More time for us? Suspended workers, abortions and fertility: evidence from Covid-19*

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September 9, 2024

Abstract

We investigate the effect of an Italian non-pharmaceutical policy aimed at counteracting the spread of Covid-19 on the fertility patterns of Italian women, with a focus on abortions (VPTs). In March 2020, the government forbade the performance of a set of "non-essential" activities; hence, we exploit the variability in the share of suspended workers across Italian municipalities to assess the impact of closures on abortion rates (AR), and pregnancy rates turning into live births 9 months later, by means of a quasi-experimental strategy. Relying on outstanding administrative data on VPTs and births, we find that, the overall drops in abortions due to social distancing notwithstanding, municipalities in the fourth quartile of the suspended workers' share distribution saw a positive effect on quarterly ARs by a value between 10-13% the average rate before the pandemic, compared to those belonging to lower sections of the distribution. Such difference is driven by industrial suspensions. A non-significant effect is retrieved on births. We make use of relevant socio-economic characteristics to inquire about the channels through which the effect might loom: 1) a reproductive health-related reason, due to a relative shift in unwanted pregnancies given more time available at home for couples; 2) to parity of pregnancies, the socio-economic insecurity triggered by the policy, added up to the bleak pandemic situation. Whereas the relevant mechanism seems to be the former, the analysis makes room for the fact that the unstable economic environment might have played some role; for the first time with respect to the literature using the same data, we exploit information on past reproductive behavior of the aborting women to shed light on the phenomenon. The effect on abortions is driven both by women who are married and not in professional condition. Plus, and more interestingly, by those who previously had children or abortions. By contrast, the occupational sector of the aborting women is independent on the sector of job suspension. The work may contribute to the knowledge about Italian birth control practices and fertility responsiveness to reproductive care-unrelated public policies.

Keywords: Abortion, Covid-19, Essential sectors, Live births, Work suspension.
JEL Classification: I12, I18, J13, J16.

*The empirical analysis has been carried out at ISTAT's Microdata Analysis Laboratory (ADELE) and complies with the relevant legislation on the protection of statistical confidentiality and protection of personal data. The results and opinions expressed are the authors' sole responsibility and do not involve official statistical officers. The analysis makes use of administrative data directly referring to the recorded universe of the variables under question, thus they need not be weighted by the coefficients of carry from surveys to the universe.

1 Introduction

Along the latest decades, the study of the links between economics and fertility has attracted many scholars. As a matter of fact, knowing the socio-economic incentives and setbacks to family planning, involving childbirth, contraception and abortion decisions, may lead to major policy implications. These may concern family and childcare subsidization, public and reproductive health, welfare schemes and the improvement of labor productivity. The topic bears particular relevance in the context of the sharp demographic declines faced by most advanced countries over the second half of the past century, which have been persisting at the beginning of the new millennium (Kohler et al., 2002, Guinnane, 2011, Spolaore and Wacziarg, 2022), giving shape to a “second demographic transition” (Lesthaeghe, 2010): amongst them, Italy has been dealing with one of the bleakest drops (ISTAT, 2023). Doepke et al., 2022 highlight the importance of such matter in the early 21^{st} century, as we have entered what they call a “new era” of the economics of fertility. The “old” economic paradigm of fertility traced its roots back to the seminal work by Becker, 1960, and focused on giving an explanation to the observed negative relationship between fertility and both income and female labor supply participation[1]. After 2000, we observe a reversal of the pattern, hinted by the positive cross-country association between GDP per capita and fertility (Doepke et al., 2022). Major explanations of such pattern mostly refer to family planning and reproductive health determinants, usually related to women’s empowerment in controlling their fertility. Some of these include the easier access to female contraceptives (Goldin and Katz, 2002, Bailey, 2010) and abortions (Myers, 2017), education and technology-driven “social sterility” (Baudin et al., 2015)[2], shifts in parental times’ usage due to marketization of childcare (Del Boca, 2002, Bar et al., 2018), improvements in women’s bargaining power within couples (Gobbi, 2018, Doepke and Kindermann, 2019), and changes in family size norms (de Silva and Tenreyro, 2020).

While the usual outcomes of a couple’s fertility decision generally articulate into an “extensive” margin result (to have or not a child) and an “intensive” margin one (how many children to have), there is another, less thought outcome which, to some extent, is independent on the anticipatory planning required to childbirths-related decisions: abortion. The decision to abort is, in turn, a fertility choice which may embed similar socio-economic considerations needed to program a childbirth, but it does not involve the same planning characteristics nor the same room for manoeuvre with respect to timing. Abortion works, in fact, as a resort to terminate an unwanted pregnancy, conditional on such pregnancy having taken place already. An abortion requires a faster decision process and it is highly time-constrained, as action must be taken not only before the birth is delivered, but before the pregnancy develops beyond the legal gestational limits as well. As a matter of fact, global statistics indicate that about 35% of European and North American pregnancies between 2015 and 2019 were unintended (Bearak et al., 2020), whereas Buckles et al., 2019 estimate that the decline in American fertility between 2007 and 2016 ought to be credited to a 35% reduction in originally unplanned pregnancies This notwithstanding, it may result naive to trace the fertility decline back entirely to abortion decisions (at least in the Italian context, where abortions have been following a long-lasting declining trend, as shown in the Ministerial Report on abortions in 2022, MoH, 2022). However, the monitoring of abortion patterns could result useful to considerations about the “second-step” choice of a fertility decision process, conditional on the occurrence of an undesired gestation. This might be

[1] Such empirical findings were brought mostly back to a twofold explanation: the trade-off between quantity and quality of children in birth decisions (Becker and Lewis, 1973, Fleisher and Rhodes, 1979, Heckman and Walker, 1990), and the opportunity cost of women’s time (Butz and Ward, 1979, Galor and Weil, 1996, 2000, Adsera, 2005).

[2] By “social sterility” they mean the involuntary childlessness caused by the absence of the proper commodities needed to procreate. On the other hand, educated women opt to childlessness due to opportunity cost reasons.

relevant in drawing not only policy implications related to the interlink between demographic trends and economic determinants, but also health assessments concerning contraception policies, women's control over their own fertility, and even domestic violence. Whereas the empirical literature on the outcomes of abortion liberalization has clearly shown that it had a substantial and favorable impact on women's welfare and empowerment (Clarke, 2023), the termination of pregnancy still requires a surgical or medical intervention, that may embed health and psychological repercussions, in addition to being a costlier treatment for the public healthcare system compared to alternative birth control practices, like preemptive contraception. On top of that, the study of abortion may gain relevance for gender equity considerations: it could be of major importance to understand, even roughly, how many abortions are sought due to situations of economic and/or psychological vulnerability, or due to fear of motherhood being a source of career cost or job displacement, or whether they are a result of sexual violence (possibly by an intimate partner - i.e., IPV).

The aim of the present paper is to study how a public health policy targeting outcomes completely unrelated to fertility, and that also have economic repercussions, may significantly affect family planning. The focus is mainly on abortions. We exploit the landmark discontinuity brought about by the outbreak of the Covid-19 pandemic, which caused a remarkable and exogenous breakthrough on multifaceted aspects of our daily lives. In particular, we leverage a public non-pharmaceutical economic policy aimed at counteracting the spread of the virus in the immediate outburst of the health crisis, to study its impact on the pattern of voluntary pregnancy terminations of Italian women, following the evolution of municipal abortion rates between 2018 and 2021. We draw this information from the administrative dataset including the universe of Italian abortions, annually collected by the Ministry of Health with the participation of ISTAT, and managed by the latter. The policy shift we examine, by employing a TWFE Difference-in-Differences methodology, is embedded in the municipal share of workers suddenly suspended from their regular activities, during the national lockdown. The suspension was imposed by Italian authorities between the end of March and May 2020, to workers in sectors deemed as "non-essential". We individuate two most plausible fashions through which the suspension of workers could affect abortions. The first is the "assignment of more free time" to suspended workers, the bulk of which time was to be spent almost entirely at home, due to the initial lock-down and the subsequent mobility restrictions after the lock-down relaxation. This might have enabled an increase in sexual intercourse between inactive individuals or between inactive individuals and their partners, leading to different outcomes in accordance to the reproductive health behaviors and contraceptive practices adopted by involved people. Therefore, a shift in abortion patterns might be driven by an underlying variation in unplanned child-bearings; if that was the case, results could help shedding more light on the family planning culture amongst Italians[3]. Second, in areas economically more affected by the pandemic-related policies, women might want to terminate unplanned pregnancies at different rates after March 2020 compared to normal times, due to the overall uncertain socio-economic context, being unwilling to carry out a motherhood in such bleak and deceiving prospects.

First, we find that the municipal areas hit more hardly by the pandemic in terms of suspended jobs (i.e., belonging to the fourth quartile of the distribution of the share of suspended population), saw an increase in quarterly abortion rates of 10-15 p.p circa, according to the specification used and compared to municipalities in the lower tail in the distribution. Such values amount to more than 10% the average quarterly municipal abortion rate in our data; however, the observed effect is short-lived, and the differential impacts get back to normal patterns, on average, after 6 months from the closures.

[3]A side channel related to a longer time spent together by couples and families, usually pointed out by sociological literature, is the exposure to domestic violence, which may be a driver of unplanned pregnancies and therefore a trigger to abortions as well. More on this in the following sections.

A major concern of our identification strategy is its integration to the main general context of the pandemic: similar non-pharmaceutical public policies and the overall trend of contagion (and deaths) may have contributed to affect the supply of abortion services, due to mobility restrictions, excessive workload of hospitals and other forms of limitations in reproductive care assistance. In this regard, the study (aggregated by municipality of residence) is provided with a further analysis of the heterogenous impact of the pandemic on the general equilibrium due to possible supply restrictions, proxied by VPTs aggregated by hospitals. Overall, we do not find a significant impact of the workers' suspension on the average provision of abortion services; concurrently, we actually find out that the governmental mobility restrictions and closures did not prevent women from aborting in areas different from those of their residence, even during the more intense phases of the pandemic.
To assess which channel is most likely to operate in the designed framework, we integrate the abortion analysis in four different directions, by employing the same DiD empirical design, but changing outcomes: first, we apply the same analysis on the municipal rates of pregnancies culminating, 9 months later, into live births, for which we have ISTAT administrative data on birth registrations as well. The aim is to check whether the suspension shock, albeit sudden and disruptive, also affected more thoughtful and time-elapsed aspects of family planning, such as deciding to actually have kids. We find no effect on pregnancies resulting into live births in the main estimates; in different specifications, we found some little and slightly significant positive impact, albeit not properly robust.
Second, we perform a thorough heterogeneity analysis by making use of the detailed available demographic and socio-economic information that we possess on aborting women (professional condition and position, economic branch of activity, marital status, education, age class), and differentiating the identification between the suspended share of industrial workers and that of service workers. We retrieve that results are mostly driven by married and women not in professional condition. Concerning the heterogeneization of the treatment, the effect seems to be brought about by the suspension of workers in the industrial sector, whereas no link seems to subsist between the sectoral share of suspension and the economic branch of activity. These results, in addition to the one concerning pregnancy rates, point out to the direction that the relevant mechanism might be the increase in underlying unintended pregnancies rather than the fact of being conditioned by the socio-economic pandemic insecurity.
Third, and for the first time in this strand of literature (in our knowledge at least), we explore the information we have on previous pregnancies of the aborting women, including previous live births and abortions. By making use of a quite rough information, we do the same for the municipal pregnancy rates, for which we know the number of minors in the family of the mothers. We retrieve that the effect of the work suspension is significant mostly for women that have already 1 or 2 kids, and for those who have already aborted in the past. Such outcomes, together with the fact that the overall effect on abortion rates in areas with higher suspended share is not accompanied to a statistically significant shift in live births, may leave some room to the hypothesis of socio-economic insecurity being part of the general explanation of the findings, although the results on previous abortions is a further argument in favor of poor family planning. On the other side, it clearly provides with relevant insights on how Italian women may respond to exogenous shocks by adjusting their fertility decisions (at least in terms of how to deal with unintended gestation), depending on their past reproductive history, which may be related to the longtime planned fertility (how many children to have), to the possibility of temporary budget constraints to parenthood (if kids are already present in the family), or to reasons to be linked to health assessments, reproductive care, or birth control experiences.
Finally, we acknowledge how both social science and medical literature have established a link between domestic violence, unintended pregnancy and its consequent voluntary termination (Hall et al., 2014), not only in developing countries but even in a high income nation like Italy (Citernesi et al., 2015).

Therefore, we account for the sociological "exposure theory", which predicts that more time available together may trigger episodes of domestic abuse for those couples where the male partner is violent (Dugan et al., 1999). In addition, socio-economic shocks that reduce the outside options of women (displacement, rise in local unemployment, negative income shock) contribute to lower their bargaining power within an abusive relationship, which may exacerbate the escalation of violent episodes (Aizer, 2010, Bobonis et al., 2013, Anderberg et al., 2016, Diaz and Saldarriaga, 2023). Our findings show that this may possibly not be the case in the present context, as we find no to an ambiguous negative effect of our identification variable on the rate of phone calls to the public hot-line for domestic violence.
The present paper contributes to three strands of literature. First, although passing through a "side path", the paper can be numbered among those in the literature that analyzes how socio-economic shocks affect fertility decisions, by adding two relatively unexplored element to the mere hypothesis of resource constraint being caused by income or job loss: first, the greater availability of time (to be devoted to copulation) due to unemployment/job suspension absent proper contraception, and second, past reproductive behavior. Concerning unemployment shocks in a broad fashion, Currie and Schwandt, 2014 found out that young women experiencing higher unemployment rates are associated to fewer live births; Bardits et al., 2023 and Cavallini, 2024 show instead that fertility rates are affected by job displacement the former, and local unemployment the latter; they both conclude that live births respond negatively. Some papers tackle the topic in the light of a work-motherhood trade-off: Del Bono et al., 2012, 2015, find out that job displacement negatively impacts fertility, albeit for high-skilled women working in career-oriented jobs mostly indeed.[4]. Local negative income shocks also have a negative effect on fertility; real estate market price increases may play a detrimental role on fertility rates (Dettling and Kearney, 2014), as well as local GDP's fluctuations (Schaller, 2016; Schaller et al., 2020). Demographic works too found an association between the general socio-economic uncertainty and bleak prospect brought about by economic crises (such as the Great Recession) and low fertility rates (Modena et al., 2014, Comolli, 2017, Caltabiano et al., 2017, Fahlén and Oláh, 2018). Second, the present work aims at contributing to the quite novel economic literature on the determinants of abortion decisions and subsequent abortion patterns. The so-called "economics of abortion policy" (see Clarke, 2023) has actually produced numerous contributions over the last three decades, mostly addressing the effect of the access to abortion (as in, abortion liberalization) on several social outcomes, improving female welfare and empowerment, while its impact on fertility is debated: Ananat et al., 2007 find out that first abortion has a worsening effect on lifetime fertility, while Mølland, 2016 challenges such conclusion by underlining the role of aborting as a timing factor of future family planning. Regarding the determinants of abortion patterns, mainly birth control practices have been tackled by research. A substantial strand of applied economic literature, mostly focusing on the Anglo-Saxon countries, assessed how abortion rates are impacted by reproductive health factors, such as contraceptive diffusion (Girma and Paton, 2006, 2011, Bailey, 2010, Ananat and Hungerman, 2012, Bentancor and Clarke, 2017, Cintina, 2017), and access restriction due to closure of abortion clinics (Colman et al., 2013, Fischer et al., 2018, Lindo et al., 2020, Venator and Fletcher, 2021). By contrast, along the past few years, a line of empirical research on the social and economic determinants of abortion demand has started soaring, mostly framing within the relationship between income (or labor market opportunities) and fertility: Herbst, 2011 displays, for instance, how increases in income

[4]Such evidence is consistent with later literature on the so-called "motherhood penalty" (Adda et al., 2017), according to which the child penalties usually associated to parenthood bring about lower earnings trajectories for women, in doing this contributing to widen the gender gap (Goldin, 2014, Angelov et al., 2016, Kleven et al., 2019, Lucifora et al., 2021). Zandberg, 2021, and Core, 2024, show that maternity risk has an harmful effect on female entrepreneurship as well, especially when exacerbated by a limited access to reproductive care.

tax-credits lowered abortions in the U.S., whereas Gonzalez and Quast, 2022 seem to observe a certain level of pro-cyclicality of the abortion rates[5]. Concerning family policies, González, 2013; González and Trommlerová, 2023 analyzed how the introduction (and cancellation) of child benefits influenced Spanish abortion rates. Some studies of abortions have already been mentioned in relation to fertility, as they also inquire on childbirth rate: for instance, Bardits et al., 2023 investigate the positive effect of mass layoffs on pregnancy termination choices amongst Hungarian women, while Cavallini, 2024, by means of a Bartik IV strategy, finds a positive association between provincial unemployment and abortion. Few recent studies focus on abortions only: González et al., 2023 assess the role of Spanish political partisanship on abortion rates, while the findings of Pieroni et al., 2023 highlight how granting legal status to immigrant women in Italy substantially reduced their abortion rates. As for Italy, which is the core subject of the present work, the analysis of the demand-side is as much relevant as the analysis of the supply of abortion services. Abortion being legal notwithstanding, gynecologists are granted the right of conscientious objection for cultural or religious reasons, and more than half of them resort to such devise. This seems to impact the exercise of the right to abort for the women seeking for it (Bo et al., 2015, Autorino et al., 2020, Muratori, 2023a; see the next section for more details). The interaction between a legal right and a restricted supply can even bring about relevant long-term repercussions. Foster et al., 2018, S. Miller et al., 2023 surveyed indeed the long-run worsening of earnings and labor outcomes of women to whom abortion is denied, albeit for gestational limits. Eventually, our work aims at extending the knowledge about the consequences of Covid-19, at least for what concerns fertility. Many social and economic aspects have been deeply covered since the outbreak of the pandemic in 2020 (see, for instance, the early review by Brodeur et al., 2021). Amongst the other things, fertility has been studied in relation to initial birth trends. Early demographic predictions by Aassve et al., 2021, displayed a baby bust in most advanced Countries in the immediate aftermath of the pandemic, with Sobotka et al., 2023, retrieving that the downturn observed just after the outbreak was mostly short-lived. A relevant economic appraisal in such heading is the one by González and Trommlerová, 2024, who assess the impact of the pandemic on Spanish fertility rates, by retrieving a pattern similar to the ones above mentioned; an initial drop and an overall increase in total fertility after 2021. In Italy, one of the countries hit the earliest and the hardest, demographic studies underlined the negative impact of the pandemic insecurity on family planning decisions (Luppi et al., 2020, Rosina et al., 2022). To this extent, fertility choices are a key matter in the context of the pandemic crisis, which has been shown to be affecting harder women relative to men, notably compared to previous crises. For the latter reason, many scholars have re-branded the pandemic recession as a "She-cession". The non-pharmaceutical policies and social distancing had indeed a sectoral-specific economic impact (Dingel and Neiman, 2020), whereas the affected sectors were characterised, on average, by larger female employment share (hospitality, commerce). Therefore, the extent of the She-cession features job loss in general, more significant for women than men (Adams-Prassl et al., 2020, Alon et al., 2021, Crossley et al., 2021, Montenovo et al., 2022, Bluedorn et al., 2023), the positive shifts of female labor supply from market to childcare and home care (Alon et al., 2020, Del Boca et al., 2020, Hupkau and Petrongolo, 2020, Zamarro and Prados, 2021, Deryugina et al., 2021), and the detrimental impact on female mental health (Galasso et al., 2020, Etheridge and Spantig, 2022, Barili et al., 2024).

In the attempt to fit into the literature, we reckon some papers as being the most similar to ours. In terms of the covered subject, we mention Trommlerová and González, 2024, who are the only ones, to our knowledge, to study the negative impact of Covid-19 on abortion patterns, which are observed in Spain due to the decrease in social interactions during lock-downs. To a certain extent, Cavallini, 2024's work is also very alike to ours, since it studies the role of local unemployment in driving up

[5] Such pro-cyclicality seems to gets non-significant at different time ranges, however.

(down) abortion (fertility) rates. In addition, by focusing on Italy, she exploits the very same dataset which we use, although her levels of frequency and aggregation are the provincial and annual ones, unlike our municipal, quarterly disaggregation[6]. In terms of empirical method, we "borrow" our identification strategy from a group of studies employing similar TWFE DiD methods to study diverse Italian phenomena, and that define the "treated" units by leveraging on the distribution of suspended workers' share: Borri et al., 2021, who compare municipality above/below the median of said distribution to assess the effect of "non-essential" sectors on mortality and mobility; Di Porto et al., 2022 who, by contrast, study the impact of "essential" workers on the virus contagion; Bordignon et al., 2023, who uses the municipal inactive share as a proxy for economic insecurity, to investigate its influence on electoral outcomes[7]. Contrarily to Borri et al., 2021's approach (and ours), the latter two works' methodologies rely on a DiD with continuous treatment.

Our study is flawed by a major drawbacks: the decision of terminating a pregnancy is extremely endogenous per se, and given that the data are drawn from the Italian universe of abortion operations, the analyzed women are already selected into the sample, since the observation is conditional on the abortion having occurred. The absence of an alternative realized outcome (as in, not having aborted) requires aggregation of data at municipal level to acquire a longitudinal dimension, which implies the impossibility to properly remove the individual endogenous drivers leading to the abortion decisions[8]; in any case, the set or robustness checks performed in the study and the comparison to pregnancy rates resulting into live births helps mitigating the issue. In terms of external validity, the uniqueness of the COVID-19 outbreak can pose a threat to the relevance of our study, as it is hardly believable that such a peculiar event could find a meaningful economic analogy in the next years to come; however, the unpredictability of the pandemic is also a strength of our settings, as it embeds a level of exogeneity which is usually hard to find amongst quasi-experimental studies. In addition, pandemic or not, the study may help to draw economically-based conclusions about the trends of female reproduction over the last years. This might contribute to future research in order to better design studies and policy interventions, either in form of family planning or public and reproductive health actions.

The work is structured as follows: after the introduction, which also includes a literature review (Section 1), we present the institutional framework on abortion laws in Italy and on how the government responded to the COVID-19 outbreak (Section 2). In Section 3 we discuss our settings in the details, whereas in Section 4 we describe the data. In Section Section 5 we present our empirical strategy, whose results are reported in Section 6. Section 7 is dedicated to robustness and sensitivity checks, aiming at validating internally our estimates, including the test for "abortion mobility", as in the plasibility of women aborting far from their residence during the pandemic. In Section 8 we discuss our results to understand whether they are driven by economic insecurity or by increased pregnancies, adding an empirical analysis where the outcome are pregnancies resulting in live births and the abortivity ratio (Section 8.1), and we report some heterogeneity estimates by making use of the very detailed information present in the dataset (Section 8.2). (Section 8.3), discusses the alternative channels of domestic violence and provides with some narrative discussion on the evolution in contraception supply and behavior in Italy. Section 9 concludes the paper.

[6] The other relevant works utilizing the same ISTAT source on abortions are Bo et al., 2015, Autorino et al., 2020, Pieroni et al., 2023, Muratori, 2023a

[7] While Borri et al., 2021 and Bordignon et al., 2023 utilize the same source of data, Di Porto et al., 2022 employ a slightly different framework and other data. See Section 3 for further information.

[8] Note that this shortcoming matters for other studies employing the same data as well

2 Institutional Background

2.1 Abortion in Italy

The Italian national healthcare system is a public, tax-funded system which offers universal coverage for a broad set of services. It is structured into the *Servizio Sanitario Nazionale* (National Healthcare Service, or SSN). The SSN was introduced in 1978 (L. no. 833 1978), albeit made effective beginning from July 1980. After having been subject to a process of devolution of its functions to the regions all over the 1990s, the Italian healthcare service was institutionally de-centralized in 2001, with the reform of the 5^{th} Title of the Italian Constitution. As a matter of fact, the Voluntary Pregnancy Termination (VPT, in Italian *Interruzione Volontaria di Gravidanza*, IVG) is a service provided by the SSN free of charge since 1978, when it was made legal by L. no. 194 1978 (usually referred as "Law 194"), which is the legal framework that still regulates the matter.

A woman can undertake a VPT within 90 days from the conception, provided that pregnancy, childbirth, or maternity may compromise her health, either psychic or physic, and by taking into consideration her health, economic, social or family characteristics, the occurrence during which the pregnancy happened, or the possibility that the newborn will suffer from malformations or anomalies. The looseness of such conditionalities basically enables any woman who demands the abortion service within the specified terms to interrupt her pregnancy, configurating abortion as a woman's legal right. After 90 days, a pregnancy can be interrupted only when the potential mother's mental and/or physical health is in danger. The service can be performed to any woman on the Italian soil, irrespective of her citizenship, her residence, her partner's consent and, if foreigner, whether she has or not a legal permit to stay. To do so, a gynaecologist must first certify the occurred pregnancy and indicate a presumed date of conception; then, unless the situation requires urgency, the woman has to wait a week of reflection before undergoing the treatment. The VPT, whether it is a surgical or medical one, must be performed inside a hospital, and the anonymity of the aborting woman shall be guaranteed. In case of a minor, undertaking the VPT requires the consent of her parent or guardian.

Art. 9 of Law 194 also regulates the right for gynaecologists and other health professionals to exercise conscientious objection, i.e. to avoid administering a VPT to a woman, unless she is in danger for her life. In Italy, conscientious objection is widespread among doctors and health professionals, mostly for religious, moral or career advancement reasons (de la Fuente Fonnest et al., 2000, Muratori, 2023a).

The hospitalization requirement is a fundamental tool to monitor the phenomena of abortion and conscientious objection in Italy; in this regard, the National Institute of Health (*Istituto Superiore di Sanità*, ISS) has maintained an epidemiological surveillance system on Italian VPTs since 1978 (*Sistema di sorveglianza epidemiologica delle IVG*), based on direct communication with health authorities. The mechanism is an integrated system of cooperation between the Ministry of Health, the ISS, the National Institute of Statistics (ISTAT) and the regions and autonomous provinces. The regions are indeed obliged to transmit the annual data on performed abortions to the Ministry of Health, which stores and manage the data thanks to the support of ISTAT. Failing to transmit will result in a fine for the non-complying regions. Information is disseminated by the Minister of Health, who annually reports to the Parliament the relevant facts and data related to the application of Law 194, and assesses whether conscientious objection materialises as an effective setback to the right to abort.

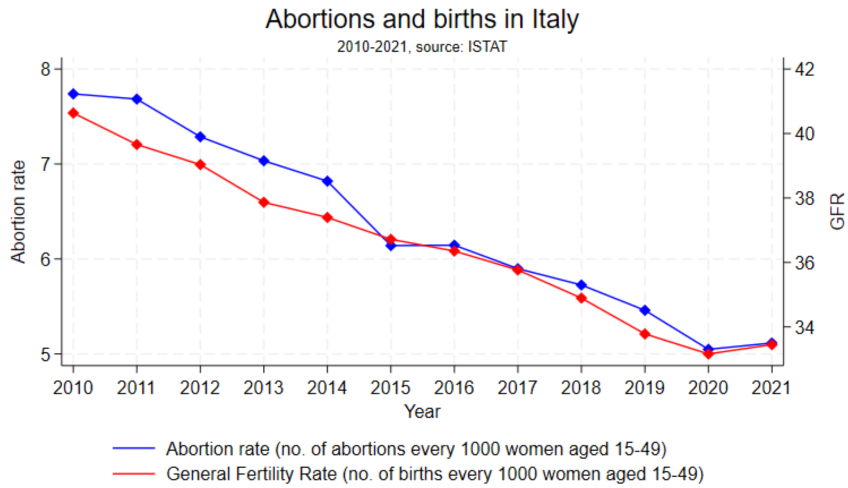
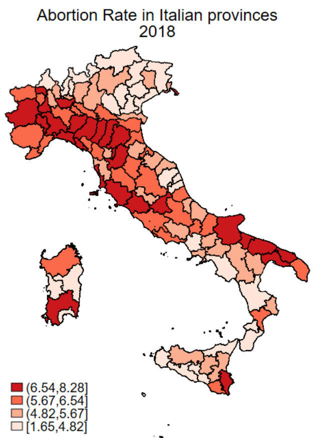


Figure 1: Source: ISTAT

Over the last decade, official data (Figure 1) show a persistent falling trend in the abortion rate, which is the number of VPTs every 1000 women aged between 15 and 49 years, as in fertile age. Demographically speaking, the General Fertility Rate (number of live births every 1000 women in fertile age) faced a similar declining pattern. In 2021, both variables seem to have faced a little rebound after the 2020's trough, possibly related to the Covid-19 outbreak aftermath (Rosina et al., 2022). The patterns are quite geographically heterogeneous (Figure 2).

The official 2021 report made by the Ministry of Health (MoH, 2022) confirmed that the trend (63.653 VPTs in 2021) was maintaining its long-lasting decline since 1983, the peaking year for VPTs, when official statistics registered 234.801 induced abortions. According to the report, the major drivers of the fall in abortion rates are the legalization of abortion itself, the increase in utilization of contraceptives and information about them, and the support provided by professionals in health centers and reproductive care facilities. Being credited as a major setback to abortion supply, some facts about conscientious objection (c.o.) are worth to mention. The Ministry reported that c.o., in 2021, involved 63.4% (in 2020 they were 64.6%) of Italian gynaecologists, a rate characterised by strong regional heterogeneities, ranging from 17% (autonomous province of Trento) to 85% (Sicily). In general, conscientious objection is mostly spread in the Southern and North-Eastern regions, as it is hown by Figure A1 in Appendix A. These percentages are not, however, deemed as a substantial obstacle to the right to abort by the Ministry of Health. Recent contributions tried to challenge the latter conclusion. According to Bo et al., 2015, conscientious objection significantly increases the workload of non-objectors and amplifies the waiting times between the certification of pregnancy and the actual abortion, often elapsing over the 2 weeks suggested by health authorities. According to the Ministry of Health itself indeed, the share of VPTs performed after 2 weeks from the gynaecologists' authentication of conception are a proxy for inefficiency. Autorino et al., 2020 find instead a positive correlation between the regional rates of objection, waiting times and the flow of women aborting outside of their region of residence. Muratori, 2023a even challenges the accuracy of the data collected by the Ministry.



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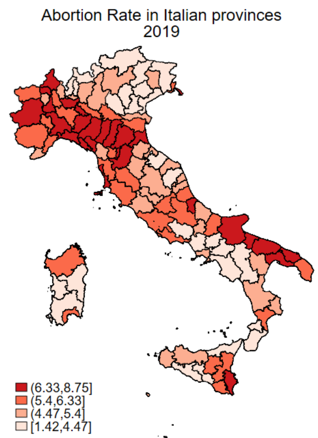

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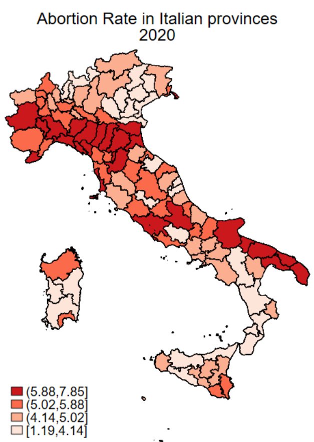

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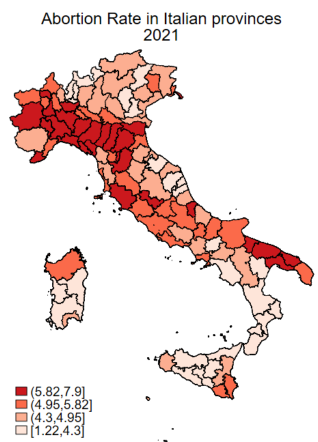


(d)

Figure 2: Provincial abortion rates, 2018-2021 (source: ISTAT)

Although the practice being illegal, objection is applied to entire hospitals sometimes, so that it is hard to obtain the actual rates of objectors. This may bring forward relevant bias to official statistics. After collecting data on objection at provincial level, she retrieves a detrimental positive correlation between objection and illegal terminations of pregnancy, that are "hidden" by miscarriage data. As a matter of fact, illegal abortions (or self-induced abortions) are a public health concern that has fortunately been decreasing over time, even though the last estimation of illegal abortions, dating back to 2016 and mentioned in the 2021's report of the Ministry, attested their number between 10.000 and 13.000 (between 10-15% of the legal VPTs).

