with more traditional gender norms are those with below-median paternity leave take-up rates. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archive*, Assegno Unico e Universale* records, and European Value Surveys.

Table A.9. Heterogeneous Responses: by Immigrant Status and Fraction of Immigrant Peers

	(1)	(2)	(3)	(4)
	Native	Immigrant	Immigrant	
			% Immigrant peers <= median	% Immigrant peers > median
Peer Fertility Rate	0.3490***	0.5230***	0.2891	0.5770***
	(0.0309)	(0.0628)	(0.2020)	(0.0681)
First-stage regressions				
Fraction Jobs Act Peers	-0.0179***	-0.0218***	-0.0162***	-0.0224***
	(0.0006)	(0.0010)	(0.0016)	(0.0011)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	972.13	516.15	95.93	409.88
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0000	0.0000	0.0000	0.0000
Mean of dependent variable	0.036	0.043	0.044	0.043
SD of dependent variable	0.187	0.203	0.205	0.202
Median peer group size	24	18	7	21
Observations	9,825,607	1,183,226	172,421	1,010,805

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: INPS Archives and *Assegno Unico e Universale* records.

Table A.10. Heterogeneous Responses by Gender and Fraction of Female Peers

	(1)	(2)	(3)	(4)
	Female		Male	
	% Female peers <= median	% Female peers > median	% Female peers <= median	% Female peers > median
Second-stage regressions				
Peer Fertility Rate	0.6290**	0.3130***	0.6103***	0.3710***
	(0.2009)	(0.0379)	(0.0784)	(0.0429)
First-stage regressions				
Fraction Jobs Act Peers	-0.0104***	-0.0253***	-0.0096***	-0.0219***
	(0.0011)	(0.0008)	(0.0007)	(0.0008)
Weak identification test				
Kleibergen-Paap rk Wald F-statistic	82.75	928.39	168.66	754.14
Weak-instrument-robust inference				
Anderson-Rubin Wald test p-value	0.0012	0.0000	0.0000	0.0000
Mean of dependent variable	0.027	0.046	0.029	0.041
SD of dependent variable	0.163	0.210	0.168	0.199
Observations	475,793	3,108,075	4,612,200	2,812,765

Notes: Each column reports second-stage estimates from the 2SLS regression. The dependent variable, *Child*, is a dummy that takes the value 1 for individuals who conceived a child. The treatment variable, *Peer Fertility Rate*, measures the average fertility rate among co-workers in the same workplace, occupation, and age group. The instrumental variable, *Fraction Jobs Act Peers*, measures the fraction of co-workers in the same workplace, occupation and age group, hired after the Jobs Act. Each specification includes individual controls, peer group controls and year, region, and sector dummies as in Table 2, column 4. Standard errors in parentheses are clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Sources: INPS Archives and *Assegno Unico e Universale* records.