2.2 The COVID-19 Pandemic in Italy

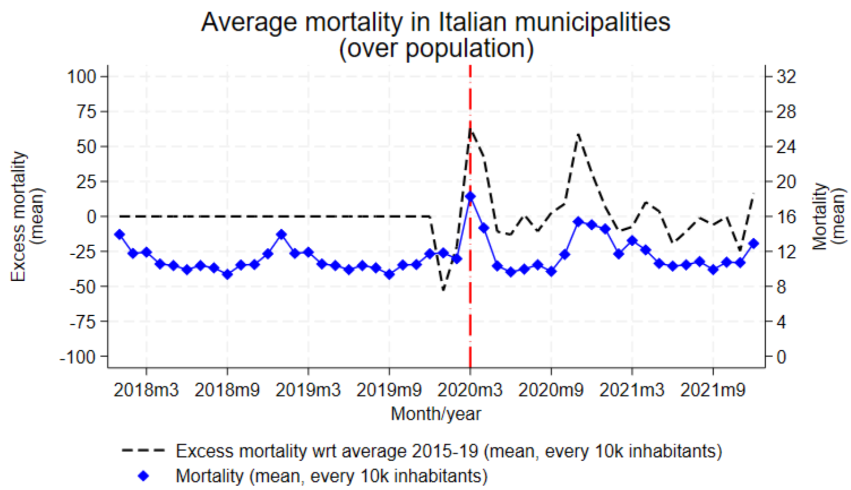


Figure 3: Mortality in Italy between 2018 and 2021. Source: ISTAT

As of the beginning of 2024, Italy results as the 8^{th} Country in the world for total cases of Covid-19 (see Worldometer). However, in January 2^{nd} 2022, with 6.442 million cases and 137k deaths, it was one of the Countries hit the most by the pandemic. After discovering the virus in China in December 2019, the first Italian case of Covid-19 was registered in Lombardy on 20^{th} February 2020; then, the disease rapidly spread across the region and the whole nation with severe impacts on mortality and public health, as documented by early studies (Buonanno et al., 2020, Depalo, 2021, Cerqua et al., 2021). The health repercussions lasted all over 2020 and 2021, as excess mortality, measured as mortality in such biennium, net of the mean of mortality in the years between 2015 and 2019, saw a significant increase (see Figure 3). Being the first European Country having to deal with a fast spread of contagions, Italy was also the first one to undertake strict counteracting measures; after applying some mobility restrictions to the early affected areas (Lombardy and Veneto), the government declared a national lockdown on 9^{th} March 2020, paralyzing the whole Country. On 11^{th} March 2020, a further decree of the President of the Council of Minister (DPCM) Giuseppe Conte imposed the suspension of common retail and schooling activities, the closing of restaurants and the ban on meetings in public spaces, introducing the first package of economic tightening. Such restrictions were exacerbated with a

DPCM on 22^{nd} March 2020, which provided with a distinction between "essential" and "non-essential" activities, based on their ATECO-5 digit classification. Non-essential activities were suspended, and therefore all the related enterprises and affiliated workers were too. The national lock-down lasted until 4^{th} May 2020, while economic closures started being loosened gradually; the process lasted until 15^{th} June 2020, when most activities had re-opened. After an almost complete return to normality over the summer, Fall 2020 saw a resurgence of cases and deaths. Starting from 6^{th} November 2020, and up until to the late June 2021, a national curfew was declared all over the country, while different degrees of restrictions were imposed at regional (in some cases provincial) level, according to the severity of the contagion. Regions started to be classified weekly as white, yellow, orange or red, in ascending order of strictness, according to their RT-index. Details on the mobility and economic restrictions imposed during the "coloring" times are described in Conteduca and Borin, 2022. After some further restrictions between the end of 2021 and the beginning of 2022 due to a new wave of cases, the emergency state, declared on 31^{st} January 2020, ceased on 22^{nd} April 2022.

3 Conceptual framework

Before proceeding to the description of the identification strategy, we pin down the most plausible mechanisms through which the effect might deploy below:

- **Increase in unplanned pregnancies**: due to both nationally homogeneous shelter-in-home policies and the heterogeneous work suspension distribution, unwanted pregnancies could rise for increasing unprotected sex within couples with more available time together ("exposure"). Furthermore, given the mentioned link between sexual IPV and unplanned pregnancies, VPTs may rise due to the same reasons tied to the "exposure theory".

- **Sudden economic vulnerability** *(given occurred pregnancies)*: as mentioned in the introductory section already, recent evidence displayed how not only individual negative income shocks and job displacement may affect individual fertility outcomes, but also macroeconomic downturns and overall socio-economic insecurity. This might remarkably holds for females in Italy during the "She-cession", where the gender unequal impact of the pandemic mostly resulted in the increase in unemployment in given service sectors (Bluedorn et al., 2023)[9], where the share of employed women was higher; as confirmed by Casarico and Lattanzio, 2022, the female proportion in "non-essential" activities was greater before the pandemic. It must be cleared that for economic insecurity it is not only meant the mere unemployment (whose provincial impact on VPT rates has already been investigated by Cavallini, 2024). Macroeconomic shocks in employment rates can hardly affect abortion decisions by women directly, as most of those making up their mind in such direction are females not in professional position, at least according to our data (see the next section). On top of that, statistics on unemployment at provincial level embody the risk of missing relevant information, firstly due to the high degree of aggregation, and secondly because many sectors hit by the pandemic are featured by informal work, absence of protection and precarious contracts (Casarico and Lattanzio, 2022). The temporary inactivity of workers caused by the pandemic may represent a quite reasonable proxy of the unexpected insecurity and perceived vulnerability for the future embedded by the shock, as it could allow to capture dynamics at municipal level and aspects of informal work not incorporated in official employment statistics. Bordignon et al., 2023 utilize survey data to observe how the condition

[9] Rather than an average *within*-sector increase in the gender gap.

of temporary inactivity was able indeed to shift the vote preferences of the sampled citizens. Therefore, to parity of unplanned pregnancies, the abrupt ominous shift in the economic situation due to the pandemic might have led to a jump in VPT decisions for women not willing to carry on the occurred conceptions in future, possibly unforeseeable and bleak prospects;

- **Increased in unplanned pregnancies due to socio-economically driven domestic violence**: eventually, as already documented, domestic sexual violence (and hence unwanted pregnancies) may increase due to the escalation of income or unemployment-related stressful situations (Card and Dahl, 2011, Diaz and Saldarriaga, 2023). Furthermore, this could be exacerbated by the impairment in job market opportunities for women due to the economic downturn and the shift in insecurity, which deteriorates female bargaining power within couples (Aizer, 2010). Data report indeed a clear peak in the calls to the Italian hot-line for domestic violence after the closure of economic activities in 2020 (Figure B1 in Appendix B). Early estimates confirmed a similar pattern in the U.S. after the introduction of shelter-in-home policies (Leslie and Wilson, 2020). However, A. R. Miller et al., 2022, 2023 found no robust evidence of increases in American IPV consistent with the exposure theory. They actually conclude that the concerns raised by policy-makers news outlet about the possible surge of IPV episodes during lockdowns were the triggering determinant in the increase of calls, which were not accompanied by a raise in actual violence. Such role of the topic's salience was retrieved in Italy as well, as Colagrossi et al., 2022 highlight how the governmental domestic violence-related sensitisation policy put in place at the beginning of the pandemic outbreak incentivized the reporting behavior, rather than assaults themselves[10]. Although this mechanism is quite complex to test due to the presence of so many mediating factors, we still devolve a part of the work to explore the channel

- **Limited access to abortion supply** (*given occurred pregnancies*): the rapid spread of the virus brought a serious burden on Italian hospitals, due to the excessive workload. This notwithstanding, according to the ISS, the public supply of VPT services was not hindered by the pandemic (INIH, 2022). However, credible anecdotal press evidence had basically contradicted in advance such official claims (Muratori and Di Tommaso, 2020, Torrisi, 2021). The restrictions on mobility may have consisted in a further setback to the supply of healthcare services (including VPTs); in addition to that, and mainly, clogged institutes due to the treating of higher numbers of infected people may have suffered problems in the undertaking of VPTs, especially those with higher shares of objectors; longer waiting times could have led women seeking for abortion to overcome the time threshold that made them eligible to undergo it. In such case, we would observe lower abortion rates in areas hit harder by the pandemic in epidemiological terms.[11]

Having acknowledged the presence of these major possible mechanisms, we provide with a clear-cut exogenous discontinuity to try and disentangle the various phenomena. When the government declared some sectors as "essential", based on their Ateco code, a substantial share of Italian workers occupied in non-essential activities were suspended from their job, along with the very firms which employed them. Such suspension lasted from March to May 2020, when the lock-down started being loosened (for some activities even middle June). Thanks to ISTAT, we are able to recover the share of suspended

[10] Outside the context of the pandemic, always Colagrossi et al., 2023 confirmed that the media coverage of episodes of femicide drives up the calls to the helpline number against DV, thus confirming how exposure to news (which may be possibly fostering the sensitisation of people regarding the seriousness of the issue) can enhance the reporting behavior.

[11] Women may also have been discouraged to access hospitals to perform abortions in zones where it was more likely to contract the virus.

workers across Italian municipalities during the first National lock-down[12]. The exploitation of the heterogeneity of such share as means of identification, as above mentioned, is not novel in the Italian economic literature: Borri et al., 2021 used the same data to see whether the municipal change in what they called "inactive" workers due to economic closures affected mortality and mobility, by means of a similar TWFE DiD. Di Porto et al., 2022 used a similar data source from the Italian National Previdence Institute (INPS) to perform a TWFE DiD with continuous treatment, to check whether the daily provincial portion of workers active in the essential sectors had an effect on the daily Covid-19 contagion (and it did). Bordignon et al., 2023 also estimate coefficients for electoral outcomes from a TWFE DiD with continuous treatment, by proxying economic insecurity with the ISTAT data source, even observing how industry and service sectors' shares differently impacted voters.

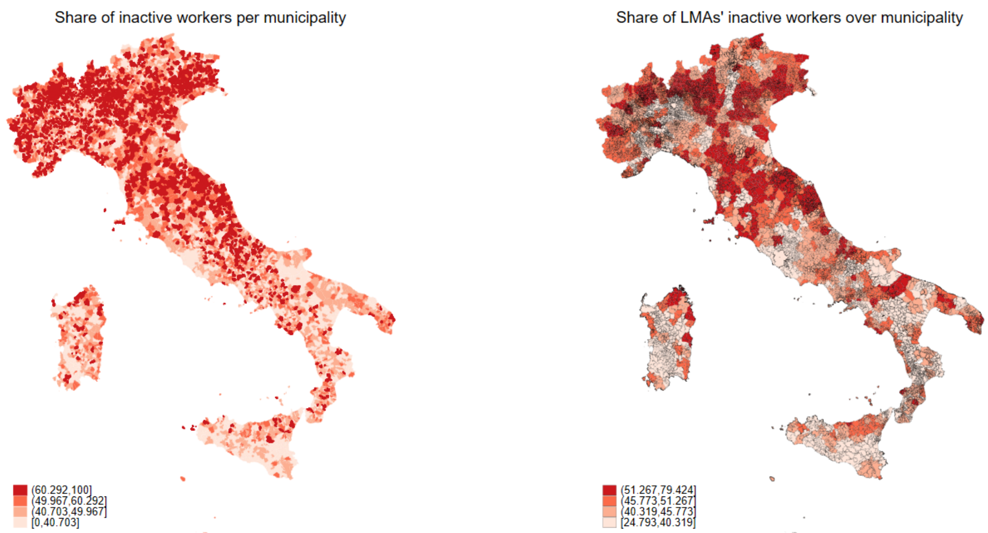


Figure 4: Municipal share of suspended, non-essential workers during the Italian national lock-down. The left map shows the municipal share of inactive workers during the period of suspension of non-essential activities, i.e. from 22^{nd} March 2020 to 4^{th} May 2020. The right map shows the LMA share of inactive workers, albeit highlighting Italian municipality borders. Both maps are shaded according to the position of the unit of reference in given quartiles of the inactive share's distributions.

The suspended workers' share functions as a compelling exogenous shift in the general economic conditions, as the distinction between essential and non-essential activities was something never thought about before the already unexpected event of the pandemic, and it was legally imposed by the government; there was no way to anticipate the closures and their heterogeneous impact on the labor market[13]. By comparing outcomes (VPTs) before and after March 2020, over the distribution of inactive workers across Italian municipalities (or Local Market Areas), we can observe the effect of the

[12] By consequence, even the provincial and local labor market share can be obtained.

[13] It is relevant to stress the difference between inactive share and unemployment. As notorious, the unemployment share is higher in Southern Italian areas, while the inactive share during the lock-down was mostly greater in the Centre-Northern parts of the Country, due to sectoral heterogeneity motifs. We can observe how (Figure C1 in Appendix C), in terms of mere correlation, the suspended workers' share across Local Market Areas, was actually negatively associated to their unemployment rate in 2020. Such North-South sectoral asymmetry in suspensions due to the pandemic and unemployment turns out to be consistent with previous literature on Covid-19 and the labor market (Cerqua and Letta, 2022).

local economic change on aggregate abortion decisions, by ruling out the explanations due to mobility restrictions and the lock-down, as the whole Country was under a homogeneous restrictive policy for a prolonged amount of time. Such identification allows for the possibility of an increase in sexual intercourse within cohabiting couples too, as to parity of the whole nation being sheltered, higher prevalence of non-essential workers staying home with their partners, might have caused a further trigger in unplanned pregnancies. We explore both possibilities by examining pregnancies resulting in live births and through heterogeneity analyses.
We illustrate the identification strategy for our main outcome (the VPTs) by means of the following two Dyrected Acyclic Graphs (DAG).

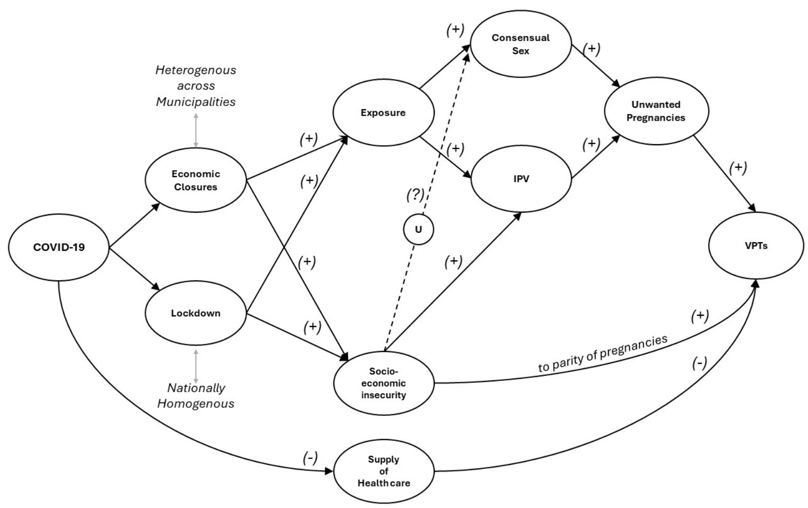


Figure 5: Supposed phenomena in action starting from the Covid pandemic: before the identification strategy.

In the graph above, we can observe the channels described insofar, without including the identifying device. We also add a dotted arrow between socio-economic insecurity and a possible, unknown shift in consensual sex, mediated by some unobservable variable U. As the economic closures were announced two weeks after the national lockdown, the consequences of the two policies basically deployed concurrently. In the DAG, we stress how they may have reasonably affected the same channels in the same direction, before reverberating on the VPTs; as a matter of fact, the outcome of both policies was the same, i.e. shelter-in-home. In addition, the lockdown was homogeneous across the whole country, hence it is not possible to disentangle its impact by identifying municipalities hit more severely, as all Italian areas were affected to the same extent by said intervention. By contrast, the distribution of the suspended workers was strongly heterogeneous across municipalities. The second DAG displays what changes in the identification of the effects after introducing such empirical device (indicated as “inactive share” in the picture).

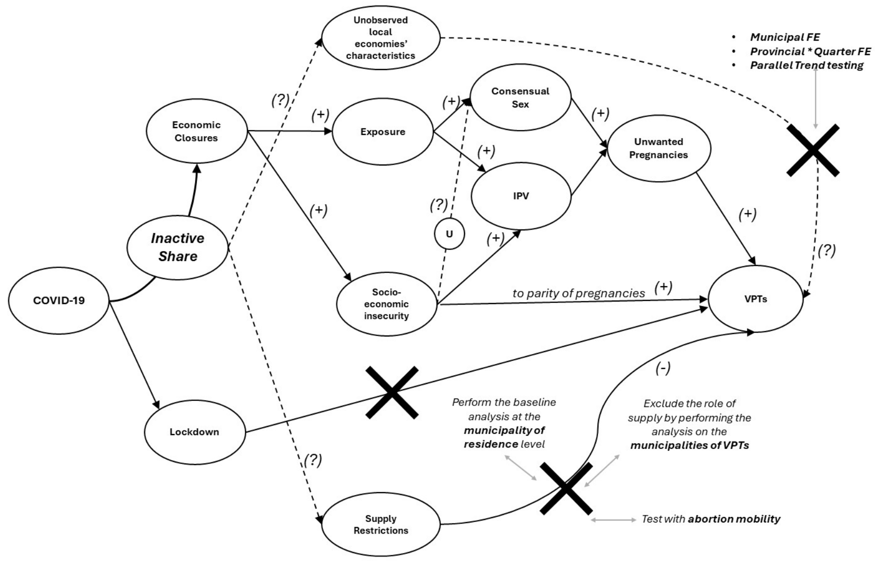


Figure 6: Identification strategy.

By means of the inactive share, we place into the framework a further dimension of variability to the exposure and socio-economic insecurity channels, which adds up to the homogeneous shift caused by the general national lockdown. The paths originating from the latter can thus be closed (as marked by the X). Note that the basic identification strategy, which gives shape to our baseline estimates, only allows to address the "raw" impact of the economic closures on the VPTs, with no discernment across the various (feasibly) operating channels. To account for that, heterogeneity and complementary analyses are necessary, which are presented in the last sections of the paper. Plus, it must be also cleared that the inactive share may open an unknown backdoor path related to the link between local economies' characteristics and VPT trends. As long as these unobservables are not time-varying, we can close such path by means of the FEs, while including interacted province by time FEs allows to a better degree of control to such extent.
These points notwithstanding, the identification methodology embeds some limitations. We expose such issues, concurrently with the strategies devised to deal with them:

- As the closures addressed the whole country, it is not possible to find a clear-cut difference between a treatment and a control group. This is the reason why both Di Porto et al., 2022 and Bordignon et al., 2023 employ a TWFE DiD with continuous treatment. More similarly to Borri et al., 2021, we perform a TWFE DiD as well, but we discretize the treatment according to distribution quantiles; contrarily to their use of the median though, we opt to the subdivision of the shares into quartiles, to have a more neat differentiation between the municipalities that we deem as treated (fourth quartile) and those who are, gradually, not (other three quartiles). In doing this we follow the example of Le Moglie and Sorrenti, 2022 who, to assess the impact of mafia penetration on the birth of new firms during the Great Recession, selected the provinces in the third tercile of the mafia penetration distribution as treated, in order to have a more clear-cut distinction between the groups. In any case, we present a sensitivity analysis (using continuous, above median and at-the-upper tercile treatment) to display how the selected threshold does not affect the outcome.

- The identification strategy relies on the assumption that the supply of VPT services, although impacted by the pandemic, is not correlated to the suspended workers' share. Such issue is partly overcome by centering the attention on the municipality of residence of the aborting women, which is the unit of measurement of the present study. Hence, we observe what happens to municipal abortion rates at the varying of the inactive share, in the same municipality of residence of the women under question. This accounts for the possibility of women moving across municipalities to abort. Nevertheless, we dedicate a substantial portion of the paper to this question, by looking at what happens to VPT rates in response to higher inactive share when aggregating at hospital level. We also devote a part of the study to the estimation of the share of women seeking for VPTs across different areas, to stress the irrelevance of the supply of health care in the present settings.

- After the end of the lockdown, and especially starting from November 2020, Italian areas started adopting heterogeneous restrictions according to the number of contagions registered within their borders (RT index). Therefore, differently from the municipally homogeneous lockdown, the "coloring zones" period might have brought about confounding effects in terms of increased time together, thus sex and/or violence. To account for that, we add up to the model some covariates proxying for the quarterly days of colored regions and for the stringency of the restrictions imposed on given areas, together with the excess quarterly mortality, by making use of the instruments devised by Conteduca and Borin, 2022, better explained in the data section and in Appendix D. However, it must be cleared that conditioning for policy restrictions and colors is not a proper way to control for confounders in a causal framework; indeed, as such variables are post-treatment regressors, conditioning on them does not ensure to fully capture unobserved, time-varying heterogeneities related to the pandemic policies, as they might be not orthogonal to the treatment variable. In any case, we choose to add them up to the specification in order to assess whether the outcome somehow follows the epidemiological pattern of the pandemic, as in Franzoni et al., 2024.

- Some people may be commuters or commuters' partners. In addition, in terms of economic insecurity, they may perceive to be more influenced by a shock applying to all such areas where they are used to live and move across, and less impacted by a disruption affecting their municipality of residence only. We make up for this by extending the analysis to Local Labor Market Areas (see Appendix ?), both concerning the clustering of SEs and the level to which we "administer" the treatment.

4 Data

The present work requires the matching of various sources of data. The municipal information on the inactive share of workers was disclosed by ISTAT on May 2020. The dataset makes use of the Statistical Register on the economic results of Italian enterprises, the *Frame SBS Territoriale*, as in *Frame of the territorial Structural Business Register*, which contains information on the Italian firms active in the private sector (4.4 million at the time under question), regarding their revenues, value added, workers and employees, and the sector within they perform their activity, according to the ATECO-5 digit classification. The sectoral share of workers refers to the local units in 2017 (the most recent one before 2020), so that we can confirm that the distribution of the working population was orthogonal to the Covid-19 pandemic outbreak[14]. ISTAT matched such data with information on the suspended sectors during the lock-down, thus enabling a detailed estimate of the number of inactive workers at municipal level after the economic closures, and their share over total working population[15]. Although the share of active and suspended workers is not available for each sector at the municipal level, we know the disaggregation between industry and service sector. The dataset, being drawn from the SBS Register, does not have information on people and firms active in agriculture, hunting and fishing, public administration, finance and insurance, household and self-production activities and international organizations. The recovered data involves 7978 municipalities, which can be aggregated into 610 Local Labor Market Areas.

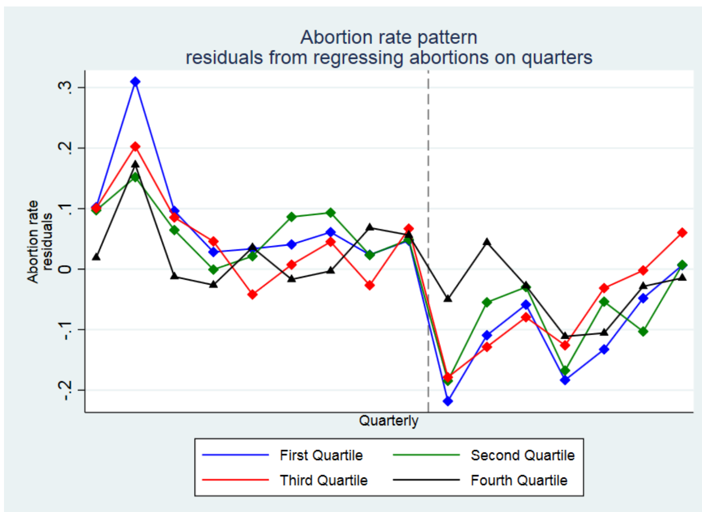


Figure 7: Pattern of the de-seasonalized mean abortion patterns across the shares of the distribution of suspended workers. The unit of aggregation is the women's municipality of residence. The x-axis represents all quarters from 2018Q1 to 2021Q4.

Concerning the outcomes, data on abortions are annually collected by ISTAT, as envisaged by the epidemiological surveillance system on Italian VPTs. They consist in annual cross-sections that are made available upon request at the ISTAT Laboratories for the analysis of microdata, ADELE. The present study makes use of the universe of VPTs performed in Italian healthcare institutions between 2018 and 2021. The choice of the time-span stems from two principal reasons: 1) it refers to an almost symmetric range around the Covid-19 pandemic outbreak; 2) only for those years the aborting women's municipality of residence has been collected. The total number of VPTs for such four-year period amounts to 276,760 abortions, collapsed at monthly frequency; in our design however, we collapse them at quarterly frequency[16].

[14]This may constitute a problem in case of relevant structural and labor market changes possibly having occurred in Italy between 2017 and 2020. However, as also highlighted by Borri et al., 2021, this is not the case under question.

[15]Estimates of workers stem from calculations on job positions and worked hours.

[16]We prefer to collapse the variable at the quarterly level for the following reasons: 1) given he high seasonality of abortion trends, such method of frequency aggregation enables the removal of the bulk of said seasonality; 2) the territorial disaggregation level refers to the municipality of residence. Measuring monthly outcomes for almost 8000 municipalities yields an astonishing number of null observations. This places a really heavy weight on the extensive margin of the phenomenon, which is partly offset by adopting the quarterly frequency; 3) the policy was introduced on

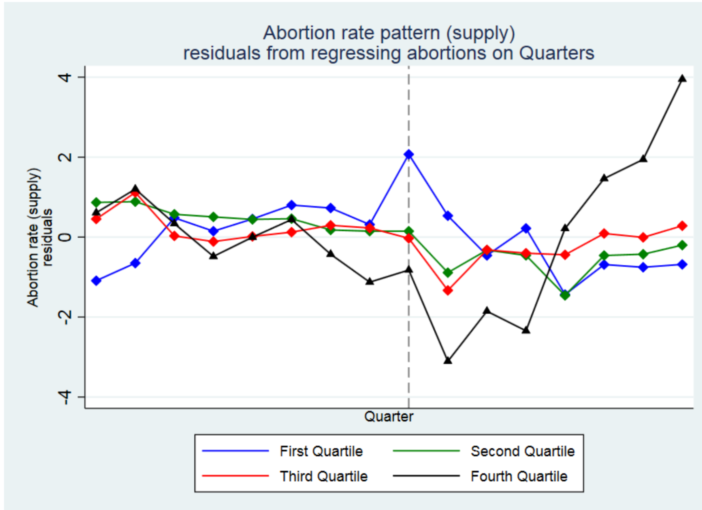


Figure 8: Difference of the de-seasonalized mean abortion patterns between the shares of the distribution of suspended workers. The unit of aggregation is municipality where the VPT is performed. The x-axis represents all quarters from 2018Q1 to 2021Q4.

From these observations, we remove 4202 abortions from women residing abroad, 125 observations for which we do not have the month of occurrence and other 4379 for which the municipality of residence is missing, coded as "888". We end up with 268,054 VPTs. The dataset contains relevant information about women's demographics (year and province of birth, macro-area, region, province and municipality of residence, citizenship, marital status, age class, whether they are minor), their socio-economic status (level of education, professional condition, professional position, economic branch of activity), some health-related data concerning previous pregnancies and the current ones (number of previous VPTs, miscarriages, pregnancies, live births and stillbirths, gestational age, fetal malformation and number of weeks of amenorrhea), which is the most interesting information contained in the data, never exploited in previous research. There are details on the operation also (urgency, analgesia, type of intervention, hospitalization regime, length of stay) and the identification code of the institute where the medical treatment is performed. Since the main analysis is made on the municipal share of abortions, the annual cross-sections are aggregated into a municipal quarterly panel of 126,448 observations. A major problem involving data collection refers to the possibility that women may not indicate their actual residence in their official generalities. If part of this issue can be overcome by performing the robustness check with the employment of the right-hand side LMA aggregation, the problem stays as an intrinsic bias of the collected data. The main outcome of interest is the abortion rate (AR), measured as follows:

$$AR = \left(\frac{Number\ of\ VPTs}{Female\ population\ between\ 15\ and\ 49\ years\ old}\right) * 1000 \tag{1}$$

the 22^{nd} March 2020, towards the end of the first quarter of 2020. Accounting for the "week of reflection" required before undergoing an abortion, the consequences of the policies of VPTs could only start unfolding since April 2020. Thereby, we can reasonably consider treated areas as such starting from the second quarter of 2020. However, to give credibility and robustness to our design, we perform the same analysis by adopting different frequencies, including the monthly one, as shown in Section 7 : results are consistent.

We also make use of the ISTAT data on municipal registration of childbirths from 2018 and 2021 to estimate the pregnancies which are not terminated. The frequency for such data is daily, and we can recover all 1,664,972 births registered in Italy in the four-year period of interest. We possess info on the date of registration of the children and their day of birth, plus their municipality of residence and their municipality of birth. We also know their parents' marital status and, eventually, the number of minors in the household of the head of the family where the kid is going to live, which is an imperfect but good proxy for the presence of siblings. Data on the official municipal population per age are recovered from the demographic section of the ISTAT website for the years 2019-2021. For 2018, the inter census reconstruction, made available by the same institution, is used.
To investigate the channel of domestic violence, we switch the outcome to the phone calls to the national hotline for domestic violence. In 2006 the Italian Department for Equal Opportunities founded, within Italian Anti-Violence Centers, of a public hotline (to be called at 1522) for women victims of domestic violence. Data on calls to 1522 have been collected, at provincial level and weekly frequency, by ISTAT since 2013. The calls registered in the dataset are only the valid ones, thus prank calls or those whose context is non-distinguishable are discarded from the dataset. ISTAT differences between calls specifically made by victims of violence and those made by general users, as in anyone interested in obtaining information, for themselves (in quality of actual or potential victims) or anyone else. Calls by victims are a subset of calls by users. Following the example of Colagrossi et al., 2022, 2023, the outcome of interest when performing the analysis on the phone calls is the call rate to 1522, as in:

$$Call\ rate\ to\ 1522 = \left(\frac{Calls\ by\ users\ or\ victims\ to\ 1522}{Provincial\ population}\right) * 100.000 \tag{2}$$

Concerning the VPTs under the hospital point of view, we elaborate a further dataset by matching the institution codes where the abortion is performed with the official dataset on healthcare institutions recovered from the open data of the Ministry of Health, to obtain information on the municipality, province, local health authority and region where the VPTs are undergone. Since hospitals are not present in all Italian municipalities, the quarterly longitudinal hospital dataset contains way fewer observations: 5,492.

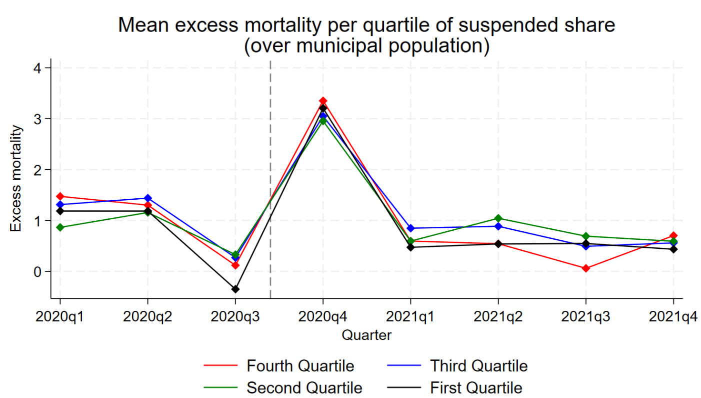


Figure 9: quarterly Covid-19 excess mortality per quartiles of inactive shares' distribution.

To account for the heterogeneity in the policy restrictions after the first lockdown, we employ the dataset constructed and disclosed by Conteduca and Borin, 2022. They collected the daily "color"

(white, yellow, orange and red) of each municipality from November 2020 to the end of the emergency state. In addition, they built a composite, multidimensional stringency index to evaluate the degree of daily tightening of each Italian municipality, starting from January 2020. The construction of the stringency index is explained in Appendix D with more details. Information is aggregated at quarterly frequency to match abortion data: for the colored area days, a variable summing up quarterly days of each given color is constructed.
Data used as complementary material, such as those on municipal quarterly excess mortality (aggregated at quarterly frequency, Figure 9) are taken from the ISTAT disclosure on COVID-19 information ushered in May 2020 (see the link at the beginning of the section).
Descriptive information about the abortion dataset , which is the most relevant focus of the paper, are presented in Table 1.

	Treated municipalities/provinces				Non-treated municipalities/provinces			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Abortion Rate (municipalities)	1.064	2.964	0	111.111	1.101	2.397	0	142.857
Abortion Rate (hospitals)	9.529	20.038	0	433.962	5.195	15.627	0	433.476
Pregnancy Rate (municipalities)	5.602	10.715	0	359.000	15.285	83.315	0	4977.000
Inactive share	70.825	9.296	60.190	100	43.396	12.091	0	60.184
Inactive share (service)	27.090	18.833	0	100	23.955	10.137	0	60.032
Inactive share (industry)	43.734	19.226	0	100	19.441	11.085	0	60.032
Municipal population	3374.588	6153.667	28	201410	8946.251	48664.501	29	2820219
Municipal population (females aged 15-49)	681.936	1295.416	2	43061	1848.408	10204.364	29	602319
Policy measures								
Avg. quarterly stringency index (since 2020)	52.660	14.374	31.925	76.552	52.635	14.410	31.925	77.192
Quarterly red area days (since 2020)	6.273	10.177	0	55	6.019	9.986	0	55
Quarterly orange area days (since 2020)	8.413	12.871	0	77	8.630	13.292	0	77
Quarterly yellow area days (since 2020)	13.272	18.581	0	56	13.465	18.653	0	56
Quarterly white area days (since 2020)	24.668	38.084	0	92	24.488	37.844	0	92
Municipal mortality	9.502	16.666	0	709	25.793	136.793	0	9320
Municipal excess mortality (since 2020)	0.441	1.1869	-14.067	75.133	1.006	7.402	-145.667	684.933
Obs.				31616				948328
Weekly 1522 call rate by users	0.588	0.549	0	4.202	0.618	0.579	0	6.608
Weekly 1522 call rate by victims	0.291	0.342	0	2.893	0.301	0.342	0	3.685
Obs.				5616				16640
Quarterly 1522 call rate by users	7.657	3.142	0.724	19.492	8.055	3.975	0	37.486
Quarterly 1522 call rate by victims	3.788	1.757	0	10.017	3.925	2.043	0	13.168
Provincial population	478143.5	309207.9	137795	584784.9	674671.4	81415	4263542	
Obs.				432				1280

Table 1: Descriptive statistics of the variables used in the present work. The definition *Treated municipalities/provinces* involves units part of the fourth quartile of the suspended workers' share distribution. The definition *Non-treated municipalities/provinces* involves the other units.

5 Empirical Strategy

We empirically explore the phenomena under question by differentiating our analysis in two parts, according to the aggregation at municipality or hospital level. The outcome, in both cases, always mirrors the general equilibrium result stemming from the interactions between the demand and supply of abortions. Although our subdivision is helpful in trying to understand the equilibrium patterns, the differentiation is spurious, as the treatment may have a heterogeneous impact on demand and supply across municipalities; we better explain the issue in the hospital-related sub-section of Section 6. As an anticipatory comment, our findings suggest that the response in abortion rates are not likely driven by a fall in the providing of abortion services.

5.1 Aggregating by municipality of residence

To assess the effect of the exogenous shift in time exposure and economic insecurity on Italian VPT rates, we estimate via OLS a Two-Way FE Difference-in-Differences model, in the form as such:

$$AR_{mpt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(Inactive\ Share_{q2/2020} \in Q_k) + X'_{mt}\beta + \tau_m + \gamma_t + \delta_{p,t} + \varepsilon_{mt} \quad (3)$$

The outcome of interest is AR_{mpt}, the abortion rate in municipality m (which is the woman's municipality of residence), part of province of residence p, in quarter-year t. Aggregating by residence accounts for women moving across municipalities to abort. $Post_t$ is a dummy taking value 1 when $t \geq Q2/2020$, 0 otherwise. $1(InactiveShare_{q2/2020} \in Q_k)$ is a binary variable which equals 1 when m belongs to the k^{th} quartile Q_k of the inactive share distribution during the lockdown, 0 otherwise. X'_{mt} is the set of municipal-level, quarterly covariates for restrictions' severity: specifically, we include the average quarterly stringency index and the total number of red, orange and yellow area days, being white area the omitted category. Among them, albeit not being a policy variable, we also include quarterly, municipal excess mortality, to proxy for the seriousness of the viral impact of the pandemic on referred areas, which further controls for both health providers' excessive workload and for a higher perception of epidemiological risk. τ_m are the municipal FEs, while γ_t the quarter-year FEs. Provided with the baseline model, we run further estimates by including $\delta_{p,t}$ in the equation; the latter is an interaction between the province of residence and quarter-year dummies, which accounts for the presence of unobservable time-varying heterogeneity that may be affecting VPTs at an aggregate level by following a persistent pattern. The chosen level of aggregation of the interaction is provincial, as the heterogeneity evolution (mirroring the "secular" decline in VPTs) may be possibly linked to the factors underlined by the ISS and the Italian Ministry of Health, such as the evolution of birth control facilities, the presence of reproductive care assistance on the territory or other healthcare-related motifs. Although Italian healthcare is administered at regional level, some of its functions are further de-centralized to Local Health Authorities, so it is meaningful to include an intermediate level of aggregation to capture the time-varying interaction between factors strictly related to healthcare and other provincial socio-demographic changing determinants. The coefficient of major interest is β_4, i.e. the coefficient on the share of distribution we deem as defining the treatment. If the distinction between treated and controlled units was neat, and thus we expected no effect of the treatment on the control groups, we could account for β_4 as the Average Treatment Effect. However, due to the nature of the research design, it is unfeasible to consider the lower quartiles of the distribution as a clear-cut control group. For such reasons, when presenting and discussing the results, we report coefficients β_2 and β_3 as well, which are included in the model itself. The reference point, as in the omitted category, is the first quartile of the distribution.

It may result evident by comparing the different figures presented in this very project that the mean AR calculated in the "municiaplity of residence dataset" is 1.064 for the treated municipalities, and 1.101 for the non-treated ones, way lower values than the official statistics: in Figure 1, we observe a rate floating around 5 during the analyzed years. The reason is that the unit of observation in our settings is municipal, and the frequency is quarterly. By consequence, the majority of observations (small Italian municipalities with few inhabitants) presents a null rate. Given such high prevalence of zeros, and provided for the count data nature of the Abortion Rate, we double-check our OLS results by estimating the non-linear model below, as in a Pseudo-Poisson Maximum Likelihood (PPML) panel regression with the same inputs, in the fashion of both Lindo et al., 2020 and Muratori, 2023b.

$$\begin{aligned} &E(AR_{mpt}|Post_t,\ Inactive\ Share_{q2/2020},\ X'_{mt},\ \tau_i,\ \gamma_t,\delta_{p,t}) = \\ &\qquad = exp(\ \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(Inactive\ Share_{q2/2020} \in Q_k) + X'_{mt}\beta + \tau_i + \gamma_t + \delta_{p,t}) \end{aligned} \tag{4}$$

The statistics of interest of the latter model are the marginal effects of the estimated coefficients $\beta_4,\ \beta_3$ and β_2.

5.2 Aggregating by hospital

The methodology slightly varies when we address abortions by aggregating to the hospital level, as the employed datasets needs some modifications. Municipalities with hospitals where abortions are performed are indeed 308, and the observations in the following analysis drop to less than 6,000.

$$AR_{hlmt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(Inactive\ Share_{q2/2020} \in Q_k) + X'_{mt}\beta + \rho_h + \gamma_t + \lambda_{l,t} + \varepsilon_{ht} \tag{5}$$

In this case, the outcome of interest is AR_{hmlt},the abortion rate performed in hospital h, managed by Local Health Authority (LHA) l, within municipality m and irrespective of the municipalities of residence of the aborting women, in quarter-year t. The inactive share-related treatment terms and the policy covariates in the RHS do not change with respect to the previous model. In turns, in addition to time (γ_t) FEs, we include hospital FEs (ρ_h) and an interaction between LHAs and a quarter-year FEs ($\lambda_{l,t}$), to account for evolving unobserved heterogeneities due to the territorial management of the healthcare supply. The coefficients of interest are, again, β_2, β_3 and β_4. A specular PPML panel regression model is estimated with the same inputs, and the marginal effects of which are reported in the next section.

6 Baseline Results

The performed estimates on abortions under the municipality of residence point of view (reported in Table 2 and Table 3, the former presenting OLS estimates, the latter the Poisson ones) display how the inactive share distribution has a positive impact on the municipal abortion rate, which increases by looking at the quartiles of the distribution in ascending order. However, only the dummy for the fourth quartile (our treatment) is statistically significant in both the OLS and PPML specifications. In Column (1) of the two tables we report the baseline specification without the policy restriction covariates. In Column (3), covariates are added, while in Column (5) the model is integrated by the mentioned provincial interactions. Columns (2), (4) and (6) of both tables display how the models are consistent when coefficients are estimated through (log-) municipal population weighing.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.13134 ***	0.11340 ***	0.12879 ***	0.11133 ***	0.13168 **	0.11087 ***
	[0.04565]	[0.03563]	[0.4587]	[0.03585]	[0.05185]	[0.04061]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05711	0.04825	0.05570	0.04698	0.06342	0.05119
	[0.04266]	[0.03300]	[0.04276]	[0.03311]	[0.04501]	[0.03488]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03486	0.02961	0.03505	0.02949	0.03353	0.02714
	[0.03950]	[0.03058]	[0.03953]	[0.03062]	[0.02949]	[0.03353]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10043	0.10529	0.10046	0.10531	0.11223	0.11621
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table 2: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.13978 ***	0.11324 ***	0.13676 ***	0.11082 ***	0.14560 ***	0.11515 ***
	[0.05105]	[0.03904]	[0.05119]	[0.03919]	[0.05580]	[0.04335]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.06016	0.04614	0.05855	0.04471	0.07307	0.05239
	[0.04669]	[0.03527]	[0.04697]	[0.03537]	[0.04834]	[0.03685]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03709	0.02896	0.03769	0.02919	0.03967	0.02714
	[0.04346]	[0.03258]	[0.04350]	[0.03205]	[0.04300]	[0.03279]
Observations	116,192	116,192	116,192	116,192	116,192	116,192
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter−year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table 3: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

Most of the coefficients of interest are significant at 1% level, with Columns (5) of Table 1 being significant at 5% level (i.e., the unweighted OLS specification with provincial interaction dummies). Estimates are comparable between the two different models, as the PPML results presented are the Marginal Effects of the regression. All statistics are included between 11 and 14.6 p.p., meaning that municipalities which were part of the fourth quartile of the suspended share's distribution during the lock-down saw augmented abortion rates by the mentioned amount after the pandemic-related closures. Such values, quite low at a first glance, appear not to be irrelevant when compared to the mean value of the municipal abortion rate of treated units (i.e., those in the fourth quartile) pre-treatment, as they range between 10% and 13% of the number of abortions every 1000 women in fertile age residing in Italy.

OLS results - By hospital						
	(1)	(2)	(3)	(4)	(5)	(6)
	AR	AR	AR	AR	AR	AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-1.34072	-1.50525	-1.20354	-1.39824	-1.15342	-1.67544
		*				
	[1.13140]	[0.87256]	[1.16186]	[0.088944]	[2.71143]	[2.21840]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.04345	-0.23301	-0.18356	-0.12472	0.78914	0.25097
	[0.80849]	[0.54258]	[0.86028]	[0.57442]	[2.75011]	[2.22934]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.42521	0.15314	0.53469	0.24105	0.38287	0.01008
	[0.78781]	[0.49816]	[0.80517]	[0.51111]	[2.73009]	[2.24476]
Observations	5,492	5,492	5,492	5,492	4,552	4,552
R-squared	0.87758	0.87388	0.87767	0.87394	0.88971	0.88212
Policy covariates			X	X	X	X
Hospital FE	X	X	X	X	X	X
Quarter˙year FE	X	X	X	X	X	X
LHA x Quarter˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	9.640	9.640	9.640	9.640	9.640	9.640

*** p<0.01, ** p<0.05, * p<0.1

Table 4: SEs clustered at hospital level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By hospital						
	(1)	(2)	(3)	(4)	(5)	(6)
	AR (ME)	AR (ME)	AR (ME)	AR (ME)	AR (ME)	AR (ME)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-0.34996	-0.34081	-0.31330	-0.31080	-0.71250	-0.76142
	[0.71949]	[0.58730]	[0.71348]	[0.58216]	[1.02622]	[0.84359]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.27605	0.18864	0.29475	0.20608	-0.91513	-0.79908
	[0.52626]	[0.45530]	[0.52362]	[0.45498]	[0.99737]	[0.82143]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.56802	0.44409	0.58490	0.46441	-0.22870	-0.28396
	[0.48842]	[0.41542]	[0.47835]	[0.40827]	[0.89360]	[0.73754]
Observations	5,492	5,492	5,492	5,492	4,548	4,548
Policy covariates			X	X	X	X
Hospital FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
LHA x Quarter−year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	9.640	9.640	9.640	9.640	9.640	9.640

*** p<0.01, ** p<0.05, * p<0.1

Table 5: SEs clustered at hospital level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment.

All coefficients on the inactive share quartiles are non-significant, except one at 10% (Column (2) of Table 4, i.e. the OLS specification with Policy covariates and weighted by population). In addition, the direction of such non-significant effect is always negative when looking at the treatment quartile, even the only significant coefficient. Before proceeding, we discuss these results, by thoroughly describing first how supply-side factors may threaten the validity of our design, and then how our findings seem to disprove this hypothesis of bias, because of which, from now on, we keep referring to abortion with respect to the municipalities of residence of women only.

What could happen in municipalities with more substantial economic closures? Would one expect a contraction in healthcare (and thus abortion) services, or their increase? The former case would hold if a higher share of inactive workers was correlated to higher levels of mortality, or to a more rapid diffusion of the virus at the beginning of the pandemic, as the descriptive, anecdotal evidence presented in Figure 9 displays, although by a negligibly small amount. However, the evidence by Di Porto et al., 2022 shows, on the opposite, that a higher share of essential workers sped up the subsequent daily infections. If we hold the former hypothesis as valuable, we need to overturn the evidence by Di Porto et al., 2022. This would mean suggesting that before the national lock-down, a higher portion of workers that would be left home few weeks later (the non-essential ones) were primarily contributing to the initial diffusion of the virus. If the inactive share had negative impact on the supply of services by bringing about hospital clogging, then the general equilibrium result of the first analysis would configure a downward distortion of the actual shift in the VPT service demand of the affected women. Which would configure as an attenuation bias.

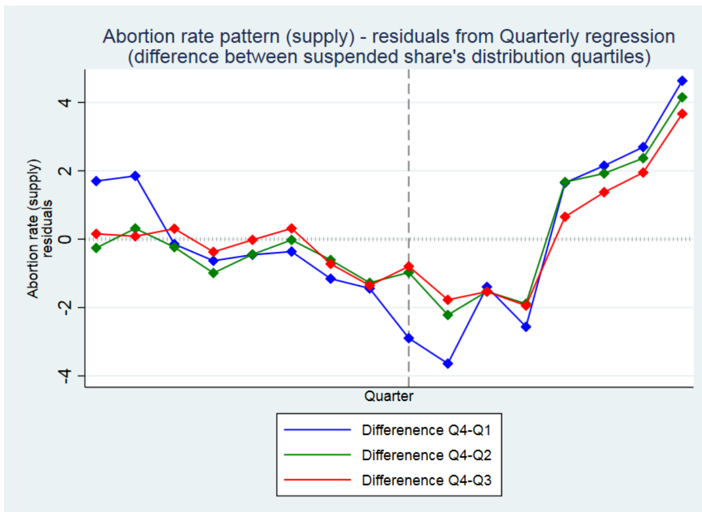


Figure 10: De-seasonalized mean quarterly differences between fourth quartile of the distribution of suspended workers and the other three. The unit of aggregation is the municipality where the VPT is performed. The x-axis represents all the quarters from 2018Q1 to 2021Q4.

A serious issue to the credibility of our results would take shape if the inactive share was positively correlated to the VPT services supply instead, as hospitals in areas with many inactive workers would increase their offered services to counteract a lack of actions in the least affected area. As a matter of fact, municipalities with lower levels of inactive share would possibly be characterised by a greater number of contagions, consistently with the evidence found by Di Porto et al., 2022 and, by consequence, by hospital clogging and reduced healthcare, and our results would not be driven by an increased demand of services in areas with more suspended workers, but by a downward shift in municipalities with fewer suspensions and more infections. In this case, the impact of the pandemic would be heterogeneous on the supply, and our results would be severely driven by that rather than by factors directly affecting the aborting women. In any case, neither our regression estimates, which deliver mostly non-significant and clearly negative results at the hospital level, nor the anecdotal aggregate evidence displayed in Figure 10 seem to show that this is the case: therefore, we can quite sensibly discard the hypothesis of supply restrictions in influencing our estimates. To further dwell on the validity of the latter conclusion, in Section 8 of the present work we estimate the effect of the economic closures on what we have called "abortion mobility". The latter is the response of the probability of undergoing a VPT outside one's own municipality of residence (or LMA of residence) to higher levels of inactive share. The outcomes of such analysis seem to confirm what has been argued so far (more on this in the mentioned section).

6.1 Parallel trend

In order for the TWFE DiD estimates to hold robustly, the parallel trend assumption needs to be met. That means, in absence of the treatment (i.e. the economic repercussions triggered by Covid-related closures), the treated and non-treated units would evolve following their pre-existing path.

$$\begin{aligned}\hat{\beta}_4 &= E[Y^1 \in Q_4|Post] - E[Y^0 \in Q_4|Post] + \\ &+ [E[Y^0 \in Q_4|Post] - [E[Y^0 \in Q_4|Pre]] - [E[Y^0 \notin Q_4|Post] - [E[Y^0 \notin Q_4|Pre]]\end{aligned} \tag{6}$$

Equation 6 analytically shows the problem. Our estimated coefficient of interest, $\hat{\beta}_4$ is the sum of the non-parallel trend bias and the Average Treatment on the Treated (first line of the equation on the RHS). The latter consists in the difference between the realized outcome on the treated unit and the unobservable counterfactual, as in what would happen on the treated units was the treatment absent. The second line contains, in turns, the non-parallel trend bias. Such bias is given by 1) the counterfactual difference between the potential outcome of the treated units before and after the time discontinuity of the treatment, was the treatment never to occur; 2) the counterfactual difference between the potential outcome of the control units before and after the time discontinuity of the treatment, was the treatment never to occur; 3) the difference of the terms above. To deliver unbiased estimates of $\hat{\beta}_4$, we should assume the non-parallel trend bias to be zero. Of course, such assumption is not empirically verifiable as we cannot factually observe the evolution of the counterfactual trend for our units in absence of the Covid-19 outbreak and its related closures. Therefore, we do not know, a priori, whether the results we obtain by observing the ARs are driven by possibly sectoral-related trends (as the treatment depends on the labor market composition of municipalities) which involve those units deemed as treated, in our model, after March 2020. To robustly control for this, we assume that the counterfactual in absence of treatment for the treated units was the same as before the treatment; then, we compare the evolution of abortion rates in treated units before the treatment, to look at what would have happened had the pandemic never happened. In order to perform such robustness check, we estimated an event-study equation as follows:

$$AR_{mpt} = \beta_0 + \sum_{j=2}^{J} \beta_j (Lead\ j)_{mt} + \sum_{k=1}^{K} \beta_k (Lag\ k)_{mt} + X'_{mt}\beta + \tau_m + \gamma_t + \varepsilon_{mt} \tag{7}$$

The equation above shall be interpreted on the basis of the event of interest, which is of course $Event_m := Q2$ 2020, where, as in Equation (3) and Equation (4), m is the municipality of residence of the women. $(Lead\ j)_{mt}$ are the pre-treatment period dummies equal to 1 if associated to the treated units (leads, indeed), with $(Lead\ j)_{mt} = 1[t = Event_m - j]\ for\ j \in \{1, ..., J\}$. On the other hand, the lags are $(Lag\ k)_{mt}$, i.e. the post-treatment period dummies equal to 1 if associated to the treated units again, with $(Lag\ k)_{mt} = 1[t = Event_m + k]\ for\ k \in \{1, ..., K\}$. $(Lead\ 1)_{mt}$ is set equal to 0 as baseline, to avoid multicollinearity. The specification involves, as in the baseline, Policy covariates, time and municipality FEs; in a further model we include the province-month interaction dummies for Province x Quarter and Year FEs as well. The coefficients of the event study are estimated both via OLS and Poisson (the latter mirroring Equation 7, albeit estimated via PPML; its MEs are reported in the graphs) and plotted below (Figure 11 and Figure 12). The event studies seem to show the absence of significant pre-trends at both 10% and 5% levels, although some level of seasonality (to be possibly credited to a cyclical pattern of sexual encounters) seems not having been removed from the quarterly-frequence aggregation. In general, we observe how, during the first two quarters of the quasi-experiment, abortion rates seemed to be significant in the 6 months after March 2020, (i.e., from April to August), before turning back to be statistically similar to zero starting from the last quarter of 2020, when coloring areas started being implemented. The observed pattern suggests that the bulk of the effect we observe in the DiD baseline estimates was concentrated in the months immediately following economic closures, which were the ones involving the actual suspension of concerned workers (April, May, part of June), the whole Summer, and September. During the latter months, the significance of the effect might have been driven by a slow reintegration of suspended workers to their usual tasks, possibly due to the presence of informal/precarious contracts and remote working. The presence of summer holidays could also work as an underlying confounder, although we would expect it to operate in the opposite direction of our estimates, as non-suspended workers ought to be more willing to go on holiday compared to suspended ones. At the beginning of 2021, the effect seemed to be already fully re-absorbed.

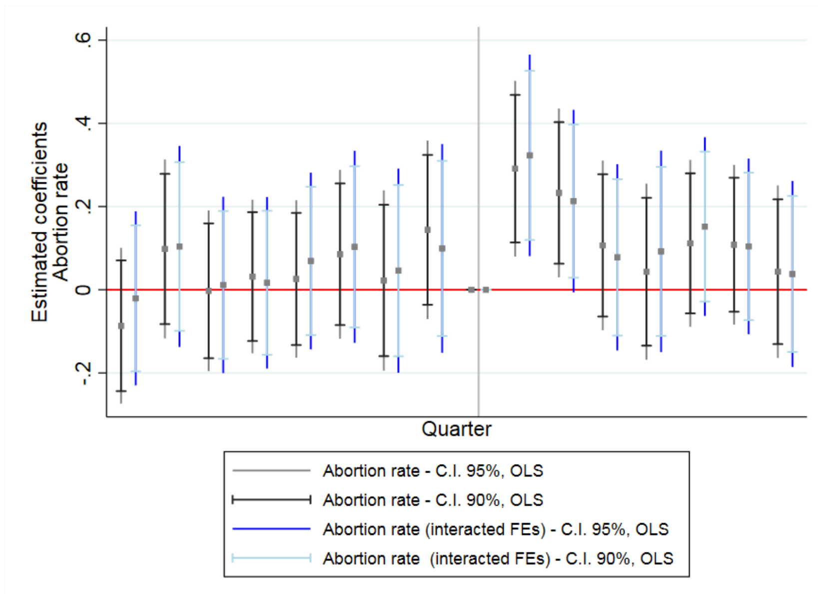


Figure 11: OLS Event-study estimates. The figure reports the coefficient on temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020.

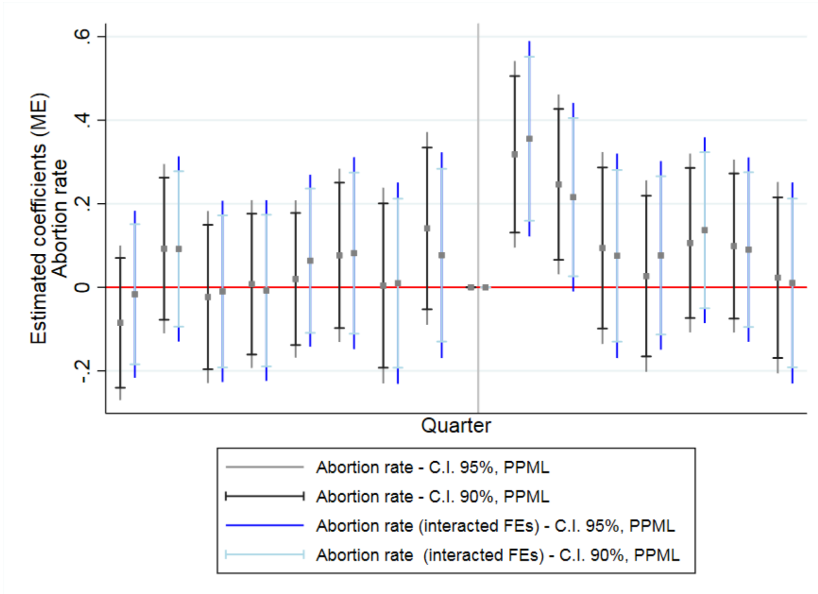


Figure 12: PPML Event-study estimates. The figure reports the marginal effects of temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020.

To support the credibility of the parallel trend assumption, we need to address the feasibility of having unobservable time-varying confounders (which may be leading to non-parallel patterns), and the low power of our basic pre-trend testing due to the low number of observations. Accounting for a hypothetical violation of common trends, we follow the approach developed by Rambachan and Roth, 2023, who enable us to perform inference and sensitivity even in presence of (small) deviation from parallel trends. Their main "honest" methodology to corroborate the event-study tests, is to appraise bounds on relative magnitude: we replicate their method by estimating the entity of the deviations from the common trend after the treatment that would make our outcomes non-valid according to the pre-trend assumption, relative to the maximum pre-treatment violation. We assess the sensitivity of our event-study results to assumed violations of parallel trends using the relative magnitude approach, by computing the break point parameter M (within a range going from 0 to 1, with 1 meaning that the hypothesis is to face a 100% deviation after treatment relative to the pre-treatment trend) which would make our results inconsistent. Figures E1 and E2 in Appendix E show the results of such estimates: the red vertical line represents the 90% and 95% confidence interval for the coefficient on the treatment in the Second Quarter of 2020; the blue lines represent, instead, the confidence intervals for the coefficients calculated by allowing a some degree relative magnitude deviation from the common trend (going from 0%, i.e. the baseline estimate, to 100%). We observe how, at 90% confidence level, we could admit a maximum 40% violation of the parallel trend assumption in our baseline specification, with the parameter dropping at 20% if we estimate the confidence sets at the 95% level.

7 Robustness

The next aim of the work is to discuss the possible channels through which the effect may work out as credible, mostly by heterogeneity analyses with the available information, in order to draw some implications from our baseline estimates. However, before proceeding with that task, we perform some robustness checks to assess the internal validity of our model, as in to confirm that the results are meaningfully driven by the Covid-related closures.

7.1 Sensitivity analysis

To assess the validity of out research design in different time frameworks, we collapse at both yearly/semestral and monthly frequency, respectively restricting and increasing the granularity of data. We adopt the same specifications as the one in Equation 3, with slight variations. For the annual and the semestral model, we consider the whole 2020 ($Post_t = 1\ if\ t \geq 2020$) and the first semester of 2020 as the time discontinuities ($Post_t = 1\ if\ t \geq S1/2020$); as for the monthly specification, the event time refers to the month of April 2020 ($Post_t = 1\ if\ t \geq April/2020$), while the Policy covariates are included in the regression lagged by one period, to account for unfolding of their heterogeneous impact on the abortion decisions with some delay (X'_{mt-1}). For the sake of brevity, we report the OLS estimations for the annual and the monthly specifications only. All PPML estimates, and semestral OLS estimates can be looked at in the Appendix E.

OLS results - By municipality of residence - Annual specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{2020} \in Q_4)$	0.45936 ***	0.40473 ***	0.44251 **	0.38749 ***	0.46248 **	0.40370 **
	[0.18155]	[0.14232]	[0.18278]	[0.14344]	[0.20957]	[0.16431]
$Post * 1(Inactive\ Share_{2020} \in Q_3)$	0.027750	0.22828 *	0.27461	0.22259 *	0.30372 *	0.24423 *
	[0.17144]	[0.13291]	[0.17227]	[0.13375]	[0.18107]	[0.14047]
$Post * 1(Inactive\ Share_{2020} \in Q_2)$	0.15870	0.13585	0.16328	0.13681	0.16474	0.13535
	[0.15953]	[0.12357]	[0.15987]	[0.12403]	[0.16327]	[0.12677]
Observations	31,612	31,612	31,612	31,612	31,612	31,612
R-squared	0.34647	0.35665	0.34674	0.35692	0.35777	0.36792
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Province x Year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	4.374	4.374	4.374	4.374	4.374	4.374

*** p<0.01, ** p<0.05, * p<0.1

Table 6: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence - Monthly specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{03/2020} \in Q_4)$	0.04378***	0.03780***	0.04125***	0.03556***	0.04285**	0.03628***
	[0.01522]	[0.01188]	[0.01530]	[0.01194]	[0.01736]	[0.01356]
$Post * 1(Inactive\ Share_{03/2020} \in Q_3)$	0.01904	0.01608	0.01989	0.01666	0.02235	0.01811
	[0.01422]	[0.01100]	[0.01414]	[0.01093]	[0.01495]	[0.01157]
$Post * 1(Inactive\ Share_{03/2020} \in Q_2)$	0.01162	0.00987	0.00120	0.00931	0.01064	0.00850
	[0.01317]	[0.01019]	[0.01325]	[0.01024]	[0.01343]	[0.01041]
Observations	379,344	379,344	371,441	371,441	371,441	371,441
R-squared	0.03428	0.03622	0.03402	0.03595	0.04544	0.04611
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Month˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.368	0.368	0.368	0.368	0.368	0.368

*** p<0.01, ** p<0.05, * p<0.1

Table 7: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

In accordance with our baseline estimates, results are consistent both at annual and monthly frequency. Coherently with expectations, in absolute values the monthly coefficients on the fourth quartile are lower in magnitude than the quarterly ones (ranging between 3.5 and 4.4 p.p), whereas the annual estimates are larger (between 38.8 and 46.3 p,p); however, relative to the mean, both monthly and yearly results are slightly lower than our benchmark estimates, the former amounting to 9.5%-11.9% circa, and the latter to 8.9%-10.6%. It is worth to note that, possibly due to the loss of granularity occurring in the annual model, in four specifications out of the six reported (Columns (2), (4), (5) and (6)) the coefficient on the third quartile gains some significance (at 10%), although its size is almost half the one of the coefficient on the treatment.

To guarantee that the results are not driven by an arbitrarily selected cut-off, we perform further sensitivity checks by considering different ways to capture the threshold of the suspended workers' share distribution after which municipalities are deemed as treated. We assess units below/above the median, and those belonging to the second and the third tercile (the first tercile being the reference category). We also estimate a DiD with continuous treatment, following Di Porto et al., 2022 and Bordignon et al., 2023. We aggregate by municipality of residence. The estimates in Table F1 and Table F2 in Appendix F are consistent with the baseline results. Lowering the threshold embody the loss of one degree of statistical significance in the model with the continuous specification and in the one with the above-median framework.

We make use of one sensitivity estimations to provide with further robustness for the hypothesis of absent pre-trends. As the "raw" treatment is given by the continuous specification of the suspended workers' share, we report the event-study, as specified by Equation 7. However, we do not identify the treated units through quartiles, but we just apply the continuous treatment specification, which is the one less subject to modifications.

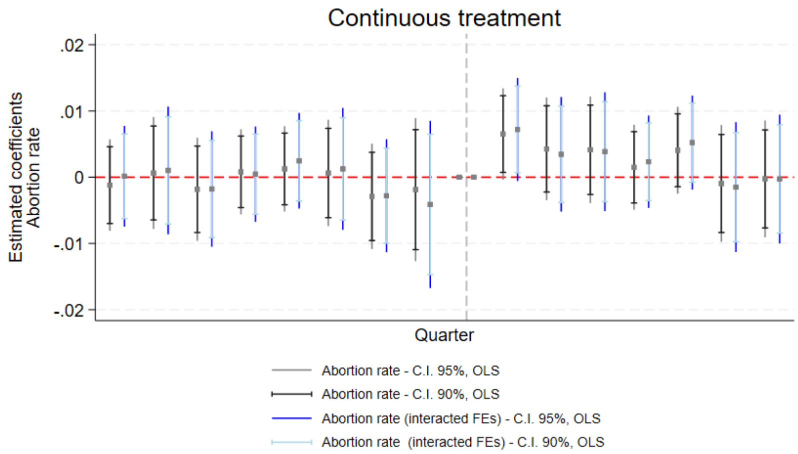


Figure 13: OLS Event-study estimates with the continuous treatment specification. The figure reports the coefficient on temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020.

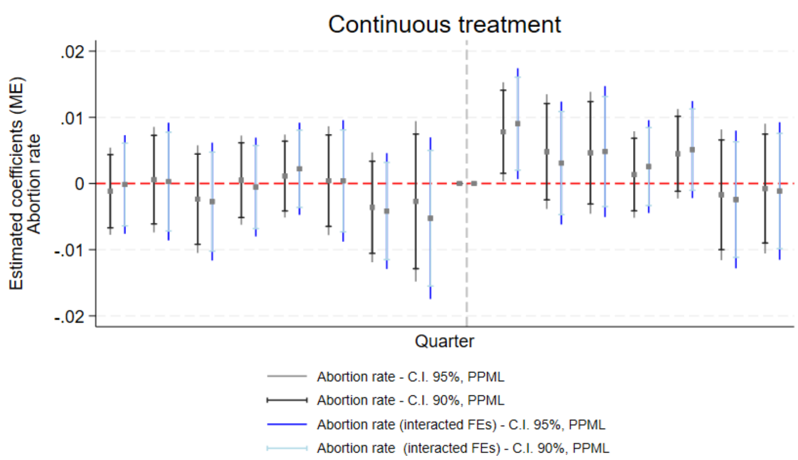


Figure 14: PPML Event-study estimates with the continuous treatment specification. The figure reports the marginal effects of temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020.

In such specification, the coefficient on the second quarter after the treatment loses significance, possibly due to the smaller aggregate effect of the treatment expressed in such granular fashion. However, the first lag after 2020Q1 still results significant at both 90% and 95% level. In addition to that, the graph displays an evident divergent pattern of the difference in the effect between "more treated" and "less treated" units in correspondence to the treatment threshold, which hints for the lack of pre-trends which go in the direction of biasing the results (which is also suggested by the heterogeneity in the estimated confidence intervals). This holds for both OLS and PPML specifications.

We also perform the estimations introduced in the baseline models on three sub-samples, to further validate the sensitivity of our results: 1) as abortions cannot be performed after the gestational limit (90 days) unless the woman's health is endangered, before aggregating at municipal level, we subtract all observations of VPTs undertaken after 90 days from the dataset, as they are to be credited to health-related necessities rather than to voluntary fertility motifs; 2) as it appears clear from Table 1, the treated municipalities are on average less populated than control ones, as bigger cities are less likely to record high shares of suspended workers. In this regard, the big cities might be driving down the estimates on abortion rates for the control units. To account for that, we re-perform the estimates removing from the municipal panel dataset all the chief towns of the 15 Italian Metropolitan Cities administrative units, which include the Italian biggest cities[17]. Eventually, we further restrict the sub-sample in point 1) by excluding all abortion interventions that are featured by the flag "urgency", which implies the observed woman aborted via an urgent treatment. In doing this, we make the very conservative and narrow assumption that all treatment performed with urgency are to be credited to health-related concerns, even when performed before the gestational limits; therefore, we hypothesize they are not the subject of a fertility decision process. The results of these three estimations are reported, respectively, in Table F1, F2, and F3. While the specifications estimated in the first two sub-samples are strongly consistent with the baseline, in Table F3 the magnitude of the coefficients is quite lowered, together with the significance in the most restrictive specification (which is null in the model with interacted provincial FEs); however, this shall not be troubling the internal validity of our research design, as it stems from a very narrow and quite unrealistic restriction of the sample.

Eventually, we perform a further sensitivity check to assess whether our results are randomly driven. Specifically, we undertake a randomization inference procedure with 1000 permutations which randomly assign the treatment to units of the sample, in doing this estimating a random density function which, if overlapping our actual baseline estimate, would hint towards the randomness of our results. We report the kernel density plot in Figures E and E. The graphs prove for the non-randomness of our estimates, as our estimated coefficient (the red vertical line, barely visible, at the extreme right of the graph) lies way rightwards of the sampled distribution from the randomization inference procedure, either in the specification with or without interacted provincial FEs.

7.2 Time placebo

As the Event-study graphs hint for the absence of pre-trends, we recognize two main aspects in our estimates: first, there is an evident presence of some level of cyclicality, which is not definitely not removed from our quarterly aggregation. Second, the identification of the effect is visibly reabsorbed after two quarters, which suggests that seasonality might be contributing in driving our estimates; which is not a problem per se, as long as such seasonality is independent upon the distribution of the suspended workers share. To account for that, we perform time placebo regressions, and separately

[17]The metropolitan cities are, in alphabetical order, Bari, Bologna, Cagliari, Catania, Florence, Genoa, Messina, Milan, Naples, Palermo, Reggio Calabria, Rome, Turin, Venice.

estimate the same models in various time-spans, always around the seasonal temporal discontinuity of March, although in different years[18]. Estimates are performed by employing both the OLS and the PPML specifications (PPML estimates in Appendix E, Table E5). The considered treatment is always a dummy equal to 1 if the municipality belong to the fourth quartile of the inactive share distribution, 0 otherwise.
The time placebo in Table 8 displays that the interaction between the inactive share distribution and the time in correspondence to which the pandemic outbreak occurred is significant in explaining the behavior of abortion patterns. The estimates hint that the growth in ARs in municipalities with higher share of suspended workers during the lock-down is plausibly driven by the COVID-related repercussions, and not by some seasonal pattern due to a link between sexual behavior between March and September and the municipal sectoral composition. The non-significant coefficients on March 2021 estimates (among which one is even negative, Column 14), are a feasible hint to the re-absorbing of the effects occurring in 2021, as displayed by the event-plots already. In addition to that, the fact that the impact of the inactive share is statistically significant after the first quarter of 2020 only, even when we use year 2020 alone as the sample of our model, seemingly corroborates our results.

7.3 Local Market Areas

As mentioned already, the municipal level of aggregation of the inactive workers' share may result restrictive for the impact evaluation of of the pandemic-related economic closures on Italian women. In such case, we may be violating the stable unit value assumption (SUTVA). We therefore undertake two sets of estimations:

1. The first set involves a robust clustering of the standard errors at the LMA level rather than the municipal one, both for OLS and PPML models, which enables to account for the possibility of VPT rates to be independently distributed within local labor markets due to workers' cross-municipal commuting[19].

2. In a second set of estimates, we directly apply the treatment at the LMA level, hypothesizing that the overall shock to the industry area of appurtenance of the municipality may matter as well as the actual shock to the municipality itself. We would expect a similar, positive significant effect on municipal ARs when extending the treatment area. Clustering is, again, at LMA level.

The level of aggregation of the outcome remains the municipal one.
In both hypotheses, the yielded estimates are consistent with the ones obtained at the municipal level; they are reported in Appendix G.

[18]The restricted samples, with their relative treatment discontinuity, are the following: 1) from 2018 to 2021 excluding 2020, with march 2018 as treatment threshold; 2) 2018 only, with march 2018 as threshold; 3) 2018-2019 only, with march 2018 as threshold; 4) 2018-2019 only, with march 2019 as threshold; 5) from 2018 to 2021 excluding 2020, with march 2019 as threshold; 6) 2019 only, with march 2019 as threshold; 7) 2019-2020 only, with march 2019 as threshold; 8) from 2018 to 2020, with march 2020 as threshold; 9) 2019-2020 only, with march 2020 as threshold; 10) 2020 only, with march 2020 as treatment threshold; 11) 2020-2021 only, with march 2020 as threshold; 12) from 2018 to 2021 excluding 2020, with march 2021 as threshold; 13) 2021 only, with march 2021 as threshold; 14) 2020-2021 only, with march 2021 as threshold; 15) from 2018 to 2021, with march 2021 as threshold

[19]A brief description of LMA level is reported in Figure G1, in Appendix G).

OLS results - By municipality of residence - SEs clustered at municipal level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR	(13) AR	(14) AR	(15) AR
$Post\ March\ 2018 * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.09653	0.06472	0.08486												
	[0.07505]	[0.08175]	[0.07739]												
$Post\ March\ 2019 * 1(Inactive\ Share_{q2/2020} \in Q_4)$				0.05436	0.01368	0.04662	0.05396								
				[0.05313]	[0.09276]	[0.06974]	[0.08085]								
$Post\ March\ 2020 * 1(Inactive\ Share_{q2/2020} \in Q_4)$								0.20488**	0.15689***	0.14117**		0.14289			
								[0.09449]	[0.05250]	[0.05838]		[0.08823]			
$Post\ March\ 2021 * 1(Inactive\ Share_{q2/2020} \in Q_4)$											0.4008		0.00559	-0.4315	0.01066
											[0.05540]		[0.10336]	[0.06281]	[0.05341]
Observations	94,836	34,612	63,224	94,836	31,612	63,224	63,224	31,612	94,836	63,224	94,836	63,224	31,612	63,224	126,448
R-squared	0.13586	0.31096	0.17926	0.13586	0.29820	0.17926	0.16994	0.28081	0.13358	0.17005	0.13589	0.16453	0.29015	0.16449	0.11216
Considered years	'18-'19, '21	'18	'18-'19	'18-'19, '21	'19	'18-'19	'19-'20	'20	'18-'20	'19-'20	'18-'19, '21	'20-'21	'21	'20-'21	'18-'21
Policy covariates								X	X		X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
OLS															
Mean	1.144	1.144	1.144	1.144	1.160	1.144	1.160	1.181	1.103	1.104	1.085	1.181	1.013	1.058	1.080

*** p<0.01, ** p<0.05, * p<0.1

Table 8: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

In the case of clustering only, the values do not change at all, as only SEs do, and not enough to compromise significance, (Table G1 and G2). In Table G3, when the treatment is considered at LMA level, coefficients on the fourth quartile of the inactive share shift down on average by a few p.p. compared to the baseline, although their magnitude is clearly comparable; the only exceptions are the unweighted estimates for both OLS and PPML, whose coefficients increase to 16.4 and 18.2 p.p. respectively (Column 5 and 11). All coefficients are significant at 1% confidence level.
In relative terms, values are still oscillating around 10% of the mean of the treated pre-treatment, with the higher unweighted estimates reaching 14-16% of the average value when including Province x Quarter−year FE indeed.
Concerning the the aggregation at hospital level, the yielded outcomes when we cluster SEs at LMA level are consistent with baseline estimates for the hospital aggregation framework. However, when we enlarge the scope of treatment administration to the LMA level, the OLS estimates return negative and slightly significant coefficients for the effect of the treatment on the municipal abortion rates by hospital. Such rates range, in absolute value, between 130 and 350 p.p., amounting to 13-36% circa of the abortion rate at hospital level, according to the specification. Estimates are significant at 10% level, except for the weighted specification without LHA x quarter FEs, which is significant at 5% (Column (4), Table G4). This may suggest the presence of significant confounders at the labor market level. However, being the direction of the effect negative (which is consistent with the anecdotal evidence in Figure 8 and Figure 10), such findings would lead us to assume that our baseline coefficients are not driven by a supply-side shortage in the control group, which is the case that could undermine our research hypothesis. The PPML checks deliver non-significant coefficients instead; such estimates can be neglected however, as the share of outcomes equal to zero substantially shrinks when we switch to the analysis at the health care facility level, as the focus is on the municipalities with hospitals only.

7.4 Geographical heterogeneity

By looking at Figure 4, a geographical stylized fact becomes immediately apparent: the inactive share, during the 2020's lock-down, was notably higher in Central and Northern Italian municipalities compared to those of the South. While the cause may reasonably be led back to the sectoral composition of the different parts of the country, it seems that the Centre-North is driving up our results however. Notwithstanding the presence of municipal FEs, which should capture all unobservable heterogeneity of such kind, we subset the sample into macro-areas (North, Center, and South), to assess whether the outcomes are brought forward by a North vs. South-type underlying asymmetry, or whether they are just being driven by septentrional towns with higher inactive share. Table 9 shows how the results are clearly driven by the Northern municipalities, as the suspended workers share has a significant impact in Northern Italy only. However, the internal consistency of the design within the Northern macro-area hints for the fact that the effect is led indeed by Northern Italy, but not by a mere North vs. South heterogeneity. As a matter of fact, in the Northern sub-sample it looks like that belonging to the third quartile of the distribution of the inactive share involves a significant increase in the AR as well, with coefficients ranging from 12 to 14 p.p., according to the specification. What emerges from the latter estimates is that the industrial and labor market composition of Northern Italian municipalities allowed for an abortion response to the inactive share at a lower "sensitivity" threshold. In such context, the median cut-off seems to matter the most. The aforementioned pattern may be due to cultural reasons, as abortions in Northern Italy concerned by the restricted sample are less hindered by cultural barriers (except for Veneto and Alto Adige). Therefore, the response in abortion rates might have been more "elastic" to the crisis. No effect seems to hold within Southern and Central areas.

OLS results - By municipality of residence - Municipal AR by macro-area

	(1) AR (North)	(2) AR (North)	(3) AR (Center)	(4) AR (Center)	(5) AR (South)	(6) AR (South)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.19098 ***	0.16360 ***	0.00555	0.03342	0.03087	0.01954
	[0.06749]	[0.05401]	[0.17073]	[0.12425]	[0.07455]	[0.06002]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.14382 **	0.12009 ***	0.18416	0.14645	0.03211	0.02817
	[0.05869]	[0.04581]	[0.14595]	[0.10643]	[0.06254]	[0.05065]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.00007	0.00375	0.03399	0.02947	0.07342	0.06292
	[0.05744]	[0.04472]	[0.13372]	[0.09751]	[0.06590]	[0.05204]
Observations	70,128	70,128	15,488	15,488	40,832	40,832
R-squared	0.11421	0.11609	0.10919	0.11644	0.10718	0.11519
Policy covariates	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter-year FE	X	X	X	X	X	X
Province x Quarter-year FE			X	X	X	X
Weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.083	1.083	1.240	1.240	1.102	1.102

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Analysis by macro-area: Columns 1 and 2 refer to the Northern municipalities' sub-sample. Columns 3 and 4 to the Central one. Columns 5 and 6 to the Southern area. *Mean* reports the mean of the treated units pre-treatment.

7.5 Abortion mobility

To strengthen our conclusion that a supply shortage of abortion services is not mattering in our baseline estimates, we follow up on our work with the model presented in this section. The restrictions in service provision would be a major issue to our findings if there was a heterogeneity in the direction of the supply behaviour of health care due to the treatment. To better clarify that, in response to higher levels of inactive share, hospitals could increase their supply in given areas, which could stimulate abortion seeking-behavior in those same zones (as we are aggregating by municipality of residence); on the other side, if areas with lower inactive share worsened their supply of VPT services, that conduct could discourage women to abort in their very same municipalities. Although this seems to be unrealistic if we look at the estimates we performed in the previous sections by aggregating at hospital level, the possibility of a supply-driven shift in VPTs is not such non-plausible hypothesis if we consider the times under exam: indeed, we are looking at the pandemic situation, characterised by a high number of mobility restrictions. To establish that our estimates are at most downward biased, we estimate, by means of an Diff-in-Diff strategy, an OLS LPM equation using, as outcome, the probability of seeking for an abortion in an area which is different of one's area of residence, the explanatory variables being, again, the three upper quartiles of the distribution of suspended workers. By "area" we mean either a different municipality or LMA, as we estimate two separate models. For the sake of validity, in the first case we remove from the sample all municipalities where no abortion service is provided (i.e., where there are no hospitals performing VPTs); in the second situation, we remove from the sample all municipalities that are part of LMAs which do not include any municipality where VPTs are performed. Although that would be of major interest, we do not disentangle whether the absence of performed abortions is due to to the lack of health care institutions in a municipality (which certainly holds for the bulk of small ones, or LMA containing mostly small ones), due to the absence of a gynaecology ward in such areas or due to conscientious objection applied to entire hospitals. In the present settings, we are just interested into seeing whether women seek for a VPT in a different place than the one where they reside in, for reasons to be credited to the treatment. Indeed, if the increase in abortion was driven by supply reductions in areas with lower inactive share, then we would observe a negative relationship between suspended workers and abortions performed in a different municipality (or LMA), since those women would be willing to travel across municipalities or broader areas to seek for the interruption of a pregnancy. In our restricted samples, we count 304 municipalities where VPTs are performed, which amount to 3.8% of the total number of Italian municipalities, for a total of 118,351 individual observations; then, we count 251 LMAs where VPTs are performed, which amount to 41% of the total number of Italian LMAs, for a total of 210,445 observations. Note that in this additional model we do not aggregate data by municipality, but just estimate the probability of aborting in another area ("abortion mobility") for individual women, conditional on the fact they have aborted already. We follow the same approach used by Balia et al., 2020, for cross-regional patient mobility flows, as they estimate the probability of seeking for health care in a different region by means of a binary outcome likewise[20]. Given that the analysis is at the woman's level, it requires the use of a set of various individual controls for the female characteristics, which are provided by ISTAT in the VPT dataset. We report some descriptives about the relevant variables (together with the total share of abortion mobility) in Table H1, Appendix H. We discard observations with missing information on the controls, so that we remain with 97,550 observations in the sample of inter-municipal VPTs, and 173,791 in the one of inter-LMA mobility. We estimate the following equation via OLS, clustering SEs at municipal level:

$$\begin{aligned} Y_{imt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(Inactive\ Share_{q2/2020} \in Q_k) + X1'_{it}\beta + X2'_{it}\beta + X3'_{mt}\beta + \\ + \tau_m + \theta_{m(VPT)} + \eta_h + \gamma_t + \delta_{p,t} + \varepsilon_{imt} \end{aligned} \tag{8}$$

The outcome is Y_{imt}, a dummy variable equalling 1 if woman i residing in municipality m undergoes a VPT in quarter-year t, in a municipality differing from m ($m \neq m(VPT)$), provided that in m there are facilities where VPTs are performed (i.e., abortions occur in such municipality); we call it inter-municipal mobility. The dummies for the treatment are the same as in the baseline specification Equation 3, and are always at the municipal level. $X1'_{it}$ is a vector including a set of health and fertility-related individual controls for the aborting woman, as in characteristics related to past reproductive behavior and health circumstances (number of previous live births, stillbirths, miscarriages and VPTs) and health-related features regarding the present VPT procedure (gestational age, weeks of amenorrhea, whether the intervention is urgent, whether there are complications or child malformations, whether the abortion is medical). Vector $X2'_{it}$ contains demographics instead (age, whether the woman is an Italian citizen, marital status) and categorical socio-economic regressors (educational attainment, professional condition and position, economic branch of professional activity). $X3'_{mt}$ are the already-used restriction policy municipal covariates, including population of females aged 15-49 also. We include FEs for the municipality of residence of the woman (τ_m), FEs for the municipality where the abortion is performed ($\theta_{m(VPT)}$), hospital FEs (η_h) and time FEs (γ_t). We also add, in a further specification, the above mentioned provincial-quarter-year interacted FEs ($\delta_{p,t}$). Then, we estimate a parallel equation which mirrors Equation 8, with few variations: the outcome becomes Y_{imlt}, a dummy variable equalling 1 if woman i residing in municipality m, part of LMA l undergoes an abortion in quarter-year t in a LMA which is different from l ($m \in l \wedge m(VPT) \notin l$), which we call inter-LMA abortion mobility. The treatment is applied at the LMA level in this case, and SEs are clustered at LMA level as well.

[20] For a more complete framework, which also embodies a theoretical modelization, see Finkelstein et al., 2016

OLS results - Mobility - SEs clustered at municipal level

	(1) Share of extra-mun. VPTs	(2) Share of extra-mun. VPTs	(3) Share of extra-mun. VPTs	(4) Share of extra-mun. VPTs	(5) Share of extra-mun. VPTs	(6) Share of extra-mun. VPTs	(7) Share of extra-mun. VPTs	(8) Share of extra-mun. VPTs
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.05254	0.05083	0.05595	0.04880	0.04717	0.05222	0.09667	0.09477
	**	**	***	**	**	**	**	**
	[0.02120]	[0.02130]	[0.02158]	[0.02120]	[0.02127]	[0.02154]	[0.04253]	[0.04406]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05587	0.05518	0.06007	0.05434	0.05373	0.05854	0.08353	0.08735
	***	***	***	***	***	***	***	**
	[0.01509]	[0.01509]	[0.01592]	[0.01528]	[0.01525]	[0.01607]	[0.03190]	[0.03371]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.00225	0.001144	0.00554	0.00223	0.00117	0.00550	0.03064	0.003457
	[0.00652]	[0.00667]	[0.00730]	[0.00589]	[0.00605]	[0.00668]	[0.03169]	[0.03305]
Observations	97,545	97,545	97,545	97,545	97,545	97,545	97,528	97,528
R-squared	0.55790	0.56319	0.56323	0.56454	0.56948	0.56952	0.57748	0.58296
Individual Controls		X	X		X	X	X	X
Policy covariates			X			X		X
Other municipal covariates			X			X		X
Municipal FE	X	X	X	X	X	X	X	X
Municipality of the VPT FE	X	X	X	X	X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE							X	X
Population weight				X	X	X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387

*** p<0.01, ** p<0.05, * p<0.1

Table 10: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

OLS results - Mobility - SEs clustered at LMA level

	(1) Share of extra-LMA VPTs	(2) Share of extra-LMA VPTs	(3) Share of extra-LMA VPTs	(4) Share of extra-LMA VPTs	(5) Share of extra-LMA VPTs	(6) Share of extra-LMA VPTs	(7) Share of extra-LMA VPTs	(8) Share of extra-LMA VPTs
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.03187	0.03224	0.03476	0.03099	0.03120	0.03429	0.04420	0.04236
	***	***	***	***	***	***	*	*
	[0.01026]	[0.01037]	[0.01074]	[0.01015]	[0.01027]	[0.01056]	[0.02464]	[0.02468]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.00914	0.00944	0.01180	0.00769	0.00796	0.01081	0.03764	0.03939
	[0.00920]	[0.00937]	[0.00950]	[0.00855]	[0.00876]	[0.00879]	[0.02397]	[0.02397]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.00056	-0.00032	0.00222	-0.00111	-0.00096	0.00211	-0.02996	-0.03278
	[0.00851]	[0.00878]	[0.00926]	[0.00777]	[0.00806]	[0.00851]	[0.03203]	[0.03201]
Observations	173,392	173,392	173,392	173,392	173,392	173,392	173,390	173,390
R-squared	0.56226	0.56692	0.56694	0.56853	0.57300	0.57302	0.57677	0.58263
Individual Controls		X	X		X	X	X	X
Policy covariates			X			X		X
Other municipal covariates			X			X		X
Municipal FE	X	X	X	X	X	X	X	X
Municipality of the VPT FE	X	X	X	X	X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X		
Population weight				X	X	X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385

*** p<0.01, ** p<0.05, * p<0.1

Table 11: SEs clustered at LMA level. *Mean* reports the mean of the treated units pre-treatment.

Conditional on having hospitals where abortions can be performed in one's own area of residence, Table 10 and 11 display that higher levels of inactive share increase the probability of seeking for a VPT in another area, thus confirming the initial conjecture that a potential restriction in supply is not undermining the validity of our estimates: we indeed observe that, mobility restrictions notwithstanding, women were moving across areas to abort. Furthermore, such women are the ones in municipalities more affected by economic closures, rather than those living in less affected municipalities, where hospital clogging was a feasibly more serious issue if we assume suspension to be negatively correlated with contagions. If we consider the inter-municipal mobility, we actually acknowledge that both coefficients on the third and fourth quartile of the distribution of the inactive share are significant and positive, at 1% and 5% respectively. Estimates range between 5.3 and 8.7 p.p for the coefficients on the third quartile, depending on the specification; such values amount to 12-22% of the mean of the treated pre-treatment. Concerning the fourth quartile, estimates range between 4.7 and 9.7 p.p. (which is 25% of the mean), at a lower level of significance. Such estimates suggest that the relevant threshold in separating treated from non-treated municipalities, for the inter-municipal abortion mobility, ought to be the median. When we look at the greater sample of abortions occurring in LMAs with abortion facilities only, by assessing the impact of suspended workers on inter-LMA mobility, the situation resembles more to our baseline estimates. Only the coefficients on the fourth quartile of the distribution are significant, and they range between 3.1 and 4.4 p.p, more or less 8-11% of the mean value of the treated units pre-treatment (although the highest coefficients are only significant at 10%). Such difference in results between inter-municipal and inter-LMA mobility comes not unexpected. It is not non-credible to seek for an abortion, irrespective of mobility restrictions, in another municipality, even when one's own municipality of residence has its own facilities. The reasons can be various: the low cost of commuting across close municipalities allows for the choice amongst different institutions, according to one's own preferences. This could hold especially for small municipalities which borders great province chief towns or big cities, and belonging to the same LMA (Rome, Milan, Naples, Turin and so forth), so that, although having healthcare facilities within the borders of their own municipalities of residence, they would rather travel few kilometres to reach metropolitan institutions. Eventually, social stigma could pressure people to change the municipality where to abort, in order to be sure of preserving anonymity. When the considered area is LMA instead, the cost of traveling increase, at a point that it may offset the social stigma pressure, whereas the reasoning about small towns bordering big cities does not hold anymore, as they are usually all part of the same LMA.

To sum up, this analysis seems to suggest that the inactive share does not play a role in shifting the supply of VPT services in directions that significantly matter in a hypothetical bias of our abortion baseline estimates. The results show that women seeking for abortion and driven by the forces identified in our settings were able to move across municipalities or even LMAs to undergo a VPT anyway. This is consistent with our initial findings, which show quarterly abortion rates of municipalities hit the most by the workers' suspension increasing by 10% circa. We check for the existence of pre-trend by estimating an Event-study in the fashion of the one specified by Equation 7, but modifying the features in order to extrapolate the coefficient on the treatment estimated, on average, by the TWFE Did model in Equation 8. Given the role of the median threshold for our mobility estimates, we report the Event-study considering the median one as the relevant threshold, in the Figure H1 and H2, in Appendix H. While the graphs hint for the absence of significant pre-trends, it is evident how, compared to the event-studies of the baseline models, in the case of mobility, the "take up" for the outcome is delayed, and it is evidently driven by seasonal patterns. In any case, this does not concern the validity of the baseline estimates, as the scope of the present exercise is to prove the supply did not concern women seeking for abortion due to restrictions and clogging in areas with more suspended jobs.

8 Discussion

We acknowledged the positive impact of the policy-related economic consequences of the pandemic outbreak on abortion rates, also showing that there was no negative effect of a credible although non-relevant restriction of the supply of the VPT services on abortion rates. If we could manage to disentangle one, it should however be downward biasing our estimations in terms of general equilibrium outcomes. After having performed robustness checks, we try to disentangle the role of the hypothesized mechanisms causing VPT rates to be relatively shifting in areas with higher shares of suspended workers in the months following the governmental closures.

8.1 Heterogeneity analysis

8.1.1 Socio-economic information

We already highlighted how our story of economic insecurity does not necessarily overlap with the shift in unemployment that can be recovered from official statistics and early studies on the pandemic, as higher rates of suspension did not coincide with higher levels of unemployment (Figure C1, see also Cerqua and Letta, 2022). However, if the economic insecurity reasoning held, we would be led to believe that a higher share of inactive workers in the service sectors, with a higher prevalence of women, would be the determinant factor in explaining the response in ARs. In parallel, we would credibly observe the abortion rates of women active in the service sector to be more "responsive" in municipalities with higher shares of inactive workers in the service sectors, and the same would hold with respect to the industry sector[21]. A greater proportion of suspended workers in one's own sector of affiliation could be leading to terminate an unplanned pregnancy because of fear of losing an already suspended job due to its "non-essentiality", a downward shift in income in such non-essential profession average (or individual) wages, an overall bleak prospect for future development in that given sector. We perform some heterogeneity estimates to see whether the overall inactive share distribution affects differently the abortion rates of women who are, in order, not in professional condition, or, if active, occupied in the private service sector, in industry or in public administration. The latter ones, in particular, shall not be answering to our treatment by hypothesis, as the suspended workers' share is based on statistics which exclude civil servants. Then, we do the same by differentiating the treatment into the distribution of inactive share of service workers and that of industry workers, to separate the two channels. We exclude women active in agriculture, hunting and fishing and those on whom we do not have professional information from the analysis.

[21] Of course, this would hold as well in the case of non-single women who are partnered to an individual whose job is more likely to have been suspended. More on this in the following pages.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR not in prof. condition	(2) AR services	(3) AR industry	(4) AR P.A.	(5) AR not in prof. condition	(6) AR services	(7) AR industry	(8) AR P.A
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.06984**	0.04511	0.01454	0.01346	0.07923*	0.06565*	0.06994**	0.03354
	[0.03532]	[0.02936]	[0.01293]	[0.01030]	[0.04143]	[0.03614]	[0.03041]	[0.02889]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05002	0.02213	0.00006	-0.00022	0.05816*	0.03723	0.01691	-0.01395
	[0.03094]	[0.02465]	[0.01083]	[0.00891]	[0.03413]	[0.03159]	[0.02738]	[0.02199]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03253	0.00178	0.00934	0.00574	0.03426	0.01468	0.07230**	0.00520
	[0.02852]	[0.02204]	[0.00968]	[0.00806]	[0.03073]	[0.02830]	[0.02840]	[0.01935]
Observations	126,448	126,448	126,448	126,448	105,104	97,719	36,465	12,136
R-squared	0.010409	0.08890	0.07934	0.07679				
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.508	0.376	0.0682	0.0350	0.508	0.376	0.00682	0.0350

*** p<0.01, ** p<0.05, * p<0.1

Table 12: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

The estimates in Table 12 seem not to be any sensitive to the professional branch background of the aborting women, thus leading us to the suggestion that the branch of activity does influence only partly the VPT decision. Actually, the only significant estimates for the abortion rates' heterogeneity by branch of activity, are the OLS and PPML coefficients on the fourth quartile of the distribution (at 5% and 10% respectively, with the third quartile for PPML estimates being significant at 10% as well) for women not in professional condition, whose AR is greater by 14%-16% the mean if residing in a municipality of the fourth quartile. PPML estimates for women in services (at 10%) and industry (at 5%) seems to be affected by the treatment in the PPML estimates, although the significant coefficient on the second quartile of the distribution for women active in industry does lead to ambiguous, non-linear conclusions (Column (7)). As expected, civil servants' municipal ARs do not respond to the treatment.

If we differentiate the inactive share across sectors (private services and industry), the hypothesis of a direct, branch-related economic insecurity trigger loses even more relevance. Although never significant, it seems like the abortion rate of service women is negatively correlated to higher quartiles of the inactive share in the service sector itself, compared to the reference category, which is the first quartile of the distribution, at least for OLS estimates. However, again, they are not statistically different from zero. The relevant significant coefficients (both for OLS and PPML) on the treatment are the ones on the fourth quartile of the distribution of inactive workers of the industry sector for women who are not active in any professional branch (Column (5) of Table 13 and Table 14; both at 5%). Both estimates range between 8 and 10 p.p., telling us about a positive percentage difference by around 20% circa in the abortion rate for that category of women.

OLS results - By municipality of residence - SEs clustered at municipal level

	(1) AR not in prof. condition	(2) AR services	(3) AR industry	(4) AR P.A.	(5) AR not in prof. condition	(6) AR services	(7) AR industry	(8) AR P.A
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (services)$	0.00888	-0.01529	0.01282	0.00827				
	[0.03517]	[0.02728]	[0.01148]	[0.01118]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (services)$	-0.01111	-0.02795	0.01076	0.00897				
	[0.03013]	[0.02217]	[0.01027]	[0.00729]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (services)$	-0.03148	-0.01314	0.00714	0.00893				
	[0.02931]	[0.02264]	[0.00957]	[0.00718]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (industry)$					0.07977 **	0.04531	-0.00052	0.00780
					[0.03712]	[0.02958]	[0.01460]	[0.00917]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (industry)$					0.03449	0.00661	-0.00830	0.0150
					[0.03519]	[0.02689]	[0.01157]	[0.01012]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (industry)$					0.05034	-0.00635	-0.01250	0.00308
					[0.03118]	[0.02338]	[0.01038]	[0.00840]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10406	0.08887	0.07932	0.07678	0.10410	0.08890	0.07933	0.07678
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.572	0.410	0.0317	0.0507	0.512	0.361	0.0757	0.0363

*** p<0.01, ** p<0.05, * p<0.1

Table 13: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR not in prof. condition	(2) AR services	(3) AR industry	(4) AR P.A.	(5) AR not in prof. condition	(6) AR services	(7) AR industry	(8) AR P.A
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (services)$	0.00316	-0.00961	0.01335	0.00681				
	[0.04292]	[0.03474]	[0.03339]	[0.02680]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (services)$	-0.01117	-0.02102	0.04114 *	0.01872				
	[0.03472]	[0.02914]	[0.02401]	[0.02135]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (services)$	-0.03788	-0.00893	0.03069	0.01074				
	[0.03450]	[0.03017]	[0.02013]	[0.02015]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (industry)$					0.10119 **	0.05653	0.03940	0.01968
					[0.04326]	[0.03707]	[0.03877]	[0.02661]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (industry)$					0.03869	0.00980	0.01252	0.02236
					[0.03911]	[0.03381]	[0.03643]	[0.02447]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (industry)$					0.05503 *	-0.01578	-0.01671	-0.00502
					[0.03343]	[0.02995]	[0.03898]	[0.02189]
Observations	105,104	97,719	36,465	42,136	105,104	97,719	36,465	42,136
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.572	0.410	0.0347	0.0507	0.512	0.361	0.0757	0.0363

*** p<0.01, ** p<0.05, * p<0.1

Table 14: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

The low significance of the analysis heterogeneized by branch of activity cannot lead us to unambiguous conclusions. However, the slightly significant role played by the inactive share of the industry sector for inactive women may suggest a different pattern in abortion decisions with respect to that of the mere economic insecurity. In fact, to parity of people sheltered at home because of the lockdown, the results may suggest that there was an increase in unplanned pregnancies amongst couples where the male partner was active in industry jobs that were suspended during the pandemic (as we only observe a, quite ambiguous, significant impact of the treatment on the abortion rate of women in industry in the PPML regressiont, though coupled with a significant effect for women in the second quartile of the distribution). This might have led to more time together and to a possible relative change in unplanned pregnancies, with such behavior ceasing after the reintegration of suspended workers. This pattern could have not been seen amongst service workers as workers active in the service sectors, although suspended, might still have performed some tasks by remote working, which is way more common amongst services rather than industrial jobs. To corroborate further such hypothesis, we perform the same analysis through the heterogeneization of the outcome by women's marital status. As the effect observed is concentrated along the months immediately after the lock-down, we would expect a higher effect amongst married couples, as unplanned pregnancies were way more unlikely to occur among non-cohabiting partners (they were actually almost impossible during the lock-down, which is the reason credited by Trommlerová and González, 2024 to the drop in Spanish abortions during the lock-down), given the restrictions on mobility and social gatherings. Restrictions were being gradually loosened during the post-lockdown period, but they were still in place until June.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR single	(2) AR married	(3) AR separated	(4) AR widowed	(5) AR single	(6) AR married	(7) AR separated	(8) AR widowed
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.07200 *	0.06963 **	-0.00023	-0.00282	0.08556 *	0.08473 **	0.00051	-0.01011
	[0.04115]	[0.02993]	[0.00511]	[0.00799]	[0.04597]	[0.03642]	[0.05367]	[0.02625]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.03583	0.03278	-0.00147	-0.00378	0.04031	0.04763	0.02850	-0.01840
	[0.038446]	[0.02634]	[0.00432]	[0.00546]	[0.03935]	[0.03020]	[0.04788]	[0.01976]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.00633	0.02771	-000166	-0.00089	0.00477	0.04359	-0.03472	-0.00135
	[0.03005]	[0.02468]	[0.00367]	[0.00469]	[0.03399]	[0.02888]	[0.03992]	[0.01950]
Observations	126,448	126,448	126,448	126,448	108,608	98,096	17,105	29,934
R-squared	0.10016	0.09405	0.08802	0.07705				
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE								
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.631	0.379	0.0284	0.0259	0.631	0.379	0.0284	0.0259

*** p<0.01, ** p<0.05, * p<0.1

Table 15: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

As expected, Table 15 shows that the coefficients on the fourth quartile of the distribution for married women are significant (at 5% level), both for OLS and PPML estimates (Columns (2) and (6)). The estimates range between 7 to 8.6 p.p. (more or less 15% of the respective AR). The treatment also impacts single women though, even if at 10% level of significance only. By contrast, when looking at the professional condition of the women, regardless their branch of activity (Table 16, we retrieve, however, a significant impact (at 10%) of workers' suspension on employed women's VPTs, possibly suggesting that the increase in unplanned pregnancies is not driven by the suspension of male partners only. Thus, although the effect does not seem to be led by the higher activity of women in pre-pandemic service sectors, and provided that their share of employment was higher in non-essential jobs relative to men, we may hypothesize that th suspension in industrial jobs may be contributing to the observed shift (which, again, ranges between 6.6 and 8.3 p.p., Columns (1) and (6) of Table 16). This is intuitive nonetheless: it is more likely, for employed women staying home because their jobs have been suspended, to review their sexual conduct upwards, compared to unemployed women, for instance. Still in line with previous expectations, we observe an effect, significant at 10% level only, on the AR of first job seekers, although for the PPML estimates. Table 17 show instead two relevant results, one in perfect line with previous estimates (as in, the significant impact of non-working women), the other quite surprising. Indeed, women employed in white collar jobs see a relative effect of 5.8 p.p. (OLS) and 8.9 p.p. (PPML) due to the treatment, which amount to a quite high 30% and 47% of the pre-treatment AR for such category.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR employed	(2) AR unemployed	(3) AR first job	(4) AR housewives	(5) AR students	(6) AR employed	(7) AR unemployed	(8) AR first job	(9) AR housewives	(10) AR students
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.06620*	0.02522	0.00635	0.02555	0.01256	0.08302*	0.02151	0.08251*	0.04394	0.02478
	[0.03878]	[0.02489]	[0.00558]	[0.01793]	[0.01422]	[0.04275]	[0.03188]	[0.04392]	[0.02926]	[0.02517]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.01299	0.02433	0.00297	0.02361	0.00077	0.02264	0.02632	0.04602	0.03494	0.00620
	[0.03095]	[0.02158]	[0.00466]	[0.01621]	[0.01212]	[0.03769]	[0.02590]	[0.03844]	[0.02463]	[0.02093]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.00507	0.01957	0.00163	0.01958	-0.00816	0.01325	0.01922	0.00205	0.02821	-0.01178
	[0.02757]	[0.01990]	[0.00466]	[0.01571]	[0.01078]	[0.03436]	[0.02408]	[0.02934]	[0.02188]	[0.01872]
Observations	126,448	126,448	126,448	126,448	126,448	105,104	84,964	12,310	79,273	66,568
R-squared	0.09782	0.08834	0.07476	0.10163	0.07800					
Policy covariates	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X
Province x Quarter¯year FE	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML
Mean	0.571	0.213	0.011	0.179	0.0929	0.571	0.213	0.011	0.179	0.0929

*** p<0.01, ** p<0.05, * p<0.1

Table 16: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR no prof. condition	(2) AR entrepreneur	(3) AR self-employed	(4) AR manager	(5) AR white collar	(6) AR blue collar	(7) AR no prof. condition	(8) AR entrepreneur	(9) AR self-employed	(10) AR manager	(11) AR white collar	(12) AR blue collar
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.06984**	-0.01412	-0.00282	0.00225	0.05799***	0.01651	0.07923*	-0.03557	0.01378	0.1933	0.08913***	0.03614
	[0.03532]	[0.01035]	[0.01039]	[0.00459]	[0.02196]	[0.02348]	[0.04143]	[0.02641]	[0.03403]	[0.03133]	[0.03113]	[0.03293]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05002	-0.00319	-0.00513	0.00570	0.01535	0.00210	0.05816*	-0.00320	-0.01639	0.04996	0.03405	0.01178
	[0.03094]	[0.00702]	[0.00750]	[0.00390]	[0.01645]	[0.02003]	[0.03413]	[0.02106]	[0.02691]	[0.02688]	[0.02601]	[0.02957]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03523	-0.00549	0.00010	0.00635*	0.00476	0.00081	0.03426	-0.02482	0.00791	0.03498	0.01946	0.00722
	[0.02582]	[0.00678]	[0.00635]	[0.00352]	[0.01498]	[0.01893]	[0.03073]	[0.01942]	[0.02468]	[0.02476]	[0.02439]	[0.02811]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	105,104	41,184	34,584	17,641	81,622	78,897
R-squared	0.10409	0.07445	0.07328	0.07299	0.07979	0.08130						
Policy covariates	X	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter_year FE	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter_year FE	X	X	X	X	X	X	X	X	X	X	X	X
Policy covariates	X	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.508	0.0517	0.0364	0.0147	0.191	0.200	0.508	0.0517	0.0364	0.0147	0.191	0.200

*** p<0.01, ** p<0.05, * p<0.1

Table 17: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

8.1.2 Women with previous pregnancies (extensive margin)

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR with previous pregnancies	(2) AR with no previous pregnancies	(3) AR with previous deliveries	(4) AR with previous abortions	(5) AR with previous pregnancies	(6) AR with no previous pregnancies	(7) AR with previous deliveries	(8) AR with previous abortions
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.10948***	0.02238	0.09800**	0.04712	0.13273***	0.2771	0.12369***	0.06329*
	[0.04144]	[0.03154]	[0.03974]	[0.03186]	[0.04645]	[0.03877]	[0.04505]	[0.03698]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.06753**	-0.00302	0.06796**	0.01226	0.08275**	-0.00484	0.08565**	0.01967
	[0.03442]	[0.02778]	[0.03243]	[0.02585]	[0.03889]	[0.03327]	[0.03699]	[0.03147]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.05178*	-0.01648	0.04370**	0.02988	0.07003*	-0.02193*	0.06365	0.04790
	[0.03132]	[0.02474]	[0.02997]	[0.02366]	[0.03513]	[0.02974]	[0.03390]	[0.02892]
Observations	126,448	126,448	126,448	126,448	109,632	100,112	107,600	95,525
R-squared	0.11128	0.07972	0.10592	0.10431				
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.729	0.366	0.650	0.357	0.729	0.366	0.650	0.357

*** p<0.01, ** p<0.05, * p<0.1

Table 18: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

We exploit a further source of heterogeneity by looking at abortion rates across women who either had or had not previous pregnancies (of any kind) before their recorded abortion. In this regard, we already acknowledged how the effect is significant and positive for women not in professional condition (and slightly for housewives), for married women and employed ones. Given that, we would expect that women having had previous pregnancies already would behave differently from those never having had one. We can distinguish between live births, stillbirths, miscarriages and previous voluntary abortions. We start by examining abortion rates of women with no previous pregnancies, those with *at least one* previous pregnancy (live births+stillbirths+miscarriages+VPTs), those with *at least* one delivery (live births+stillbirths), and those with *at least* one previous abortion (miscarriages+VPTs). We only flag women with dummy indicators equal to 1 if they report one of such characteristics and 0 otherwise, without accounting for the actual number of previous pregnancies, in doing this accounting for the extensive margin of fertility choices only. Table 18 shows that the coefficients on the abortion rate for women with previous pregnancies are positive for municipalities in the upper three quartiles reported in the table, relative to the reference category, both for PPML and OLS estimates (Col. (1) and (5)). Although in this case the difference between the upper quartile (which we assumed to be the treatment in the baseline DiD specification) and the other two is not so clear-cut, we observe how both the statistical significance (5% for the 2^{nd} and 3^{rd} quartiles, 1% for the 1^{st}) and the magnitude of the coefficients are definitely increasing in the inactive share portions of the municipal distribution, although SEs does not suggest the linear increase ought to be considered significant. On the other side, we observe no effect for women with no previous pregnancies before the reported VPT (Col. (2) and (6)). The effect is mostly driven by women who had already delivered newborns before the abortion, whose pattern mirrors the abortion rate of women with previous pregnancies without distinguishing between abortions and deliveries. Nonetheless, there is a slightly significant impact (at 10%), amounting to 1.6 p.p. (13% of the mean of the treated pre-treatment) of being a municipality in the fourth quartile of the inactive share of the distribution and the abortion rate of women with

previous VPTs and miscarriages, but only in the PPML estimates (Col. (8)).
The table commented above shed some light on the categories of women led to either terminate or not their pregnancies. It appears that women with previous deliveries (many of them mothers already, possibly) aborted more in treated municipalities. The reason we observe this result might be twofold:

1. Women with previous deliveries are more likely to be mothers already, therefore to currently be in a relationship, and possibly even married. As married women are the ones more likely to significantly abort, according to our estimates, the positive coefficient may be uniquely pushed upwards by the larger amount of time spent home by partners during the job suspension, which boosted sexual activity;

2. Women who become unwillingly pregnant during the pandemic may be more likely to abort if they had previous deliveries, since they are possibly mothers already, and they may prefer to pause their fertility in such hard times due to socio-economic considerations, to parity of sexual activity.

One mechanism does not exclude the other; 1) women with no previous pregnancies are more likely not to be in a stable relationship or married, thus VPTs may fall due to a decrease in sexual activity during lockdowns and closures (although we observe some level of significance for single women also); 2) women in a relationship but without kids are less economically constrained (or they perceive to be less economically constrained in a context of overall economic insecurity) if they get pregnant, so they may be willing to carry on their pregnancy.
Since we still cannot be able to distinguish between an increase in sexual activity and the insecurity-related socio-economic considerations, we need to further explore the heterogeneous results according to 1) the type of pregnancy experienced by the aborting women in the past (stillbirth, livebirth, miscarriage, or VPT); 2) the actual number of delivered children or VPTs performed prior to the current abortion; 3) the overall response of pregnancies resulting into live births in the time-span under consideration (we tackle the latter in the next section).

8.1.3 Type of previous pregnancy (extensive margin)

We build another index telling whether the woman had a previous pregnancy, distinguishing by one of the four mentioned types (livebirth, stillbirth, miscarriage, voluntary abortion), irrespective on the actual number of pregnancies. Then, we perform the estimates on the municipal abortion rates in the very same fashion as the ones put in place in the previous paragraph.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR with previous live births	(2) AR with previous stillbirths	(3) AR with previous miscarriages	(4) AR with previous VPTs	(5) AR with previous live births	(6) AR with previous stillbirths	(7) AR with previous miscarriages	(8) AR with previous VPTs
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.09660	0.00297	-0.01574	0.05414	0.12274	0.02151	-0.01620	0.07755
	**			**	***			**
	[0.03957]	[0.00321]	[0.02222]	[0.02446]	[0.04481]	[0.03845]	[0.03022]	[0.03266]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.06636	0.00354	-0.01006	0.01331	0.08431	-0.02675	-0.00769	0.01510
	**				**			
	[0.03236]	[0.00250]	[0.01667]	[0.02181]	[0.03690]	[0.03254]	[0.02549]	[0.02880]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.04171	0.00376	-0.01272	0.03215	0.06177	0.00298	-0.01149	0.04935
		*			*			*
	[0.02990]	[0.00218]	[0.01554]	[0.01979]	[0.02282]	[0.03003]	[0.02367]	[0.02574]
Observations	126,448	126,448	126,448	126,448	107,552	8,909	77,276	84,020
R-squared	0.10601	0.07487	0.08131	0.09652				
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE								
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.649	0.00672	0.166	0.227	0.649	0.00672	0.166	0.227

*** p<0.01, ** p<0.05, * p<0.1

Table 19: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

Estimates from Table 19 help corroborating the hypothesis that there is a positive relationship between the abortion rates for women who had delivered at least once already and the position of the municipality in the distribution of the inactive share. The coefficients, again, are increasing as the distribution gets closer to the right tail (relative to the lowest quartile), with the estimates on the fourth quartiles being greater and more significant (9.7 p.p. for the OLS, 12.8 p.p. for the PPML, about 15% and 20% of the mean respectively, Col. (1) and (5) of Table 23). Coefficients on stillbirths are non significant, except for the 2^{nd} quartile of the OLS estimates (Col. (2)); overall, they contribute to suggest that mothers with kids already are the ones more likely to abort, conditional on being gotten pregnant already in the past. Concerning abortions, we observe that mostly previous VPTs matter in influencing upwards the abortion rates with respect to the inactive share. Being a municipality in the treatment quartile means having a differential effect in the AR of women with had voluntary aborted in the past by 5.4 p.p. (OLS) and 7.8 p.p. (PPML) at the 5% level, about 25% and and 34% of the average pre- average rate, compared to other quartiles. In this regard, this might be a hint towards the fact that women who, on average, had already voluntary aborted, are more likely to voluntarily abort again in the context of an exogenous shock.

8.1.4 Number of previous live births and VPTs (intensive margin)

The investigation of the link between abortion and previous fertility shall not be limited to considerations regarding the extensive margin of motherhood only, as women may be deciding to abort depending on the number of children they have already (intensive margin) and not only on whether they had children or not. This might hold for VPTs too. In addition, differentiating across the abortion rates of women according to how many newborns they delivered in the past, allows to shed a bit of light on the driving mechanisms. Women with at least one livebirth and thus, plausibly, a current kid, are more likely to be in a stable relationship than those with no previous live births. In case of women who undertake VPTs and that had more than one previous livebirth, the likelihood of an increase in sexual activity being the driver of the abortion decision is intuitively lower: being at home a prolonged time with few or many children (in times of lockdowns and school closures) means a greater time devoted to childcare, thus making less plausible a positive shift in sexual activity. On the other hand, a higher number of children can be reasonably tied to larger economic constraints, which would lead mothers of many to resort to abortion in cases of vulnerable socio-economic condition. This would be consistent with fertility studies showing how highly educated women (possibly earning more) are more likely to become mothers, but they opt to smaller families (Aaronson et al., 2014, Baudin et al., 2015). We build a number of dummy indicators which are set equal to 1 if women had delivered already 1, 2, 3, 4 or at least 5 live births in the past, and 0 otherwise. In a subsequent analysis, we employ a similar set of indicators for the VPTs.

Both for OLS and PPML estimates (Table 20), we observe that the abortion rate for women with 1 or 2 previous live births is significant on the fourth and third quartiles of the inactive share distribution, at the 10% and 5% level respectively, at least for the OLS. Only women with 2 previous livebirth have a positive coefficient in the PPML framework on the upper quartile (at 5%). Compared to the Poisson estimates, the OLS estimates apparently slightly deflates the link between the inactive share distribution and the outcome.

There is no statistically and positive significant effect on the abortion rate of women with no children at the upper quartile (Col. (1) and Col. (7)), consistently with the results on women without previous pregnancies in Table 19.

Table 21 reports instead the effect of the economic closures on the municipal AR of women, according to their number of previous voluntary abortions. The Italian Ministry of Health highly stressed that not only the overall rates of VPTs have been decreasing over the years, but even more those of women who had already aborted once or multiple times in life, in doing so highlighting the importance of reproductive care facilities', and the enhancement of healthy sexual behavior and sensitisation (MoH, 2022). Here it looks like that, relative to the number of previous VPTs, only women who had already aborted once were more likely to do so in the described framework, as in those who were residing in a municipality in the upper quartile of the inactive share. The coefficient on such treatment is indeed significant at 5% for both OLS and PPML, amounting to 4.6 p.p. in the former case, and to 7.1 p.p. in the latter (Col. (2) and Col. (7)). If anything, the results corroborate the hypothesis that abortion rates increase with growing shares of suspended workers. When the outcome considered is the AR for women with zero previous VPTs, or women with more than one previous VPTs, findings are all negligible; the only exception is the OLS-estimated change in the AR of women with at least 4 VPTs, which amounts to 0.014 p.p. at the 5% level, 1% of the mean. This does not pass the PPML double-check testing though. The results seem to suggest that there could be an average disutility from the first abortion that may be dropping once women have already aborted once, being more "prepared" to the occurrence and thus less resistant to undergo a VPT in an altered conditions. It would be reasonable to think that, once used to the procedure, women who had prior plural abortions may be facing lower marginal costs in additional VPTs (possibly decreasingly due to health concerns), compared to the cost one would hypothetically face when undergoing the first abortion; as in, if the situation suddenly changes (because sexual activity rises or the socio-economic environment impairs), they would not hesitate more than others (those that have never aborted or did so fewer times) to abort. However, the estimates seem to completely disproof and actually contradict such hypothesis by lacking significance, except for 1 (both specifications) and 4 (only at OLS) prior VPTs, possibly due to the low statistical power of our estimations.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR with no previous live births	(2) AR with 1 previous livebirth	(3) AR with 2 previous live births	(4) AR with 3 previous live births	(5) AR with 4 previous live births	(6) AR with at least 5 live births	(7) AR with no previous live births	(8) AR with 1 previous livebirth	(9) AR with 2 previous live births	(10) AR with 3 previous live births	(11) AR with 4 previous live births	(12) AR with at least 5 live births
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.03527	0.03973*	0.06118**	-0.00059	-0.00570	0.00179	0.04195	0.04869	0.09200**	0.02031	-0.04016	0.00008
	[0.03425]	[0.02407]	[0.02716]	[0.01439]	[0.00536]	[0.00430]	[0.04081]	[0.03068]	[0.03624]	[0.02281]	[0.00000]	[0.03769]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	-0.01844	0.01232*	0.02547*	0.03007	-0.01330	-0.00304**	0.04051**	0.03069	0.05358	0.04526	0.06918	0.01153
	[0.02990]	[0.02111]	[0.02097]	[0.01158]	[0.00462]	[0.00417]	[0.03539]	[0.02618]	[0.02818]	[0.01953]	[0.00000]	[0.03769]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.00640	0.03297*	0.02566	-0.00948	-0.00648	-0.00274	-0.00974*	0.04180*	0.04765	-0.00539	-0.02907*	-0.06613
	[0.02644]	[0.01818]	[0.01986]	[0.01122]	[0.00484]	[0.00349]	[0.03137]	[0.02281]	[0.02657]	[0.01871]	[0.00000]	[0.03652]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	103,632	86,862	90,721	61,719	25,289	13,717
R-squared	0.08540	0.09021	0.10048	0.08365	0.07765	0.12733						
Policy covariates	X	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter`year FE	X	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.445	0.247	0.287	0.0901	0.0199	0.0140	0.445	0.247	0.287	0.0901	0.0199	0.0140

*** p<0.01, ** p<0.05, * p<0.1

Table 20: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

OLS and PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR with no previous VPTs	(2) AR with 1 previous VPT	(3) AR with 2 previous VPTs	(4) AR with 3 previous VPTs	(5) AR with at least 4 VPTs	(6) AR with no previous VPTs	(7) AR with 1 previous VPTs	(8) AR with 2 previous VPT	(9) AR with 3 previous VPTs	(10) AR with at least 4 VPTs
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.07773	0.04618**	0.00601	0.00162	0.00014**	0.08889	0.07133**	0.02992	0.03649	0.02478
	[0.04403]	[0.02013]	[0.01618]	[0.00405]	[0.00415]	[0.04875]	[0.02850]	[0.02747]	[0.03551]	[0.06687]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05121	0.00927	0.00404	0.00001	-0.00110	0.06112	0.01321	0.01946	0.00722	-0.02844
	[0.03427]	[0.01458]	[0.01296]	[0.00361]	[0.00329]	[0.03756]	[0.02258]	[0.01967]	[0.02191]	[0.04080]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.00315	0.02862	0.00375	-0.00173	-0.00027	0.00257	0.05102**	0.00904	-0.01681	-0.02844
	[0.03427]	[0.01458]	[0.01296]	[0.00361]	[0.00329]	[0.03756]	[0.02258]	[0.01967]	[0.02191]	[0.04080]
Observations	126,448	126,448	126,448	126,448	126,448	113,968	78,815	39,447	14,225	11,664
R-squared	0.09458	0.09009	0.07543	0.07370	0.13794					
Policy covariates	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE FE	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML
Mean	0.867	0.178	0.0380	0.00733	0.0132	0.867	0.178	0.0380	0.00733	0.0132

*** p<0.01, ** p<0.05, * p<0.1

Table 21: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

8.2 Live births

If sudden economic insecurity was the unique leading factor in the increase in VPTs, then we would possibly observe a drop in the pregnancies conceived in the period under question and resulting into live births nine months later. For instance, Lindo et al., 2020, show that the decrease in abortions caused by the closure of abortion clinics is paralleled by an increase in newborns, even if it still does not offset the drop in VPTs[22]. Similarly, when Cavallini, 2024, finds out that a SD increase in unemployment leads to a 0.25 SD increase in the abortion rate (IV estimates), the General Fertility Rate decreases by 0.95 SD. Was economic insecurity the main determinant, we would observe not only a rise in termination of unplanned pregnancies, but also a decrease in planned pregnancies (that turn to live births). To recover the number of pregnancies in the time under question, we use the daily data on birth registrations from 2018 and 2021. Since we are interested in the pregnancies occurring in the available time-span, we shift backwards the day of birth of the children by 270 days (9 months), to obtain a rough estimate of the daily conceptions occurring in Italy in the period under consideration and resulting into live births. In doing this, we unfortunately lose the last nine months of our sample, as we do not have the birth registrations in 2022, hence we cannot estimate conceptions happening from April to December 2021. We do not know the mother's municipality of residence, so we aggregate the births at the level of the municipality where the birth is registered. Aggregating by municipalities of birth would be meaningless, as almost all newborns are delivered in hospitals and healthcare institutions.[23]. We aggregate data at quarterly frequency to be consistent with our estimates on abortions. The model of reference is the same as Equation 3, but we use the General Fertility Rate as outcome (number of live births every 1000 women aged 15-49), although in terms of pregnancies (hence, the number of pregnancies resulting into live births 9 months later every 1000 women aged 15-49).
Although definitely non-significant at any level, we observe how all coefficients on the treatment have a positive direction (Table 22, PPML estimates in the Appendix K, Table K1). However, even if such coefficients were statistically significant, they would basically loom as a series of very low variations in the outcome, as they range between 8.3 and 19 p.p, at most 0.2% of the mean of the treated units pre-treatment. We further explore the pregnancy outcome by performing our analysis on a variety of temporal subsets, as we already did with the time placebo for abortion rates. The considered ranges are the same as those presented in Table K2, but without considering the march 2021 threshold. Table 22 shows however that the treatment has some slight impact on pregnancy rates, but is most likely random or seasonality-driven, as the dummy on post 2019 reports coefficient statistically different from zeros. Nevertheless, this is a further suggestion to the fact that higher shares of suspended workers increased the frequency of conceptions during the months following the policy, and while that brought about a significant differential effect in abortion rates in areas with many suspended jobs compared to

[22] Their conclusion leads to suggest the existence of alternative channels to explain what happens to "missing pregnancies" which do not end up neither in abortion statistics nor live births; possibly, clandestine or self-induced abortions.

[23] Some issues emerge nevertheless: in fact, assuming the kid's municipality of registration as the one where the mother resides too, would be a more precise restriction if we considered children of mothers who are married with the fathers of the registered kids only, possibly living together in a unique household. However, we do not know the "joint" parental marital status (as in, we can see whether both parents are married or not, but not whether they are married with each other), and we cannot conclude whether the husband of a married mother is the actual child's father and, thus, whether the municipality of residence of the newborn is the same as the mother's, in the case they live altogether. However, if both parents are individually married, it is highly unlikely the child has been conceived between two individuals not married with each other; only cheating is a reasonable exception to the previous circumstance. In any case, even when children are born out of wedlock, they usually live with their mothers, especially along the first months of their life; this holds even more for single mothers. Thus, we can reasonably assume that the municipality where the child is recorded is the one where the mother lives as well, regardless of her marital status, by which we do not need to restrict the sample eventually

those with fewer closures, a heterogeneous impact on live births during the following 9 months was not concurrently and unambiguously observed, possibly due to the different characteristics of childbirth conception decisions compared to that of VPTs. This still leaves some room for the economic insecurity conjecture.

To further highlight such conclusions, we perform our estimates on the abortivity ratio, i.e. the ratio between quarterly municipal VPTs and 1000 registered live births. This allows to assess whether the magnitude of the differential impact on abortions is statistically significant compared to what non-significantly happens to live births. OLS and PPML results are reported, respectively, in Table K3 and K4 in the appendix. OLS estimates in Columns 1-4 show that the coefficient on the treatment for the ratio ranges from 9.8 to 10.3 p.p. (about 8.4% of the mean average pre-treatment), and it significant at 5%. However, when the model is integrated by provincial trends, which is our most restrictive specification, the coefficients lose significance. PPML results are consistent, although the degree of statistical significance drop to 10%. Such estimations prove consistent with our baseline framework, although the most conservative ones seem to suggest that differential birth trends at the local level may be able to capture part of the investigated effects.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Pregnancy rate	(2) Pregnancy rate	(3) Pregnancy rate	(4) Pregnancy rate	(5) Pregnancy rate	(6) Pregnancy rate
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.18441	0.09482	0.18762	0.09508	0.19109	0.08248
	[0.15293]	[0.11474]	[0.15364]	[0.11531]	[0.17377]	[0.13211]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.07355	0.05142	0.06774	0.04531	0.04755	0.02530
	[0.12351]	[0.09754]	[0.12426]	[0.09808]	[0.13557]	[0.10721]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.05488	0.02759	0.05190	0.02512	0.03168	0.01163
	[0.11799]	[0.09259]	[0.11817]	[0.09278]	[0.12208]	[0.09572]
Observations	102,739	102,739	102,739	102,739	102,739	102,739
R-squared	0.12070	0.13008	0.12088	0.13024	0.13025	0.13877
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	7.722	7.722	7.722	7.722	7.722	7.722

*** p<0.01, ** p<0.05, * p<0.1

Table 22: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

8.2.1 Heterogeneity and live births

Data on birth registrations contain some valuable (albeit noisy) information about the family of provenience of the newborn: we perform some heterogeneity estimates to see whether some phenomenon of interest emerges. To mirror the estimates undertaken by using VPTs as outcome, we would need to know the mother's marital status. While we have the exact information on the maternal individual marital status, we do not know whether the mother had previous children exactly. We assume that the maternal municipality of residence coincides with the registration one; such assumption, appearing sloppy at first, has been already argued as credible; thus, individual marital status can work in the next heterogeneity analysis, reported in Table 23. As in the baseline specifications for pregnancies,

heterogeneizing by marital status and keeping the overall inactive share distribution in the right-hand side of the identifying equation does not deliver any significant, unambiguous estimate (Table K5, Appendix K). The pattern, although coefficients are all statistically close to zero, seems to mirror the one retrieved in the baseline. This why we disentangle the inactive share by industry and services to provide with some information more.
Contrarily to the results mentioned above, it seems like that there is a slight impact on the pregnancy rate of married women (or who are in a civil union) living in municipalities with the highest inactive share in the service sector. The coefficient is slightly positive and amounting to 27 p.p. (18.5% of the mean), statistically significant at 5% (OLS, Table 23, Col. (2)). However, the fact that OLS estimates are statistical significant may suggest that there was a slight trigger in planned pregnancies in municipalities with higher share of suspended workers from the service sectors for non-single parents (with respect to less affected municipalities), who possibly exploited the time available with their partners to adapt their fertility. The presence of an overall positive differential impact on pregnancies seems to be offset by municipalities with higher shares of suspended industrial workers, for which coefficients on most distributional dummies are non-significant (although this does not hold for divorced/separated women). It is worth noting, however, the the coefficients for pregnancies of single and married women, although not statistically different from zero, are negative on the upper quartiles relative to the reference for the industry sector. In this regard, especially considering the sectoral distribution of the impact on VPTs, it looks like that, while the shift in unplanned pregnancies (and therefore in abortion rates) is driven by municipalities with higher shares of suspended industrial workers, there was possibly a modest differential impact in sexual activity (either recreational or aimed at planned fertility) amongst married couples due to closures, which resulted in live births in municipalities with higher shares of service workers, counteracted in the overall pregnancy framework by including industrial workers to the specification.
No evident pattern is retrieved by differentiating the outcome according to the number of minor children already present in the household of the head of the family (Table K6).

8.3 Ancillary evidence

8.3.1 Domestic violence

As our analyses point towards credibly believing that the differential impact on VPTs was due mostly to a change in the underlying pregnancies, especially unplanned ones, we can inquire about whether the heterogeneous shift in such pregnancies was led by sexual violence by intimate partners. We reckon indeed how the phone calls to the national public hotline for domestic violence (1522) faced a visible spike immediately after the economic closures (Figure B1).
We aim at verifying whether a higher share of suspended workers brought about higher rates of calls to 1522 for Intimate Partner Violence, in a TWFE DiD specification which is almost the same as that we use as baseline for the abortions and live births. As many works underlined the role of salience in triggering reporting behaviors (A. R. Miller et al., 2022, 2023, Colagrossi et al., 2022, 2023), we try to overcome such bias by exploiting the provincial heterogeneity in the inactive share distribution. Indeed, the relevance of the domestic violence concern was highlighted at the national level by television campaigns, which were accessible by anyone staying home during the lock-down; Colagrossi et al., 2022 found heterogeneous effects depending on the exposure to the campaign itself, proxied by public television audience shares.

OLS results - By municipality of residence - SEs clustered at municipal level

	(1) Pregnancy rate (single)	(2) Pregnancy rate (married or in civil union)	(3) Pregnancy rate (divorced or separated)	(4) Pregnancy rate (widow)	(5) Pregnancy rate (single)	(6) Pregnancy rate (married or in civil union)	(7) Pregnancy rate (divorced or separated)	(8) Pregnancy rate (widow)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	0.13308	0.27145 **	-0.02234	0.00308				
	[0.11315]	[0.11902]	[0.01722]	[0.00340]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	0.06007	0.15189	0.00930	-0.00026				
	[0.07897]	[0.09768]	[0.01392]	[0.00314]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	0.01078	0.24291	-0.00146	0.00276				
	[0.07624]	[0.09539]	[0.01406]	[0.00278]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$					-0.01129	-0.05927	0.03041 *	0.00001
					[0.12338]	[0.12956]	[0.01629]	[0.00263]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$					-0.04940	-0.01671	0.02447 *	0.00216
					[0.11442]	[0.11609]	[0.01407]	[0.00299]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$					-0.02661	-0.05316	0.01628	0.00246
					[0.10511]	[0.10823]	[0.01229]	[0.00251]
Observations	102,739	102,739	102,739	102,739	102,739	102,739	102,739	102,739
R-squared	0.12964	0.14516	0.09100	0.08719	0.12962	0.14508	0.09099	0.08718
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter'year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	2.712	1.467	0.121	0.00868	2.177	1.806	0.138	0.00862

*** p<0.01, ** p<0.05, * p<0.1

Table 23: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

We hence estimate the following model by OLS:

$$Call\ Rate_{pt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(InactiveShare_{p12/2020} \in Q_k) + X'_{pt}\beta + \tau_p + \gamma_t + \delta_{p,t} + \varepsilon_{mt} \quad (9)$$

Where $Call\ Rate_{pt}$ is the total call to 1522, either by users or victims, every 100k inhabitants, in province p and quarter-year t. The treatment variable follows the same logic as the one in Equation 3, although here the inactive share distribution is taken at provincial level. Covariates for the restrictions' severity are included as well (X'_{pt}), aggregating the municipal value from Conteduca and Borin, 2022 at the province level (weighting by population). In addition to quarter-year (γ_t) and provincial FEs (τ_p) we also add up provincial quarterly interaction dummies ($\delta_{p,t}$) to the baseline framework. We estimate a parallel Poisson model by means of PPML, adopting the same specification. In addition, since data on calls to 1522 are collected weekly, we re-perform the same analysis but at weekly level (Table B1 and Table B2).

SEs clustered at provincial level; 2018-2021	(1) Calls by users	(2) Calls by users	(3) Calls by users	(4) Calls by users	(5) Calls by users	(6) Calls by users	(7) Calls by users	(8) Calls by users
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-0.54188	-0.64470	-0.56786	-0.70936	-0.03438	-0.01809	-0.03459	-0.02275
	[0.41952]	[0.56157]	[0.42165]	[0.56397]	[0.04324]	[0.05229]	[0.04267]	[0.05106]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.17320	0.22739	0.14448	0.16240	0.04635	0.09504 *	0.04518	0.09024 *
	[0.49035]	[0.59952]	[0.48681]	[0.60158]	[0.05206]	[0.05514]	[0.05083]	[0.05380]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.57632	-0.82312	-0.59057	-0.83515	-0.03282	-0.03531	-0.03301	-0.03542
	[0.44929]	[0.54712]	[0.45280]	[0.54662]	[0.04858]	[0.05564]	[0.04784]	[0.05458]
Observations	1,712	1,664	1,712	1,664	1,712	1,664	1,712	1,664
R-squared	0.67587	0.72934	0.68392	0.73554				
Province FE	X	X	X	X	X	X	X	X
Region x quarter-year FE		X		X		X		X
Provincial trends								
quarter-year FE	X	X	X	X	X	X	X	X
Pop. weight			X	X			X	X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	7.657	7.657	7.657	7.657	7.657	7.657	7.657	7.657

*** p<0.01, ** p<0.05, * p<0.1

Table 24: SEs clustered at provincial level. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

SEs clustered at provincial level; 2018-2021	(1) Calls by victims	(2) Calls by victims	(3) Calls by victims	(4) Calls by victims	(5) Calls by victims	(6) Calls by victims	(7) Calls by victims	(8) Calls by victims
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-0.23919	-0.50435	-0.26151	-0.55169	-0.01676	0.01258	-0.01683	0.00743
	[0.26084]	[0.36837]	[0.26453]	[0.37355]	[0.04446]	[0.05714]	[0.04350]	[0.05577]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.09622	-0.12410	0.07768	-0.16942	0.03860	0.09995 *	0.03873	0.09556 *
	[0.29742]	[0.35366]	[0.29684]	[0.35796]	[0.05547]	[0.05467]	[0.05372]	[0.05316]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.35888	-0.58615 *	-0.37717	-0.59867 *	-0.03499	-0.02175	-0.03696	-0.02232
	[0.25717]	[0.31585]	[0.26213]	[0.31820]	[0.04572]	[0.05275]	[0.04449]	[0.05110]
Observations	1,712	1,664	1,712	1,664	1,712	1,664	1,712	1,664
R-squared	0.62030	0.68493	0.63010	0.69234				
Province FE	X	X	X	X	X	X	X	X
Region x quarter-year FE		X		X		X		X
Provincial trends								
quarter-year FE	X	X	X	X	X	X	X	X
Pop. weight			X	X			X	X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	3.789	3.789	3.789	3.789	3.789	3.789	3.789	3.789

*** p<0.01, ** p<0.05, * p<0.1

Table 25: SEs clustered at provincial level. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

According to our estimates, in all specifications the inactive share distribution has no significant effect on reporting calls to 1522 for domestic violence. There are few specifications estimated both via OLS and PPML, which report significant coefficients at 10% level, and they do not highlight particular patterns (Table 24 and 25). If anything, the direction of coefficient of upper quartiles is opposite to the one we would expect, as provinces which are part of the fourth quartile of the inactive share's distribution face a differential negative effect in the 1522 call rate, although such decrease is not statistically significant. Since data on calls are collected at weekly level, we re-perform the analysis at this frequency, coming up to not very different conclusions, as shown in Table B1 and B2. In the latter case, we observe how OLS estimates for calls by users are statistically significant and negative in two specifications (Col. (2) and (4), Table B1). This would suggest that the suspension of non-essential workers did not have a significant effect on DV rates (and when it did, it was negative)[24]. We could look at these results in the perspective of suspended workers being the perpetrators. If abusive partners, usually prone to violence, are suspended from the job and thus more exposed to sensitisation campaigns, they may become more cautious and reconsider their violent conduct, in order to avoid reporting and possible allegations[25]. Although understanding the determinants of such findings would have interesting policy implications, it goes beyond the scope of the present work, as long as we are able to conclude that the differential change in VPTs and unplanned pregnancies during the Covid-19 crisis was not driven by violence; which appears to be the case.

8.3.2 Contraception

Whereas the effect on abortions shall be convincingly credited to a heterogeneous response in unplanned pregnancies due, possibly, to more time spent home of suspended workers, the fact that we do not observe a significant difference in live births leaves room to the hypothesis that the economic insecurity which characterised the pandemic times may have played a role in fertility decisions anyway. However, we cannot make a claim with such suggestion only. There is a channel that may have credibly shift unwanted conceptions in a heterogenous way, by leaving the patterns of planned pregnancies unchanged: as in, the access and usage of contraception methods. If there was some impact of the suspension of non-essential workers in the access or usage of birth control by the involved couples, then the observed results would mostly be driven by this factor. Unfortunately, to our knowledge, there is no available data source able to disentangle the evolution of contraceptive usage and reproductive care services at such a granular disaggregation as the one we are employing for our analysis. However, we can recur to two different sources of data to provide with a descriptive picture of the situation of birth control and family planning services in Italy, and possibly steer future deeper research with some anecdotal evidence. The Ministry of Health reports data on reproductive care facilities (family planning centres, *consultori familiari* in Italian) and the consumption of emergency contraception (ECPs), as in, birth control drugs that can be assumed after an unprotected sexual intercourse. ISTAT platform

[24]This result would be quite counterintuitive, if significant; as a matter of fact, there are three most plausible channels that could feasibly work out in shifting the calls to domestic violence upwards. First, according to the exposure theory, suspended workers and their partners would spend more time together, and this shall exacerbate episodes of physical and sexual violence (Dugan et al., 1999); second, the economic insecurity channel could be a fostering effect in stress-related violence episodes or in abuses driven by the reconfiguration of bargaining power within couples Aizer, 2010). Third, the inactive share could actually foster the reporting bias highlighted by Colagrossi et al., 2022 already: by spending more time home, suspended workers could be more exposed to television campaigns and thus the rate of reporting ought to increase irrespective of actual violence occurring. Notwithstanding the latter form of upward bias to the estimates, we still retrieve non-significant, negative results.

[25]Or they may actively operate to physically prevent the victims to report, a more dramatic albeit less realistic hypothesis.

Health For All collects instead regional data on contraceptive usage in Italy. Concerning the former, family planning centres are healthcare facilities introduced by Italian Law 405 1975, with the purpose of providing assistance concerning the topics of family and motherhood. Among the other things, healthcare professionals of family planning centres offer psychological and social assistance to prepare couples to parenthood, offering advice on the adequate tools to improve the likelihood to procreate or, on the other side, to prevent unwanted pregnancies, especially concerning the usage of birth control methods. The centres work with a twofold aim, in order to protect both the social value of motherhood and the assurance of the legal right of abortion, providing information on a broad set of topics around the mentioned subjects. Amongst them, sensitisation on prevention is a major task performed by family planning centres. If there was a disruption in the services provided by family planning centres due to the pandemic outbreak (and correlated to the inactive share), the observed increase in VPTs may be due to a decrease in cautious and responsible prevention due to a lack of reproductive care facilities' assistance. Unfortunately, we cannot track the evolution of family planning centres all along the years, but we can look at their annual numbers at regional level.
In general, family planning centers are more spread in Central regions (especially Emilia Romagna and Umbria, Figure L1 in Appendix L). Between 2019 and 2020, however, some Italian regions seem to have faced a reduction in the ratio of family planning centers to the number of women aged between 18 and 49; among them, there is Lombardy, one of the regions most hit by the pandemic, epidemiologically and economically. On the other side, two regions like Veneto and Piedmont, which had the greatest numbers of municipalities with a high share of suspended workers as well as Lombardy, actually faced an increase in family planning facilities. It is hard do disentangle an operational channel working through this mechanism to explain the differential change in VPTs, mostly because we only have data which are collapsed at such a large administrative unit. We can plot however some merely correlational evidence to assess whether it is the case to believe that such channel deserves to be further investigated.

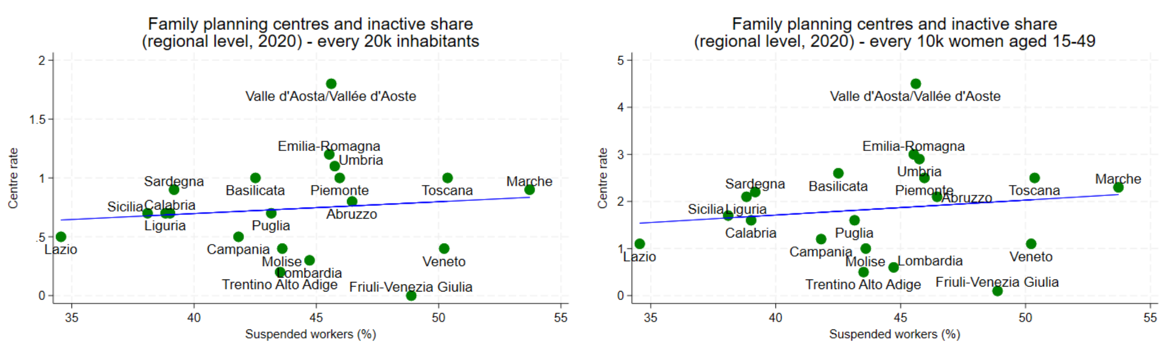


Figure 15: Family planning centres in Italy and regional inactive share. Left panel: number of family planning centres every 10,000 women aged between 18 and 49 between 2018 and 2021. Right panel: number of family planning centres every 10,000 women aged between 18 and 49 in 2020. Source: Ministry of Health.

Albeit insufficient to discard the hypothesis, we observe how, in Figure 15, the regional share of suspended workers in 2020, seems not to be very significantly and negatively correlated with the rate of family planning centers, which is what we would expect if our narrative was the correct one, in case of the presence of some spurious correlation between our treatment and the variable under question. It is more difficult to assess whether there was a disruption in services over 2020. The last two plots

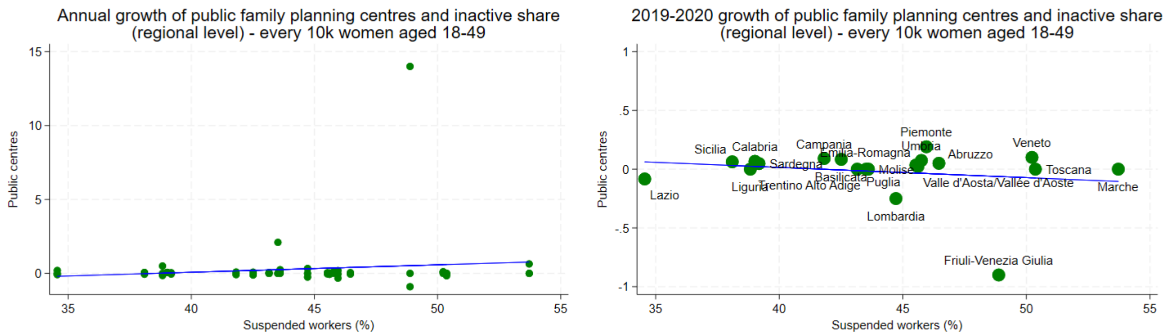


Figure 16: Annual growth of family planning centres in Italy and regional inactive share. Left panel: annual growth of family planning centres every 10,000 women aged between 18 and 49 between 2018 and 2021. Right panel: 2019-2020 growth of family planning centres every 10,000 women aged between 18 and 49 in 2020. Source: Ministry of Health.

(Figure 16), seem however to show that there exists little to no correlation between the suspended workers' share and the growth in reproductive care facilities. Given the statistical insignificance of the analyses above, although we are not able to rule out the hypothesis, we may hint that it does not appear that, from the scarce available data, a major disruption in reproductive care facilities could be the one leading the increase in unplanned pregnancies.

Another factor, usually deemed as fundamental in bringing down unwanted pregnancies, is the emergency contraceptive pill (Girma and Paton, 2006, 2011, Durrance, 2013, Cintina, 2017, Bentancor and Clarke, 2017, Core, 2024), or ECP, the so-called "day-after pill" (or "5-days after pill"). Emergency contraceptive pills enable birth control after the occurrence of an unprotected sexual intercourse, conditional on assuming them as soon as possible; in any case, they do not constitute an interruption of pregnancy, as they operate in a time-frame within which pregnancy has not emerged yet. Their effectiveness, however, is reduced at any additional use, and they do not protect from pregnancies if an intercourse happens after their assumption (MoH, 2023). In Italy, emergency contraception is mostly available by means of two main pharmaceuticals: Levonorgestel (Norlevo), to be taken within 5 days from the intercourse; Ulipristal (EllaOne), to be taken within 72 hours from the intercourse. They were not available OTC until 2015, and required a medical prescription together with a certification of occurred pregnancy. In May 2015 AIFA (the Italian Medicine Agency) made them available OTC for all adult women, with no certification requirement whatsoever. In October 2020, AIFA made them available OTC for minor women too (MoH, 2023). We cannot recover the geographical disaggregation of ECP sales in Italy over the studied years, nor their quarterly evolution. However, we can acknowledge that, in the considered time framework, no evident disruption in the overall sales of the drug occurred, nor was it reported by health authorities. As a matter of fact, there has been no noticeable shortage in the supply of such kind of medicines, nor one that could be feasibly correlated to the non-essential workers' suspension. Their OTC availability made them easy to be acquired by any woman who requested them, as the access to pharmacies was always guaranteed all along the duration of the state of emergency; furthermore, the pharmacists' conscientious objection for these drugs is not legally allowed. A reason not to go to pharmacies to purchase them could be linked to the fear of getting the virus (and in fact Figure L2 shows how 2020 was the year with the fewest sales of ECPs along the last 4), but that shall not be any correlated to the increase of VPTs we observe in areas with more suspended workers. In addition, the only evident institutional discontinuity which specifically concerns

ECPs is the fact they were made available OTC to minors in October 2020; in 2021 there is indeed an increase in ECP purchases by almost 10% compared to 2020, to be reasonably credited to such policy change. Also, an overturn in the market share of the two ECP medicines happens in that year. If such event had any effect on VPTs, it was certainly a reducing one. However, the change occurred in October 2020, two month after the estimated effect we observe loses its significance. Furthermore, it should have contributed to reduce unplanned pregnancies (and thus VPTs) for minor women. They are feasibly not the ones leading the results in the months beforehand, as in our framework the trigger was due to labor market reasons (work suspension), which possibly affected already married couples. However, to sensibly rule out such confounder, we run two TWFE DiD models (one estimated via OLS and the other via PPML), where the outcome is the AR for minor women only, whereas the treatment variable, as in the municipal share of suspended worker, is interacted with a temporal dummy which takes unitary value after the 3^{rd} quartile of 2020 (i.e., after the AIFA issue on ECP), rather than the convential pandemic discontinuity. Table L1 and L2 prove for the non-significance of such hypothesis in explaining our results.

Eventually, the increase in unplanned pregnancies may be not due to a supply change, but to a behavioral shift in the consumption of contraceptives during the pandemic. ISTAT reports data on contraceptive consumption in Italian regions, taken from the WHO database "Health For All" (HFA). Unfortunately, the regional statistics on birth control are not registered longitudinally, as they come from answers to surveys which were undertaken in 2013 and 2019. We have information on Men's birth control for 2013 only, while for women such statistics are available in both years. Obviously, this data result pointless if we want to draw any conclusion about changes in birth control usage over the time frame under question, especially 2020. However, to have a glance on the Italian distribution of birth control practices in the latest year available (2019, for women), can be helpful in picturing the overall framework on the subject.

Figure 17 displays the distribution in the usage of at least one contraceptive method in Italian regions, showing how birth control, in 2019, was a practice mostly spread in Central and Northern regions, the ones which are, on the other side, driving up our results. However, statistics on the usage of "at least a contraceptive", also include withdrawal (interrupted coitus), which is deemed as old-fashioned and possibly the least effective contraceptive method (CDC, 2023,WHO, 2023). This notwithstanding, the North-South asymmetry in contraceptive usage does not vary when we disentangle by type of birth control method, with the exception of withdrawal (Figure L3, panel (a)), whose pattern does not seem to follow a North vs. South heterogeneity.

Beyond coitus interruptus, contraception is evidently more diffused in the Centre-North, for what concerns the utilization of condoms, contraceptive pills (non-ECP) and modern control methods (diaphragm, intrauterine device, vaginal ring, contraceptive patch, sterilization, ISTAT, 2017). Insular Italy provides a seemingly further exception when considering the usage of contraceptive pills and modern methods (Figure L3, panel (c) and (d)). In particular, the modern methods of female contraception are evidently scarcely utilized in non-insular Southern Italy.

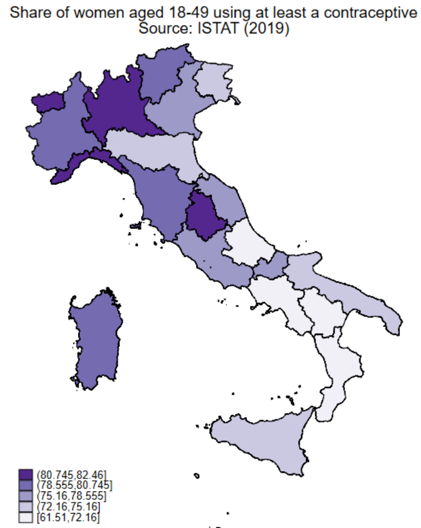


Figure 17: Share of women aged between 18 and 49 using at least a contraceptive method when having sexual intercourse in 2019. Source: ISTAT

These statistics offer good narratives to understand, broadly speaking, the contraceptive behavior across Italian regions. However, they cannot go beyond anecdotal evidence in order to help us explaining our results. The figures refer to 2019, so we would be able to state that our results in VPTs are driven by different conception patterns (possibly linked to economic insecurity and past reproductive behavior), but not by a shift in contraception only if we assumed that no abrupt behavioral birth control change happened, along 2020, in such a way that people residing in Northern Italy (especially those in municipalities with higher inactive share) reduced their consumption of contraceptives. The assumption cannot be proven further, but is plausible. We would ostensibly need additional surveys on Italians' sexual behavior to be able to come up to more clear-cut conclusions on the matter.

8.4 Implications

So far we have devolved our efforts to the corroboration of the baseline estimates and to the performance of heterogeneity analyses, in order to set a benchmark to a possible exploration of some plausible mechanisms in action. Before coming up to the concluding remarks, we briefly discuss the potential policy implications of our findings. As a matter of fact, we have been able to establish a causal claim about the differential impact of what we identified as our treatment on the VPT municipal patterns of Italian women. However, one might be led to question whether such exercise is even sensible, as the outbreak of the pandemic clearly brought about, in its immediate aftermath, a visible drop in abortion rates (see Figure 1 and Figure 7). As also shown by Trommlerová and González, 2024, for the Spanish case, the drop shall be reasonably attributed to the social distancing policies put in place in 2020, which reduced the possibility of sexual intercourse. However, by looking at the heterogenous effect on different types of municipalities/subsets, we can draw relevant conclusions on how women (and, more generally, couples) adjust their fertility and reproductive behavior following an unexpected event. By exploiting the exogenous shock of Covid-related work suspensions, we can abstract from a relevant portion of the endogeneity embedded in the individual abortion decisions, to stress the most remarkable findings, and try to interpret them under the policy point of view. First of all, we are able to identify about a 11% significant differential effect on the mean ARs in treated municipalities after the policy closure, relative to the control ones. As the average AR pre-Covid amounts to 1.1 VPTs every 1000 women in fertile age, that means that in such municipalities there is one additional quarterly abortion every 9000 women. This does not add much valuable information to the economic setting of our study per se, especially accounting for the fact that treated municipalities are, on average, less populous than the untreated ones. However, it must be noted that such numbers refer to the ATE of our estimates, although we observe that the bulk of the shift in ARs occur in the second and the third quarters of 2020, which are the only ones shown by the Event-Study estimates as reporting significant coefficients (Figure 11 and 12). In Q2/2020, the effect was about 30 p.p., while in Q3/2020 about 20 p.p.: 27% and 18% of the average AR pre-treatment respectively. This means one additional VPT every 3700 and 5555 women in such periods, which shrinks the "quantitative" population threshold required to observe a meaningful change in the abortion rates. These periods coincide with the harsher restriction ones, and they are actually concomitant with the work suspension that we use as our treatment. Such values may result relatively important for women who reside in smaller municipalities where VPTs are less frequent, in particular in a time of uncertainty as that of Covid. In such regards, and with respect to the strict economic implications of our findings, we find no correlation between the distributional share of the two macro-sectors of work suspension and those in which aborting women result employed; as a matter of fact, the municipal ARs significantly responding to the exogenous shock are mainly those of women who are not in professional condition. Overall, the differential variation for women residing in treated municipalities and not in professional condition amounts to 7 p.p., 14% the pre-Covid mean, thus a slightly greater but similar proportion (and, consequently, also similar raw numbers) compared to the overall, baseline results. The fact that, however, municipal ARs of women not in professional condition significantly respond to the industrial distribution treatment only, and live births do not, makes room for the hypothesis that the main reason why there is a differential impact on VPTs is driven by a heterogeneous effect on the unplanned pregnancies due to differential time patterns spent together with respective male partners, likely more significantly employed in the industry sector in our current settings. This mirrors quite consistently our results on the ARs relative to marital status, as our estimates display a significant difference by 7 p.p. (OLS, PPML amounts to 8.5 p.p.) for married women's ARs, which correspond to 18%-22%, i.e. one additional VPT amongst married women every 5000 females in fertile age. Note that the less significant and smaller effect on single women's AR may be driven by cohabiting couples who are not registered as either married nor in a civil union, although we have no available information to dwell too much on this clue. However, to draw also some consistent policy conclusions, we briefly discuss the two most interesting results of our study (which have never been tackled yet by the Italian literature using the same data), for which the magnitude of the differential impact may actually result quite substantial for a potential health policy-maker. First and foremost, we reckon how there is no differential impact distinguishable from zeros for women with no previous pregnancies (Table 18, Cols. (2) and (6)), whereas there is a significant effect at all quartiles of the distribution relative to the first for those with a previous gestation, especially if carried over. However, it results still quite hard to draw any implication without differentiating for the type of pregnancies and deliveries carried over. In Table 19 we observe how actually women with previous live births and VPTs mainly matter for our heterogenous shift in ARs. It is however quite hard to quantify the effect for already-mothers, as the coefficients are clearly significant at more than one quartile of the distribution, thus suggesting a linear positive relationship between the share of suspended workers and the abortion responses for this kind of women. To better quantify the impact

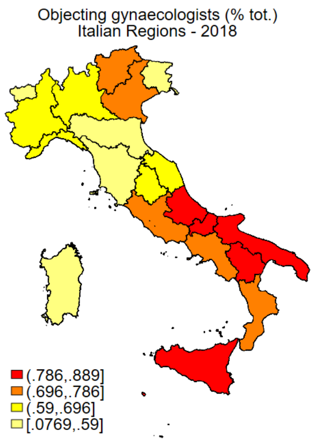
for the sake of some policy assessment, we look at the ARs for different subsets of women, according to the actual number of both previous deliveries and VPTs. The main non-ambiguous and significant result concerning live birth, obtainable from Table 20, tells us that there is positive differential impact on women residing in treated municipalities and with at least two children (proxied by previous live births). Such impact is 6 p.p. when estimated via OLS, and reaches 9.2 p.p. in the PPML method, which respectively amount to 21% and 32% of the pre-Covid mean, mirroring one additional VPT every 4761 and 3125 fertile women. Note that in the OLS case the third quartile results significant also at 10%, whereas all OLS estimates for the effect on ARs of women with 1 previous live birth are significant at 10%. Magnitudes rise when looking at previous VPTs, with women with 1 previous voluntary abortion responding significantly to the treatment. OLS estimates show an effect of 4.6 p.p. for treated units (26%, as in 1 VPT every 3846 women). The PPML coefficient results magnified, as in 7.1 p.p. (40%, 1 every 2500 women), although the estimates are statistically significant at 5% for the second quartile coefficient as well, thus suggesting for a non-clear cut interpretation.
Although these results alone cannot help us disentangling whether economic insecurity actually played a major role, the fact that the past reproductive behavior is somehow able to predict abortion decisions, may be a hint towards the hypothesis that the budget constraint imposed by having children in a family already may trigger positively abortion decisions. A summing up explanation may refer to the fact that, provided with additional time together, couples employed in industry jobs mostly, or where the woman is not in professional condition but partnered to an industrial worker, are characterised by a positive shift in unintended fertility. Among such women, those with already 2 children or that have already aborted once are more likely to resort to a VPT. That may be due to family planning strategies in the live birth case, and to adaptation to the practice for the abortion one.
The second interesting result (which may provide further robustness to the "available time" hypothesis) concerns female employees in white collar, non-executive nor entrepreneurial jobs, whose municipal ARs is impacted positively and significantly at 1% by 30% (OLS) and 47% (PPML) compared to the mean and relative to untreated units, which means a differential increment of 1 VPT every 3333 and 2127 women (Table 17, Cols. (5) and (11)). This may result consistent with the significant (albeit at 10%) effect on employed women displayed in Table 16, showing that when women are in professional condition (thus, either employed or not), the ones who are more likely to adjust their reproductive behavior in response to the exogenous shock are the employed ones, for whom the additional time stock due to work suspension may actually result significant compared to the unemployed ones, for whom more time available shall impact less their free time, which was higher even before work suspensions due to unemployment. These are however rough speculations that stem up from indirect interpretation of the results, which are intended at corroborating some hypothesis by putting up together all the findings in the work; although most of them result consistent, it is quite hazardous to try to establish definitive economic conclusions. This holds especially if we look at the geographical distribution of our findings, which show significant results in the North only, where contraception is way more spread, and where both the epidemiological and economic impact were substantially higher. If we look at the coefficient on the treatment for the North, it amounts to 19 p.p., whereas it amounts to 14 p.p. for the third quartile, hence lowering the relevant threshold for the treatment at the median level. This amount to a total percentage of 30% of the mean, implying one additional VPT every 3333 fertile women. Note that in this case this holds without having even distinguished the ARs according to marital status, suspension sector, employment condition or past reproductive behavior.
Provided with the latter discussion, we try to appraise how our work could matter somehow in the steering of reproductive health and fertility policy strategies. The first theme pertains to contraception: when faced with exogenous shocks, able to modify the allocation of free time, coupled with a disruption

of ordinary activities, one may push towards incentivizing couples with children (and women with previous VPTs) to improve their birth control practices, by sensitising campaigns, or by financially encouraging the use of contraceptives with co-payments or shifting the burden on the NHS. The second point concerns the abortion right strictly. Literature has already underlined how objections matter in shaping abortions patterns (Bo et al., 2015, Autorino et al., 2020, Muratori, 2023a). Due to having identified the most plausible categories of women who are more likely to respond to the shock in terms of unintended pregnancies, it seems like they belong to groups of women to whom to find non-objecting gynaecologists across areas could result as a major setback. We refer to women whose mobility or budget possibilities may be reduced due to presence of children, due to lack of resources as not in professional condition, or due to stigma or psychological pressure associated to having already aborted once. In such regards, as long as to policy makers it results adequate to equally value both the right to objection and that to abort, which matters to the institutional context, the Italian NHS should deepen the way objection shapes abortion decisions, as although on overall terms the official reports seem not to show that objectors prevent women for seeking for VPTs, that may not be the case when looking at particularly vulnerable women. In such case, one should implement targeted policies in order to provide with preferential channels and adequate services to grant their right, which may be facing obstacles due to their fragile situation. In addition, the issue of preventing entire health care structure to undertake "institutional" objection, as highlighted by Muratori, 2023a, should be addressed. Finally, although it does not relate strictly to the main findings of our work, the economic basis of fertility decisions shall not be neglected. As already shown in Cavallini, 2024, local negative shocks decrease fertility and increase abortions. In our Covid-19 case, we observe a drop of both due to social distancing, so that to we cannot draw properly likewise conclusions by looking at our results. However, the differential impact of an economic variable such as work suspension on abortion patterns, which stems from exogenous shocks on the local economic structure, seem to matter significantly in shaping family planning, especially in the presence of children already. In such regards, anti-cyclic targeted transfers to households with specific characteristics (not in professional condition mother, employment characterised by a particularly volatile industry job, presence of children in the family already), either in the direction of fostering filiation or just to enhance contraceptive behaviors. This may turn out to be helpful for the people's family planning decisions, which seem to be affected by temporary shocks as well as by long-term consideations.

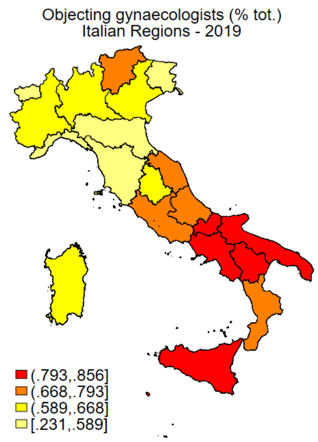
9 Conclusions

We investigated the effect of an Italian non-pharmaceutical policy intervention aimed at counteracting the spread of the Covid-19 on the patterns of pregnancies of Italian women, focusing on abortions (VPTs). Exploiting the variability in economic closures' effect of March 2020, we observed that abortion rates rose by about 13% in municipalities which were part of the fourth quartile of the inactive share distribution. No significant effect is found on pregnancy rates turning into live births 9 months later. By looking at sectors, we realize that the sectoral share driving the effect is the industrial one, and mostly on women who are not in professional condition, married, or having had previous kids or abortions; secondary, also women looking for their first job. We are not able, in conclusion, to distinguish with certainty between the increase in exposure (and consequent sexual activity and unplanned pregnancies), and the one in social insecurity, although the absence of association between the women's economic branch of activity and the sectoral share of suspended workers, in addition to the absence of an effect on births, suggests that insecurity is a secondary channel with respect to poor family planning due to more available time together. The effect seems however to be driven more by consensual intercourse rather than domestic abuse. The major result of this study, which has to our knowledge never been tackled before, is the role played by past reproductive behavior of women in shaping the response of abortion patterns to the studied policy: only women who had previous children or abortion seem be affected significantly by the work suspension, even in a more Further research is needed to "elastic way" compared to the aggregate sample of analyzed women. When looking at the intensive margin, women with 2 children delivered already increased the AR by % of the average pre-pandemic rate, while for women who aborted in the past, significant response is displayed by women who already had 1 (%) or at least 4 VPTS (although the effect amounts to % the pre-treatment mean only). We wish for more thorough inquiries on the evolution of Italian reproductive care and family planning in the future, either in terms of supply and demand, to provide with more clear-cut conclusions. The takeaway point is that, due to given health behaviors, public health policies not aiming at having any effect on fertility decisions may instead have significant effects on family planning choices, especially amongst married couple where women had an active repoductive past.

A Conscientious objection

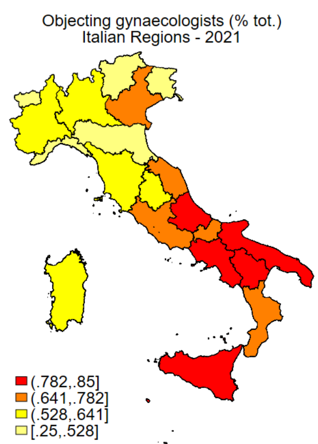


(a)



(b)

(c)



(d)

Figure A1: Objecting gynaecologists - % tot. gynaecologists - 2018-2021 (source: MoH)

B Domestic Violence

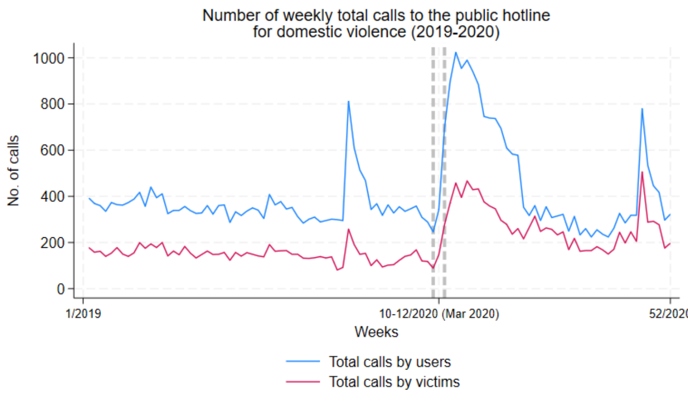


Figure B1: Weekly calls to the Italian public hotline for domestic violence (1522) in 2019 and 2020.

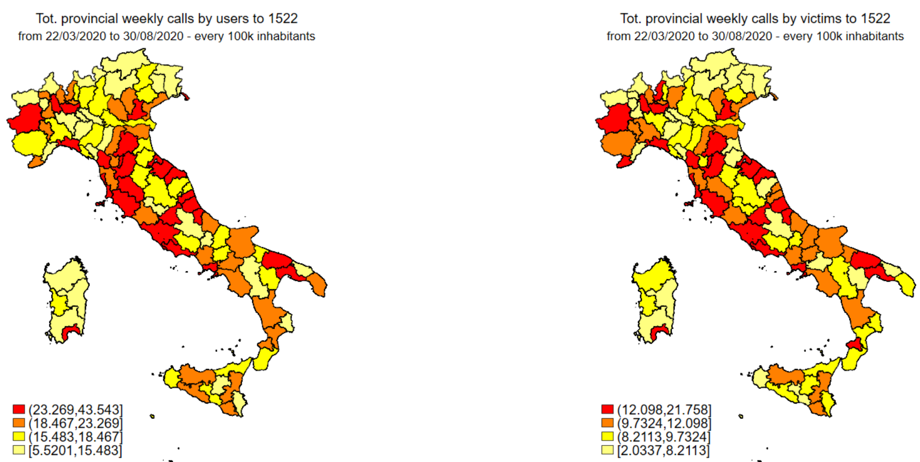


Figure B2: Total calls to 1522 over provincial population, from the week of closures in March 2020, to the last week of August 2020. Left panel reports the heat map for calls by all users, whereas the right panel reports the heat map for the calls by victims only. Calls with missing provenience are discarded.

SEs clustered at provincial level; 2018-2021

	(1) Users	(2) Users	(3) Users	(4) Users	(5) Users	(6) Users	(7) Users	(8) Users
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-0.04726	-0.10055 **	-0.04921	-0.10427 **	-0.04017	-0.04010	-0.11557	-0.11693
	[0.03344]	[0.04807]	[0.03361]	[0.04780]	[0.04489]	[0.04427]	[0.07337]	[0.07180]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.00882	0.03197	0.00671	0.02733	0.04743	0.04669	0.09403	0.09020
	[0.03689]	[0.04924]	[0.03675]	[0.04919]	[0.05087]	[0.04978]	[0.07494]	[0.07410]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.04464	-0.06970	-0.04556	-0.07024	-0.03157	-0.03157	-0.06175	-0.05994
	[0.03560]	[0.04940]	[0.03584]	[0.04916]	[0.04972]	[0.04887]	[0.07166]	[0.06927]
Observations	22,256	22,256	22,256	22,256	22,256	22,256	22,256	22,256
R-squared	0.27477	0.28633	0.28279	0.29438				
Province FE	X	X	X	X	X	X	X	X
Province x Week˙year FE		X		X			X	X
Week-Year FE	X	X	X	X	X	X	X	X
Pop. weight			X	X		X		X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.610	0.610	0.610	0.610	0.610	0.610	0.610	0.610

*** p<0.01, ** p<0.05, * p<0.1

Table B1: SEs clustered at provincial level. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

SEs clustered at provincial level; 2018-2021

	(1) Victims	(2) Victims	(3) Victims	(4) Victims	(5) Victims	(6) Victims	(7) Victims	(8) Victims
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-0.02069	-0.04505	-0.02218	-0.04780	-0.02214	-0.02136	-0.08869	-0.08869
	[0.02020]	[0.03317]	[0.02045]	[0.03288]	[0.04561]	[0.04460]	[0.09213]	[0.09213]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.00262	0.00564	0.00120	0.00286	0.03688	0.03739	0.06318	0.06318
	[0.02149]	[0.03193]	[0.02160]	[0.03189]	[0.05189]	[0.05050]	[0.08054]	[0.08054]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.02844	-0.04771	-0.02959	-0.04932	-0.03843	-0.03967	-0.08288	-0.08288
	[0.01972]	[0.03239]	[0.02013]	[0.03246]	[0.04532]	[0.04421]	[0.08433]	[0.08433]
Observations	22,256	22,256	22,256	22,256	22,256	22,256	22,256	22,256
R-squared	0.16877	0.17673	0.17489	0.18294				
Province FE	X	X	X	X	X	X	X	X
Province x Week˙year FE		X		X			X	X
Week-Year FE	X	X	X	X	X	X	X	X
Pop. weight			X	X		X		X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	0.298	0.298	0.298	0.298	0.298	0.298	0.298	0.298

*** p<0.01, ** p<0.05, * p<0.1

Table B2: SEs clustered at provincial level. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

C Suspended workers and unemployment

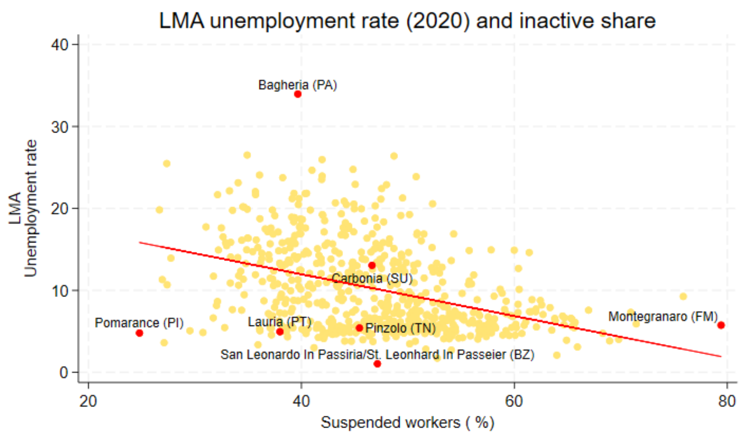


Figure C1: Predicted values between Local Market Areas' unemployment rate (2020, left panel) and suspended workers' share. The highlighted LMAs correspond to the ones having the maximum/minimum 2020's unemployment rate and inactive share. Carbonia (SU) has the median value of the inactive share.

D Policy restrictions' data

Below we report the method through which Conteduca and Borin, 2022 build their measures of policy restrictions during the pandemic outbreak. For what concern the stringency indexes, each index is constructed by looking at a set of variables, which take daily values, for each municipality, according to the severity of the applied restrictions, as explained in the table reported in Figure D3 and Figure D4 , directly drawn from the paper by Conteduca and Borin, 2022.
Each variable in the tables gives birth to a sub-index I_{mti} as follows:

$$I_{mti} = 100 * \frac{v_{mti}}{V_i} \tag{10}$$

- v_{mti} = values associated with variable i at date t in municipality m;
- V_i = is the maximum value of indicator i.

After the implementation of the Green Pass (6 August, 2021), the computation of I_{mti} slightly changes:

$$I_{mti} = 100 * \frac{\sigma^g_{mt} v^g_{mti} + (1 - \sigma^g_{mt}) v^{ng}_{mti}}{V_i} \tag{11}$$

- v^g_{mti} = variables indicating the restrictions *with* Green Pass;
- v^{ng}_{mti} = variables indicating the restrictions *without* Green Pass;
- σ^g_{mti} = share of individuals holding a GP at time t in municipality m.

The sub-indicators I_{mti} are aggregated to produce a **stringency index** $ItSI_m$ as follows:

$$ItSI_{mt} = \sum_i w_i I_{mti} \tag{12}$$

- $w_i = \frac{1}{9}$ for all indicators, except for **C2_1_Production**, **C2_2_Shops**, **C2_3_Bar_Restaurants** (for this subset, $w_i = \frac{1}{27}$).

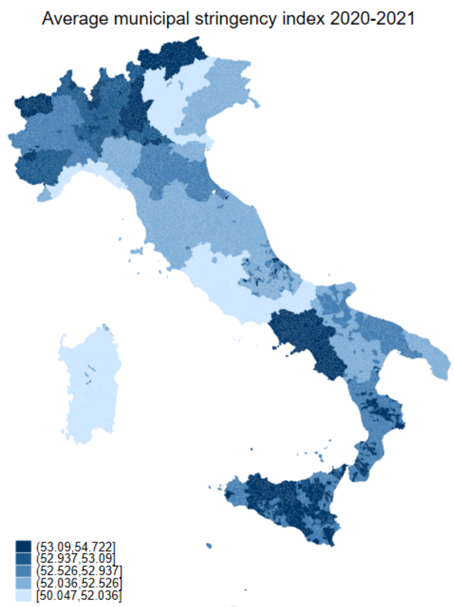


Figure D1: Data source: Average municipal stringency index across Italian municipalities. The map describes the quintile distribution of the municipal daily stringency index calculated by Conteduca and Borin, 2022, averaged across 2018 and 2021.

Table 1 Policy indicators available in the dataset

Variable	Description	Value	Label
		0	No restrictions
		0.5	Partial remote learning in upper secondary schools
		1	Full remote learning in upper secondary schools
C1_Schools	Restrictions on in-person schooling	1.5	Full remote learning in upper secondary schools and final two years of lower secondary schools
		2	Full remote learning in upper and lower secondary schools
		2.5	In-person activities only in pre-school education
		3	No in-person activity
		0	No restrictions
C2_1_Production	Restrictions on in-person production activities	1	Remote working recommended
		2	Mandatory remote working for most activities
		3	Shutdown of all but essential production activities
		0	No restrictions
		1	Limited restrictions (e.g., people allowed in stores)
C2_2_Shops	Restrictions on shops and personal services activities	2	Closure of some shops
		3	Shutdown of all but essential production activities
		0	No restrictions
C2_3_BarsRestaurants	Restrictions on bars and restaurants	1	Dine-in allowed at some times of day
		2	Dine-in not allowed; takeaway and delivery allowed
		3	Closure of all bars and restaurants
		0	No restrictions
C3_PublicEvents	Restrictions on in-person public events	1	Cancellation of some public events
		2	Cancellation of most public events
		0	No restrictions

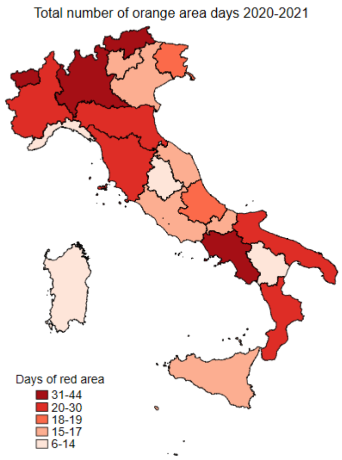
Figure D2: Source: Conteduca and Borin, 2022

Table 1 continued

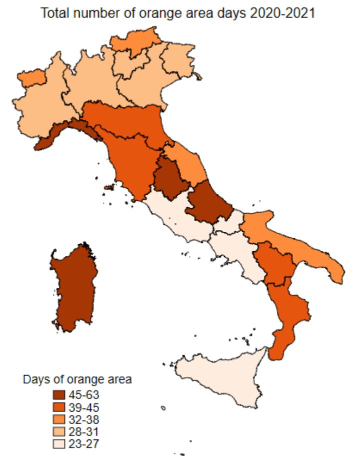
Variable	Description	Value	Label
		1	Gatherings over 1,000 people allowed
C4_Gatherings	Restrictions on in-person gatherings	2	Gatherings up to 1,000 people allowed
		3	Gatherings up to 100 people allowed
		4	Gatherings up to 10 people allowed
		0	No restrictions
C5_PublicTransport	Restrictions on public transportation	1	Reduced capacity
		2	Shutdown of public transport
		0	No restrictions
C6_StayAtHome	Restrictions on quarantines and isolation	1	Recommended sheltering
		2	Mandatory sheltering (excluded essential activities)
		3	Mandatory sheltering (with very few exceptions)
		0	No restrictions
		1	Limited restrictions (e.g., curfew)
C7_InternalMovement	Restrictions on domestic travel and movement	2	No movement between regions
		3	No movement between municipalities
		4	No movement within a municipality
		0	No restrictions
		1	Limited control (e.g., negative test)
C8_InternationalTravel	Restrictions on international travel	2	Mandatory quarantine
		3	Entry ban on some countries
		4	Entry ban on all countries
		0	No campaigns
H1_PublicCampaigns	Presence of public information campaigns	1	Public campaigns on some media
		2	Coordinated campaigns on all media

Source: Authors' elaboration adapting Hale et al. (2021) to the restrictions and provisions in place in Italy since January 1, 2020

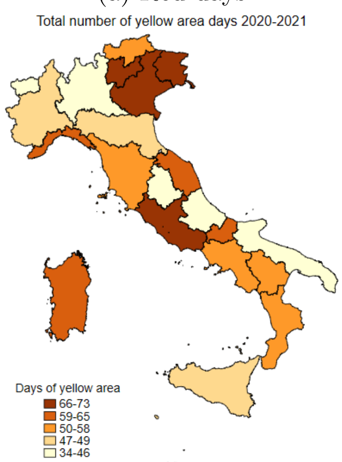
Figure D3: Source: Conteduca and Borin, 2022



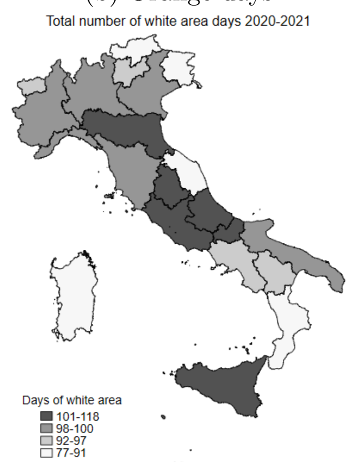
(a) Red days



(b) Orange days



(c) Yellow days



(d) White days

Figure D4: Elaboration on the data by Conteduca and Borin, 2022

E Temporal sensitivity

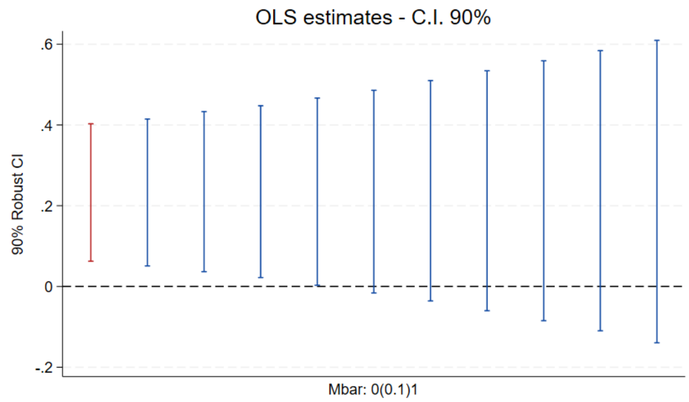


Figure E1: Parallel trends sensitivity analysis, — break points for the treatment coefficient on the second quarter of 2020, based on estimates from Equation 7. Confidence interval at 90%. The x-axis reports the varying magnitude of the break parameter M, allowing for deviations from the common trend, ranges from 0% to 100%, by intervals of 10%.

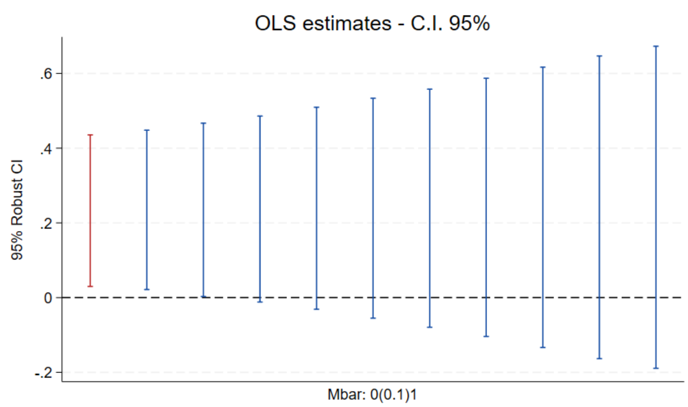


Figure E2: Parallel trends sensitivity analysis, — break points for the treatment coefficient on the second quarter of 2020, based on estimates from Equation 7. Confidence interval at 95%. The x-axis reports the varying magnitude of the break parameter M, allowing for deviations from the common trend, ranges from 0% to 100%, by intervals of 10%.

PPML results - By municipality of residence - Annual specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{2020} \in Q_4)$	0.48261 **	0.40296 ***	0.46742 **	0.38752 **	0.54760 **	0.42632 **
	[0.19869]	[0.15296]	[0.20052]	[0.15456]	[0.22249]	[0.17294]
$Post * 1(Inactive\ Share_{2020} \in Q_3)$	0.29128	0.22390	0.29055	0.22038	0.35035 *	0.25932 *
	[0.18411]	[0.13928]	[0.18542]	[0.14043]	[0.19054]	[0.14573]
$Post * 1(Inactive\ Share_{2020} \in Q_2)$	0.16671	0.13396	0.17390	0.13784	0.19209	0.14084
	[0.17143]	[0.12889]	[0.17192]	[0.12965]	[0.17193]	[0.13113]
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Province x Year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	4.374	4.374	4.374	4.374	4.374	4.374

*** p<0.01, ** p<0.05, * p<0.1

Table E1: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - Monthly specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{03/2020} \in Q_4)$	0.04659 ***	0.03775 ***	0.04413 ***	0.03568 ***	0.04807 **	0.03810 ***
	[0.01702]	[0.01301]	[0.01708]	[0.01305]	[0.01865]	[0.01446]
$Post * 1(Inactive\ Share_{03/2020} \in Q_3)$	0.02005	0.01358	0.02110	0.01617	0.02566	0.01866
	[0.01563]	[0.01176]	[0.01556]	[0.01170]	[0.01606]	[0.01224]
$Post * 1(Inactive\ Share_{03/2020} \in Q_2)$	0.01236	0.00965	0.01198	0.00919	0.01279	0.00865
	[0.01449]	[0.01050]	[0.01458]	[0.01091]	[0.01439]	[0.01095]
Observations	348,576	348,576	340,609	340,609	340,519	340,519
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Month˙year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.368	0.368	0.368	0.368	0.368	0.368

*** p<0.01, ** p<0.05, * p<0.1

Table E2: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence - Semestral specification	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{03/2020} \in Q_4)$	0.22968 **	0.20237 ***	0.22546 **	0.19714 ***	0.23061 **	0.20126 **
	[0.09077]	[0.07116]	[0.09114]	[0.07150]	[0.10459]	[0.08196]
$Post * 1(Inactive\ Share_{03/2020} \in Q_3)$	0.13875	0.11414 *	0.13668	0.11126 *	0.15137 *	0.12155 *
	[0.08572]	[0.06646]	[0.08600]	[0.06675]	[0.09039]	[0.07009]
$Post * 1(Inactive\ Share_{03/2020} \in Q_2)$	0.07935	0.068793	0.08049	0.06764	0.08222	0.06726
	[0.07976]	[0.06178]	[0.07984]	[0.06193]	[0.08149]	[0.06325]
Observations	63,224	63,224	63,224	63,224	63,224	63,224
R-squared	0.19149	0.19967	0.19158	0.19974	0.20417	0.21164
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Semester−year FE	X	X	X	X	X	X
Province x Semester˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	2.187	2.187	2.187	2.187	2.187	2.187

*** p<0.01, ** p<0.05, * p<0.1

Table E3: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence - Semestral specification	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{03/2020} \in Q_4)$	0.24131 **	0.20148 ***	0.23656 **	0.19705 **	0.25776 **	0.21183 **
	[0.09935]	[0.07648]	[0.09988]	[0.07695]	[0.11101]	[0.08623]
$Post * 1(Inactive\ Share_{03/2020} \in Q_3)$	0.14565	0.11195	0.14389	0.10965	0.17412 *	0.12821 *
	[0.09220]	[0.06964]	[0.09258]	[0.07004]	[0.09504]	[0.07263]
$Post * 1(Inactive\ Share_{03/2020} \in Q_2)$	0.08336	0.06698	0.08571	0.06788	0.09578	0.06953
	[0.08572]	[0.06444]	[0.08589]	[0.06470]	[0.08574]	[0.06536]
Observations	58,096	58,096	58,096	58,096	58,096	58,096
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Semester−year FE	X	X	X	X	X	X
Province x Semester˙year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	2.187	2.187	2.187	2.187	2.187	2.187

*** p<0.01, ** p<0.05, * p<0.1

Table E4: SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR	(13) AR	(14) AR	(15) AR
$Post\ March\ 2018 * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.07931	0.06583	0.07583												
	[0.07533)	[0.10626]	[0.08493]												
$Post\ March\ 2019 * 1(Inactive\ Share_{q2/2020} \in Q_4)$				0.04414	-0.00377	0.04229	0.04748								
				[0.05396]	[0.11132]	[0.07427]	[0.08611]								
$Post\ March\ 2020 * 1(Inactive\ Share_{q2/2020} \in Q_4)$								0.27922 **	0.19013 ***	0.18673 ***		0.14851 *			
								[0.11336]	[0.06092]	[0.06854]		[0.08940]			
$Post\ March\ 2021 * 1(Inactive\ Share_{q2/2020} \in Q_4)$											0.03807		0.01624	-0.05485	0.00500
											[0.06325]		[0.12063]	[0.07733]	[0.05947]
Observations	84,804	23,669 53,824	84,804	23,080	53,080	52,824	52,792	22,472	84,756	52,792	84,804	52,200	22,372	52,200	116,192
Policy covariates								X	X		X	X	X	X	X
Excess mortality							X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Quarter-year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter-year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Time-span	18-19, 21	18	18-19	18-19, 21	19	18-19	19-20	20	18-21	19-20	18-19, 21	20-21	21	20-21	18-21
Mean	1.114	1.144	1.144	1.144	1.160	1.114	1.160	1.181	1.103	1.104	1.085	1.181	1.013	1.058	1.080

*** p<0.01, ** p<0.05, * p<0.1

Table E5: SEs clustered at municipal level. *Mean* is the mean of the treated pre-treatment. Coefficients on the treatment for the PPML report marginal effects.

F Treatment sensitivity

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020})$ (*continuous*)	0.00325 **			0.00327 **		
	[0.00141]			[0.00158]		
$Post * 1(Inactive\ Share_{q2/2020} \geq median)$		0.07450 ***			0.07678 **	
		[0.02858]			[0.03177]	
$Post * 1(Inactive\ Share_{q2/2020} \in Tercile_3)$			0.10914 ***			0.11317 ***
			[0.03744]			[0.04301]
$Post * 1(Inactive\ Share_{q2/2020} \in Tercile_2)$			0.01415			0.02023
			[0.03371]			[0.03484]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10048	0.10043	0.10046	0.11225	0.11221	0.11224
Policy covariates	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE				X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.164	1.134	1.103	1.164	1.134	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F1: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment, except for the continuous framework, where the reported mean is just the sample average.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020})$ (*continuous*)	0.00360 **			0.00388 **		
	[0.00161]			[0.00174]		
$Post * 1(Inactive\ Share_{q2/2020} \geq median)$		0.07825 ***			0.08517 **	
		[0.03170]			[0.03428]	
$Post * 1(Inactive\ Share_{q2/2020} \in Tercile_3)$			0.11610 ***			0.12601 ***
			[0.04193]			[0.04647]
$Post * 1(Inactive\ Share_{q2/2020} \in Tercile_2)$			0.01754			0.02838
			[0.03694]			[0.03734]
Observations	116,192	116,192	116,192	116,192	116,192	116,192
Policy covariates	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE				X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.164	1.134	1.103	1.164	1.134	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F2: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment, except for the continuous framework, where the reported mean is just the sample average.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.12711***	0.10910***	0.12504***	0.10737***	0.12628**	0.10531***
	[0.04446]	[0.03469]	[0.04469]	[0.03492]	[0.05043]	[0.03949]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05544	0.04717	0.05413	0.04595	0.05906	0.04760
	[0.04168]	[0.03228]	[0.04177]	[0.03238]	[0.04397]	[0.03411]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03729	0.03291	0.03742	0.03276	0.03403	0.02866
	[0.03844]	[0.02980]	[0.03847]	[0.02984]	[0.03897]	[0.03028]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10189	0.10664	0.10192	0.10666	0.11380	0.11759
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F3: OLS estimates performed on the sub-sample without abortions undertaken after the gestational limit. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.13487***	0.10765***	0.13240***	0.10562***	0.13769**	0.10738***
	[0.05016]	[0.03829]	[0.05031]	[0.03844]	[0.05461]	[0.04238]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05787	0.04417	0.05639	0.04282	0.06745	0.04757
	[0.04611]	[0.03468]	[0.04619]	[0.03476]	[0.04750]	[0.03620]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03919	0.03186	0.03985	0.03215	0.04074	0.02891
	[0.04252]	[0.03185]	[0.04256]	[0.03192]	[0.04199]	[0.03199]
Observations	115,504	115,504	115,504	115,504	115,504	115,504
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F4: PPML estimates performed on the sub-sample without abortions undertaken after the gestational limit. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.13125	0.11333	0.12888	0.11156	0.13183	0.11136
	***	***	***	***	***	***
	[0.04576]	[0.03580]	[0.04598]	[0.03602]	[0.05200]	[0.04082]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05615	0.04712	0.05482	0.04603	0.06231	0.05009
	[0.04276]	[0.03316]	[0.04284]	[0.03325]	[0.04513]	[0.03506]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03411	0.02915	0.03433	0.02913	0.03270	0.02673
	[0.03960]	[0.03075]	[0.03957]	[0.03075]	[0.04017]	[0.03128]
Observations	126,224	126,224	126,224	126,224	126,224	126,224
R-squared	0.10030	0.10501	0.10033	0.10503	0.11212	0.11594
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter−year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F5: OLS estimates performed on the municipal panel without the Italian Metropolitan Cities. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

PPML results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.14015	0.11406	0.13732	0.11191	0.14597	0.11630
	***	***	***	***	***	***
	[0.05119]	[0.03925]	[0.05133]	[0.03938]	[0.05596]	[0.04358]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05962	0.04587	0.05798	0.04450	0.07222	0.05199
	[0.04703]	[0.03549]	[0.04708]	[0.03554]	[0.04847]	[0.03707]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03665	0.02929	0.03704	0.02934	0.03854	0.02689
	[0.04362]	[0.03283]	[0.04359]	[0.03282]	[0.04312]	[0.03299]
Observations	115,968	115,968	115,968	115,968	115,968	115,968
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter−year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F6: PPML estimates performed on the municipal panel without the Italian Metropolitan Cities. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.09557	0.08961	0.08975	0.08505	0.07036	0.06337
	**	***	**	***		*
	[0.03902]	[0.03069]	[0.03938]	[0.03097]	[0.04490]	[0.03524]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05835	0.05018	0.05477	0.04720	0.04516	0.03498
		*		*		
	[0.03581]	[0.02812]	[0.03599]	[0.02827]	[0.03789]	[0.02973]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.01108	0.00975	0.01050	0.00911	0.00467	0.00327
	[0.03380]	[0.02639]	[0.03385]	[0.02644]	[0.03444]	[0.02693]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.09908	0.10414	0.09913	0.10418	0.11107	0.11519
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter−year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F7: OLS estimates performed on the sub-sample without abortions undertaken with urgency. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

PPML results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.10303	0.08936	0.09639	0.08429	0.07855	0.06404
	**	***	**	**		*
	[0.04473]	[0.03432]	[0.04508]	[0.03457]	[0.04910]	[0.03829]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.06003	0.04651	0.05595	0.04327	0.04834	0.03193
	[0.04066]	[0.03089]	[0.04088]	[0.03104]	[0.04140]	[0.03198]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.01091	0.00663	0.01076	0.00645	0.00775	0.00177
	[0.03820]	[0.02876]	[0.03826]	[0.02883]	[0.03752]	[0.02888]
Observations	112,576	112,576	112,576	112,576	112,576	112,576
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter−year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table F8: Estimates performed on the sub-sample without abortions undertaken with urgency. SEs clustered at municipal level. The aggregation of the units concerns the municipality of residence. *Mean* reports the mean value of the treated units pre-treatment. Reported statistics refer to Marginal Effects on the presented variables.

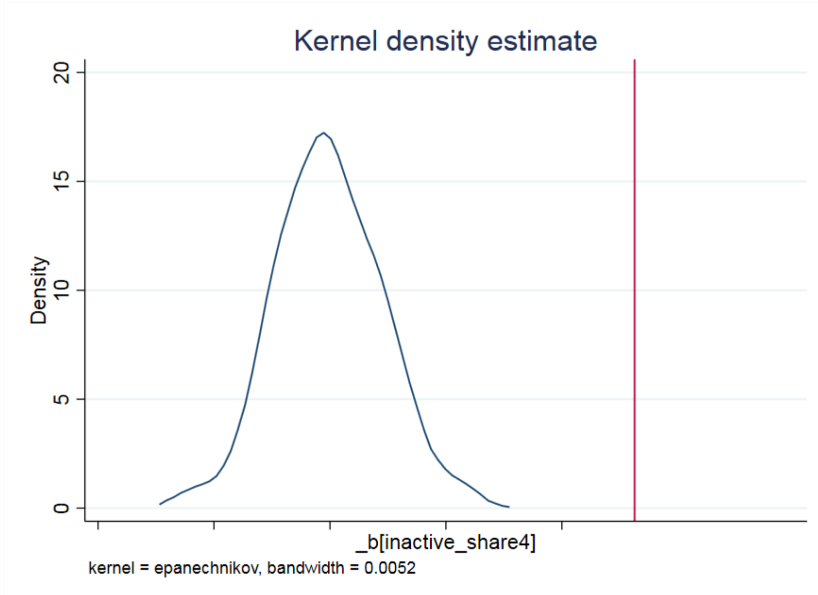


Figure F1: Randomization inference test with 1000 repetitions. The graph reports the density kernel for the coefficients estimated by randomly assigned the treatment to the observed units, modelling the empirical strategy as in Equation 3. The x-axis reports the estimated coefficients, the y-axis their density. The specification does not include interacted provincial FEs. The actual estimated baseline coefficient is the red line at the extreme right of the distribution.

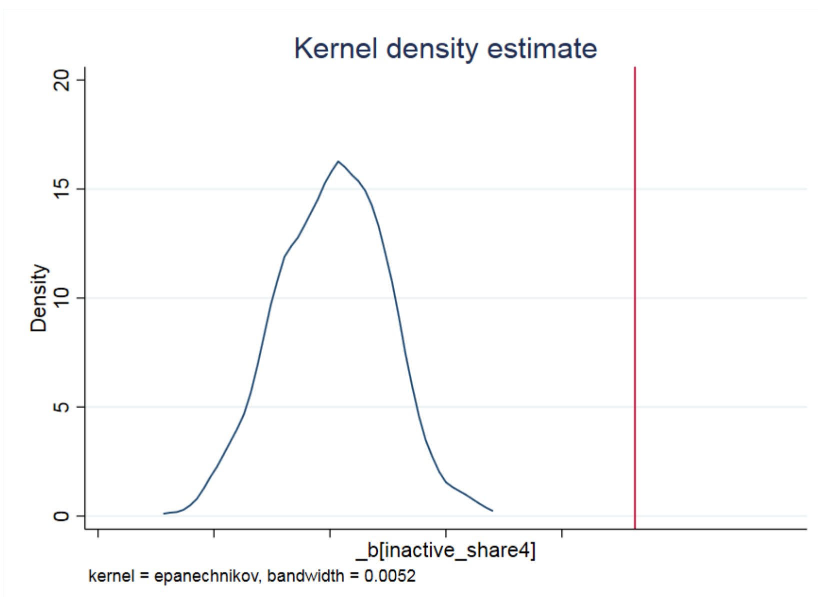


Figure F2: Randomization inference test with 1000 repetitions. The graph reports the density kernel for the coefficients estimated by randomly assigned the treatment to the observed units, modelling the empirical strategy as in Equation 3. The x-axis reports the estimated coefficients, the y-axis their density. The specification does include interacted provincial FEs. The actual estimated baseline coefficient is the red line at the extreme right of the distribution.

G Labor Market Areas

Figure G1: Italian LMAs (*Sistemi Locali del Lavoro*), introduced in 2011, as of 2018. They consist in 610 sub-regional areas where the bulk of the labour force lives and works, where establishments find the main part of their labour force (...); defined on a functional basis, the key criterion being the proportion of commuters who cross the LMA boundary on to work.

OLS and PPML results - By municipality of residence - SEs clustered at LMA level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.13134 ***	0.11340 ***	0.12879 ***	0.11133 ***	0.13168 **	0.11087 ***	0.13978 **	0.11324 ***	0.13676 **	0.11082 ***	0.14560 **	0.11515 ***
	[0.04862]	[0.03783]	[0.04878]	[0.03794]	[0.05419]	[0.04142]	[0.05449]	[0.04169]	[0.05461]	[0.04178]	[0.05762]	[0.04386]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.05711	0.04825	0.05570	0.04698	0.06342	0.05119	0.06016	0.04614	0.05855	0.04471	0.07307	0.05239
	[0.04341]	[0.03324]	[0.04377]	[0.03550]	[0.04587]	[0.03450]	[0.04797]	[0.03569]	[0.04836]	[0.03597]	[0.04954]	[0.03668]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.03486	0.02961	0.03505	0.02949	0.03353	0.02714	0.03709	0.02896	0.03769	0.02919	0.03967	0.02714
	[0.03874]	[0.03022]	[0.03879]	[0.03028]	[0.03960]	[0.03066]	[0.04280]	[0.03220]	[0.04284]	[0.03226]	[0.04247]	[0.03216]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	116,192	116,192	116,192	116,192	116,192	116,192
R-squared	0.10043	0.10529	0.10046	0.10531	0.11223	0.11621						
Policy covariates			X	X	X	X			X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X
LHA x Quarter˙year FE					X	X					X	X
Population weight		X		X		X		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table G1: The treatment is “administered” at municipal level. SEs are clustered at LMA level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

OLS and PPML results - By hospital - SEs clustered at LMA level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ -1.34072	-1.50525	-1.10354 *	-1.39824	-1.15342	-1.67544	-0.34996	-0.34081	-0.31330	-0.31080	-0.71250	-0.76142	
	[1.14351]	[0.87902]	[1.17667]	[0.89810]	[2.73537]	[2.23116]	[0.71083]	[0.58151]	[0.70246]	[0.57532]	[0.82663]	[0.69564]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.04345	-0.023301	-0.18356	-0.12472	0.78914	0.25097	0.27605	0.18864	0.29475	0.20608	-0.91513	-0.79908
	[0.83474]	[0.55897]	[0.88937]	[0.59377]	[2.82470]	[2.28710]	[0.52522]	[0.45456]	[0.52026]	[0.45353]	[0.70823]	[0.60443]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.42521	0.15314	0.53469	0.24105	0.38287	0.01008	0.56802	0.44409	0.58490	0.46441	-0.22870	-0.28396
	[0.81118]	[0.51662]	[0.82681]	[0.52848]	[2.76255]	[2.26002]	[0.47325]	[0.40107]	[0.46256]	[0.39367]	[0.72580]	[0.61486]
Observations	5,492	5,492	5,492	5,492	4,552	4,552	5,492	5,492	5,492	5,492	4,548	4,548
R-squared	0.87758	0.87388	0.87767	0.87394	0.88842	0.88018						
Policy covariates			X	X	X	X			X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X	X	X	X	X
LHA x Quarter˙year FE					X	X					X	X
Population weight		X		X		X		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640
9.640												

*** p<0.01, ** p<0.05, * p<0.1

Table G2: The treatment is "administered" at municipal level. SEs are clustered at LMA level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

OLS and PPML results - By municipality of residence - SEs clustered at LMA level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.11716 ***	0.10023 ***	0.11368 ***	0.09756 ***	0.16362 ***	0.12432 ***	0.12117 ***	0.09695 ***	0.11632 ***	0.09328 **	0.18155 ***	0.13264 ***
	[0.03876]	[0.03233]	[0.03864]	[0.03226]	[0.04492]	[0.03757]	[0.04501]	[0.03682]	[0.04467]	[0.03058]	[0.04974]	[0.04091]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.03891	0.03939	0.03684	0.03760	0.03655	0.02933	0.03660	0.03514	0.03393	0.03284	0.04065	0.03081
	[0.03765]	[0.03105]	[0.03771]	[0.03108]	[0.03998]	[0.03347]	[0.04291]	[0.03459]	[0.04277]	[0.03455]	[0.04561]	[0.03717]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.02931	0.01995	0.02870	0.01925	0.02503	0.00985	0.03901	0.02550	0.03788	0.02445	0.03718	0.01803
	[0.04500]	[0.03683]	[0.04477]	[0.03668]	[0.04229]	[0.03434]	[0.04911]	[0.03911]	[0.04868]	[0.03882]	[0.04573]	[0.03692]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	116,192	116,192	116,192	116,192	116,192	116,192
R-squared	0.10041	0.10528	0.10044	0.10530	0.11224	0.11621						
Policy covariates			X	X	X	X			X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X
LHA x Quarter˙year FE					X	X					X	X
Population weight		X		X		X		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103	1.103

*** p<0.01, ** p<0.05, * p<0.1

Table G3: The treatment is "administered" at LMA level. SEs are clustered at LMA level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

OLS and PPML results - By hospital - SEs clustered at LMA level

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR	(7) AR	(8) AR	(9) AR	(10) AR	(11) AR	(12) AR
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	-1.59668*	-1.38130**	-1.50190*	-1.30699**	-3.52320*	-2.92751*	0.08147	0.01667	0.06704	-0.00093	0.21808	0.10688
	[0.82203]	[0.64204]	[0.78201]	[0.62266]	[2.05417]	[1.72123]	[0.49445]	[0.41051]	[0.50055]	[0.41560]	[0.69830]	[0.57214]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	-1.30605	-1.13811*	-1.22759	-1.07970*	-1.78576	-1.63318	-0.20918	-0.19645	-0.20896	-0.20609	-0.16009	-0.16518
	[0.79314]	[0.64147]	[0.79692]	[0.64453]	[1.86803]	[1.62213]	[0.75595]	[0.57875]	[0.75261]	[0.57780]	[0.65246]	[0.53912]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.21040	-0.16667	-0.17162	-0.13891	-1.53414	-1.03436	0.44859	0.35898	0.42071	0.33360	0.36593	0.38315
	[0.38327]	[0.30783]	[0.37955]	[0.30387]	[2.24630]	[1.91039]	[0.56366]	[0.44101]	[0.56095]	[0.44009]	[0.79613]	[0.65268]
Observations	5,492	5,492	5,492	5,492	4,552	4,552	5,492	5,492	5,492	5,492	4,548	4,548
R-squared	0.87758	0.87381	0.87765	0.87386	0.88856	0.88016						
Policy covariates			X	X	X	X			X	X	X	X
Hospital FE	X	X	X	X	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X	X	X	X	X
LHA x Quarter˙year FE					X	X					X	X
Population weight		X		X		X		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML
Mean	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640	9.640

*** p<0.01, ** p<0.05, * p<0.1

Table G4: The treatment is "administered" at LMA level. SEs are clustered at LMA level. The aggregation of the units concerns the municipality where the VPT is undergone. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

H Abortion Mobility

	Descriptive statistics							
	Inter-municipal mobility				Inter-LMA mobility			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Abortion mobility	0.233	0.423	0	1	0.249	0.432	0	1
Number of previous live births	1.100	1.157	0	20	1.125	1.156	0	30
Number of previous stillbirths	0.008	0.118	0	10	0.008	0.115	0	10
Number of previous miscarriages	0.191	0.534	0	11	0.192	0.534	0	11
Number of previous VPTs	0.393	0.809	0	20	0.360	0.762	0	20
Gestational age (<90 days)	0.961	0.195	0	1	0.959	0.198	0	1
Gestational age (>90 days)	0.039	0.195	0	1	0.041	0.198	0	1
Weeks of amenorrhea	8.588	2.824	3	26	8.612	2.851	3	26
Urgent abortion	0.244	0.429	0	1	0.242	0.428	0	1
Non-urgent abortion	0.756	0.429	0	1	0.758	0.428	0	1
Presence of child malformations	0.048	0.213	0	1	0.049	0.216	0	1
Absence of child malformations or not indicated	0.952	0.213	0	1	0.951	0.216	0	1
Presence of complications	0.029	0.167	0	1	0.028	0.166	0 1	
Medical abortion	0.357	0.479	0	1	0.348	0.476	0	1
Surgical abortion	0.643	0.479	0	1	0.652	0.476	0	1
Italian citizenship	0.669	0.471	0	1	0.704	0.457	0	1
Age	30.787	7.356	10	60	30.910	7.363	10	60
Level of education								
Elementary school	0.051	0.221	0	1	0.044	0.206	0	1
Middle school	0.367	0.482	0	1	0.370	0.483	0	1
High school	0.430	0.495	0	1	0.448	0.497	0	1
University degree or others	0.151	0.358	0	1	0.138	0.345	0	1
Marital status								
Single	0.614	0.487	0	1	0.598	0.490	0	1
Married	0.344	0.475	0	1	0.358	0.480	0	1
Separated	0.017	0.127	0	1	0.017	0.130	0	1
Widow	0.026	0.158	0	1	0.027	0.162	0	1
Professional condition								
Employed	0.440	0.496	0	1	0.448	0.497	0	1
Unemployed	0.234	0.423	0	1	0.222	0.415	0	1
Looking for first job	0.017	0.128	0	1	0.017	0.130	0	1
Housewife	0.191	0.393	0	1	0.202	0.402	0	1
Student	0.112	0.315	0	1	0.107	0.309	0	1
Other	0.006	0.079	0	1	0.007	0.082	0	1
Professional branch of activity								
Not in professional condition	0.560	0.496	0	1	0.552	0.497	0	1
Agriculture, hunting and fishing	0.006	0.074	0	1	0.008	0.089	0	1
Industry	0.028	0.165	0	1	0.028	0.164	0	1
Trade, services, hospitality (private)	0.136	0.343	0	1	0.147	0.348	0	1
Public administration	0.042	0.200	0	1	0.041	0.198	0	1
Other private services	0.229	0.420	0	1	0.216	0.412	0	1
Obs.				97,550				173,791

Table H1: Descriptive statistics of the variables used for the analysis of inter-municipal and inter-LMA mobility of abortions.

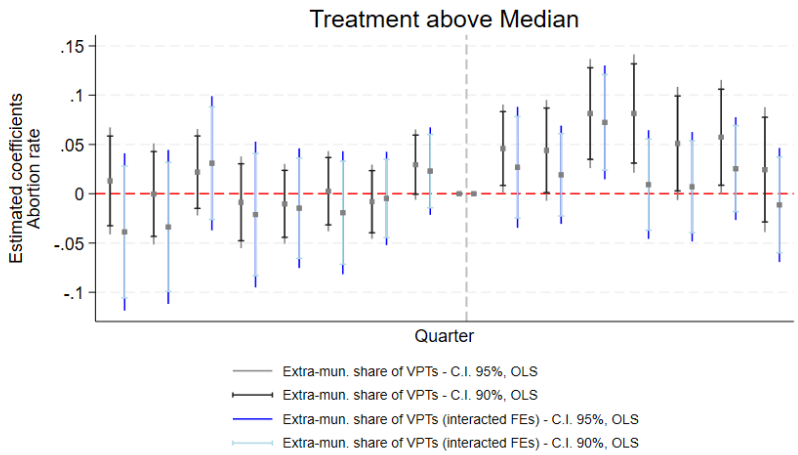


Figure H1: OLS Event-study estimates. The figure reports the coefficient on temporal units and their confidence intervals, for the specification using inter-municipal mobility as outcomes, both for the baseline and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95%. The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020. The women deemed as treated are the one residing in municipalities above the median of the distribution of the inactive share.

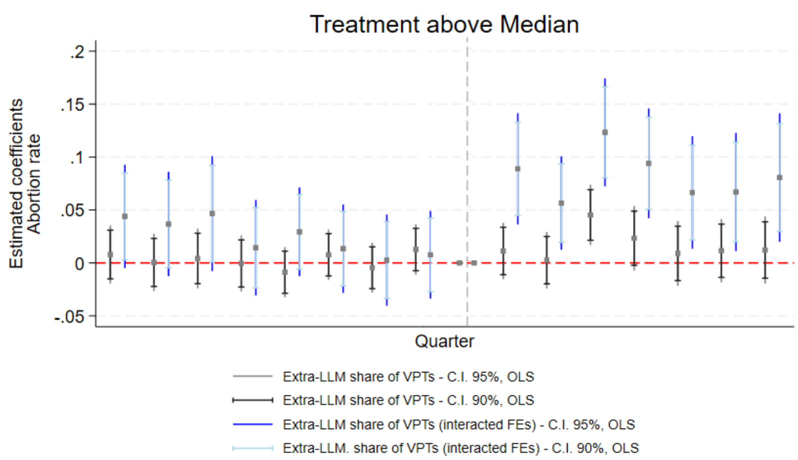


Figure H2: OLS Event-study estimates. The figure reports the coefficient on temporal units and their confidence intervals, for the specification using inter-LMA mobility as outcomes, both for the baseline and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95%. The x-axis represents all quarters from 2018Q1 to 2021Q4. The vertical line is set on quarter 9, which corresponds to the first quarter of 2020, the first lead before the treatment, occurring on Q2 2020. The women deemed as treated are the one residing in municipalities above the median of the distribution of the inactive share.

I Socio-economic Information

OLS results - By municipality of residence - SEs clustered at municipal level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR single	AR married	AR separated	AR widow	AR single	AR married	AR separated	AR widow
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	0.00107	-0.02319	0.00026	0.00941				
	[0.04030]	[0.02880]	[0.00432]	[0.00767]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	-0.01561	-0.02276	0.00061	-0.00599				
	[0.02999]	[0.02681]	[0.00371]	[0.00553]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	-0.02311	-0.03385	0.00303	0.00048				
	[0.03611]	[0.02929]	[0.04846]	[0.02652]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$					0.08384*	0.03899	0.00360	-0.00737
					[0.04353]	[0.03038]	[0.00470]	[0.00832]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$					0.01386	0.02836	0.00009	-0.01190**
					[0.03960]	[0.02784]	[0.00434]	[0.00566]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$					-0.00482	0.01194	0.00414	-0.00311
					[0.03595]	[0.02420]	[0.00411]	[0.00470]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10013	0.09401	0.08803	0.07710	0.10019	0.09401	0.08803	0.07708
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.700	0.385	0.0295	0.0214	0.585	0.412	0.0284	0.0275

*** p<0.01, ** p<0.05, * p<0.1

Table I1: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR single	(2) AR married	(3) AR separated	(4) AR widow	(5) AR single	(6) AR married	(7) AR separated	(8) AR widow
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	0.00666	-0.05523	-0.03730	0.05348**				
	[0.04582]	[0.03603]	[0.05273]	[0.02684]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	-0.01534	-0.03143	-0.01379	-0.01448				
	[0.03577]	[0.03038]	[0.05832]	[0.02402]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	-0.02515	-0.04631	-0.05966	0.00028				
	[0.03611]	[0.02929]	[0.04846]	[0.02652]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$					0.09310*	0.07597**	0.09492*	-0.06138**
					[0.04874]	[0.03778]	[0.05293]	[0.02603]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$					0.01029	0.05643*	-0.05002	-0.06404***
					[0.04297]	[0.03363]	[0.05082]	[0.02190]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$					-0.01201	0.02515	0.05996	-0.02966
					[0.03904]	[0.03039]	[0.04146]	[0.01815]
Observations	108,608	98,096	17,105	29,934	108,608	98,096	17,105	29,934
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.700	0.385	0.0295	0.0214	0.585	0.412	0.0284	0.0275

*** p<0.01, ** p<0.05, * p<0.1

Table I2: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence - SEs clustered at municipal level

	(1) AR employed	(2) AR unemployed	(3) AR first job	(4) AR housewives	(5) AR students	(6) AR employed	(7) AR unemployed	(8) AR first job	(9) AR housewives	(10) AR students
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ *(services)*	-0.01780	-0.01276	-0.00114	-0.00435	0.03525**					
	[0.03615]	[0.02306]	[0.00626]	[0.01845]	[0.01557]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ *(services)*	-0.02741	0.00574	-0.00067	-0.00376	-0.00887					
	[0.02796]	[0.02157]	[0.00512]	[0.01625]	[0.01079]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ *(services)*	-0.02600	-0.00473	0.00273	-0.01743	-0.00929					
	[0.02762]	[0.02083]	[0.00490]	[0.01520]	[0.01035]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ *(industry)*						0.04632	0.05505**	0.01405***	0.02439	-0.01977
						[0.03873]	[0.02592]	[0.00535]	[0.01860]	[0.01530]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ *(industry)*						-0.00068	0.05289**	0.01087**	0.00324	-0.03077**
						[0.03627]	[0.02411]	[0.00532]	[0.01740]	[0.01463]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ *(industry)*						-0.02914	0.05632***	0.00609	0.01353	-0.02691**
						[0.03226]	[0.02164]	[0.00507]	[0.01610]	[0.01307]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.09778	0.08833	0.07475	0.10162	0.07813	0.09782	0.08841	0.07481	0.10163	0.07804
Policy covariates	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.573	0.234	0.0153	0.209	0.107	0.554	0.212	0.00868	0.187	0.0945

*** p<0.01, ** p<0.05, * p<0.1

Table I3: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR employed	(2) AR unemployed	(3) AR first job	(4) AR housewives	(5) AR students	(6) AR employed	(7) AR unemployed	(8) AR first job	(9) AR housewives	(10) AR students
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	-0.01475	-0.03564	-0.00628	-0.02072	0.06611***					
	[0.04163]	[0.03139]	[0.04498]	[0.03163]	[0.02549]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	-0.02394	-0.00117	0.00942	-0.00216	-0.00431					
	[0.03346]	[0.02643]	[0.03846]	[0.02547]	[0.02244]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	-0.02547	-0.01494	0.02273	-0.02464	-0.00826					
	[0.03332]	[0.02667]	[0.04129]	[0.02409]	[0.02178]					
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$						0.05835	0.07110**	0.15885***	0.05323*	-0.03169
						[0.04423]	[0.03289]	[0.03916]	[0.03123]	[0.02561]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$						0.00782	0.06623**	0.11414***	0.01499	-0.04891**
						[0.04166]	[0.02857]	[0.03930]	[0.02747]	[0.02341]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$						-0.03659	0.07105***	0.06191**	0.02190	-0.04543**
						[0.03874]	[0.02616]	[0.03004]	[0.02340]	[0.02025]
Observations	105,135	84,964	12,910	79,276	66,668	105,135	84,964	12,910	79,276	66,668
Policy covariates	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.573	0.234	0.0153	0.209	0.107	0.554	0.212	0.00868	0.187	0.0945

*** p<0.01, ** p<0.05, * p<0.1

Table I4: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

OLS results - By municipality of residence - SEs clustered at municipal level

	(1) AR prof. cond.	(2) AR entrepreneur	(3) AR self-employed	(4) AR manager	(5) AR white collar	(6) AR blue collar	(7) AR prof. cond.	(8) AR entrepreneur	(9) AR self-employed	(10) AR manager	(11) AR white collar	(12) AR blue collar
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	0.00888	-0.03556***	-0.00849	0.00165	0.01421	0.00965						
	[0.03517]	[0.01043]	[0.01041]	[0.00434]	[0.02157]	[0.02111]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	-0.01111	-0.00673	-0.00569	-0.00138	0.00518	-0.01224						
	[0.03013]	[0.00710]	[0.00728]	[0.00388]	[0.01629]	[0.01784]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	-0.03148	-0.01040	0.00311	-0.00277	-0.00180	-0.00489						
	[0.02931]	[0.00706]	[0.00610]	[0.00327]	[0.01578]	[0.01792]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$							0.07977**	0.02303**	0.00405	0.00037	0.02866	-0.01051
							[0.03712]	[0.01010]	[0.00814]	[0.00433]	[0.02339]	[0.02433]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$							0.03449	0.00453	0.00202	0.00170	-0.00274	-0.00272
							[0.03519]	[0.01047]	[0.00894]	[0.00361]	[0.02079]	[0.02165]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$							0.05034	0.00861	0.00106	0.00203	-0.00418	-0.03103
							[0.03118]	[0.00866]	[0.00699]	[0.00377]	[0.01805]	[0.01950]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10406	0.07456	0.07329	0.07297	0.07970	0.08131	0.10410	0.07447	0.07328	0.07296	0.07973	0.08133
Policy covariates	X	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.572	0.0627	0.0453	0.0138	0.196	0.174	0.512	0.0338	0.0288	0.0140	0.201	0.209

*** p<0.01, ** p<0.05, * p<0.1

Table I5: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR prof. cond.	(2) AR entrepreneur	(3) AR self-employed	(4) AR manager	(5) AR white collar	(6) AR blue collar	(7) AR prof. cond.	(8) AR entrepreneur	(9) AR self-employed	(10) AR manager	(11) AR white collar	(12) AR blue collar
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(services)$	0.00316	-0.08429***	-0.02247	0.01661	0.02474	0.01763						
	[0.04292]	[0.02521]	[0.03620]	[0.03242]	[0.03124]	[0.03206]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(services)$	-0.01117	-0.01329	-0.02154	-0.02221	0.01495	-0.01708						
	[0.03472]	[0.02175]	[0.02827]	[0.02797]	[0.02434]	[0.02632]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(services)$	-0.03788	-0.02813	-0.01355	-0.03124	-0.00286	-0.00181						
	[0.03450]	[0.02119]	[0.02580]	[0.02755]	[0.02373]	[0.02653]						
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$ $(industry)$							0.10076**	0.05242**	0.01229	-0.00192	0.05381	-0.00950
							[0.04318]	[0.02397]	[0.03107]	[0.00000]	[0.03292]	[0.03522]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$ $(industry)$							0.03834	0.00137	0.00749	0.02692	0.00789	-0.00137
							[0.03904]	[0.02218]	[0.03066]	[0.00000]	[0.02916]	[0.03268]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$ $(industry)$							0.05479	0.00699	0.00491*	0.01751	-0.00295	-0.05319
							[0.03339]	[0.01966]	[0.02359]	[0.00000]	[0.02647]	[0.03116]
Observations 105,104	41,184	34,584	17,641	81,622	78,897	105,104	41,184	34,584	17,641	81,622	78,897	105,104
Policy covariates	X	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.572	0.0627	0.0453	0.0138	0.196	0.174	0.512	0.0338	0.0288	0.0140	0.201	0.209

*** p<0.01, ** p<0.05, * p<0.1

Table I6: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

J Previous pregnancies

OLS results - By municipality of residence - SEs clustered at municipal level								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR	AR	AR	AR	AR	AR	AR	AR
	with previous pregnancies	with no previous pregnancies	with previous deliveries	with previous abortions	with previous pregnancies	with no previous pregnancies	with previous deliveries	with previous abortions
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (services)$	0.00760	-0.00740	0.00939	0.00138				
	[0.01270]	[0.00992]	[0.01220]	[0.00961]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (services)$	0.00420	-0.01712 **	0.00718	-0.00038				
	[0.01078]	[0.00767]	[0.01040]	[0.00799]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (services)$	-0.00253	-0.01558 **	0.00032	-0.00221				
	[0.01069]	[0.00776]	[0.01030]	[0.00792]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (industry)$					0.02952 **	0.00168	0.03140 ***	0.01173
					[0.01270]	[0.00992]	[0.01220]	[0.00961]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (industry)$					0.01859	-0.00984	0.01786	0.00274
					[0.01240]	[0.00922]	[0.01168]	[0.00946]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (industry)$					0.01047	-0.00454	0.01378	0.00478
					[0.01144]	[0.00911]	[0.01076]	[0.00914]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.03397	0.02404	0.03188	0.03137	0.03399	0.02403	0.03190	0.03137
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.245	0.138	0.216	0.125	0.242	0.119	0.217	0.118

*** p<0.01, ** p<0.05, * p<0.1

Table J1: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

PPML results - By municipality of residence - SEs clustered at municipal level

	(1) AR with previous pregnancies	(2) AR with no previous pregnancies	(3) AR with previous deliveries	(4) AR with previous abortions	(5) AR with previous pregnancies	(6) AR with no previous pregnancies	(7) AR with previous deliveries	(8) AR with previous abortions
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (services)$	0.00810	-0.00836	0.00984	0.00206				
	[0.01512]	[0.01242]	[0.01474]	[0.01316]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (services)$	0.00607	-0.02173 **	0.00934	0.00065				
	[0.01237]	[0.01015]	[0.01209]	[0.01064]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (services)$	-0.00286	-0.02059 **	0.00027	-0.00286				
	[0.01243]	[0.01040]	[0.01212]	[0.01073]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)\ (industry)$					0.03367 **	0.00090	0.03705 ***	0.01407
					[0.01405]	[0.01187]	[0.01349]	[0.01252]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)\ (industry)$					0.02183	-0.01306	0.02187	0.00285
					[0.01430]	[0.01136]	[0.01362]	[0.01235]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)\ (industry)$					0.01055	-0.00633	0.01511	0.00466
					[0.01335]	[0.01119]	[0.01270]	[0.01205]
Observations	321,057	292,810	315,229	279,321	321,057	292,810	315,229	279,321
R-squared								
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.245	0.138	0.216	0.125	0.242	0.119	0.217	0.118

*** p<0.01, ** p<0.05, * p<0.1

Table J2: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment. The coefficients on the treatment for the PPML estimates report marginal effects.

K Live births

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Pregnancy rate	(2) Pregnancy rate	(3) Pregnancy rate	(4) Pregnancy rate	(5) Pregnancy rate	(6) Pregnancy rate
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.18648	0.09564	0.19157	0.09772	0.19198	0.08489
	[0.15421]	[0.11545]	[0.15473]	[0.11593]	[0.17103]	[0.13174]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.07411	0.05157	0.07043	0.04717	0.05417	0.02808
	[0.12459]	[0.09789]	[0.12520]	[0.09835]	[0.13563]	[0.10705]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.05540	0.02771	0.05419	0.02651	0.04106	0.01579
	[0.11916]	[0.09300]	[0.11930]	[0.09318]	[0.12193]	[0.09547]
Observations	101,816	101,816	101,816	101,816	101,816	101,816
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	7.722	7.722	7.722	7.722	7.722	7.722

*** p<0.01, ** p<0.05, * p<0.1

Table K1: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Pregnancy rate	(2) Pregnancy rate	(3) Pregnancy rate	(4) Pregnancy rate	(5) Pregnancy rate	(6) Pregnancy rate	(7) Pregnancy rate	(8) Pregnancy rate	(9) Pregnancy rate	(10) Pregnancy rate	(11) Pregnancy rate
$Post * 1(Inactive\ Share_{q2/2018} \in Q_4)$	0.14968	0.27593	0.15891								
	[0.23275]	[0.24249]	[0.23310]								
$Post * 1(Inactive\ Share_{q2/2019} \in Q_4)$				0.04109	0.43332 *	0.06468	0.48555 **				
				[0.13925]	[0.22139]	[0.15492]	[0.20271]				
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$								0.33835	0.23009	0.29522 *	0.26974
								[0.25577]	[0.15803]	[0.16219]	[0.24524]
Observations	71,127	31,612	63,224	71,127	31,612	63,224	63,224	31,612	94,836	63,224	39,515
R-squared	0.16697	0.30120	0.17944	0.16697	0.27891	0.17944	0.16780	0.27321	0.13491	0.16778	0.23611
Policy covariates								X	X	X	
Excess mortality							X	X	X	X	
Municipal FE	X	X	X	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Time-span	’18-’19, ’21	’18	’18-’19	’18-’19, ’21	’19	’18-’19	’19-’20	’20	’18-’20	’19-’20	’20-’21
Mean	8.113	8.113	8.113	7.759	7.454	7.759	7.454	7.640	7.722	7.631	7.640

*** p<0.01, ** p<0.05, * p<0.1

Table K2: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Abortivity ratio	(2) Abortivity ratio	(3) Abortivity ratio	(4) Abortivity ratio	(5) Abortivity ratio	(6) Abortivity ratio
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	9.80620**	10.11692**	9.98114**	10.31095**	6.23252	6.83577
	[4.38194]	[4.33384]	[4.38197]	[4.33737]	[4.81508]	[4.80299]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.37257	0.65708	0.58223	0.87678	-1.49803	-1.28786
	[4.41271]	[4.26418]	[4.41333]	[4.26832]	[4.58851]	[4.45510]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-3.21523	-1.94473	-3.11239	-1.85594	-4.34428	-3.23510
	[4.32421]	[4.15086]	[4.32240]	[4.15039]	[4.40992]	[4.22969]
Observations	102,739	102,739	102,739	102,739	102,739	102,739
R-squared	0.15676	0.15528	0.15679	0.15533	0.17062	0.16935
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	117.9	117.9	117.9	117.9	117.9	117.9

*** p<0.01, ** p<0.05, * p<0.1

Table K3: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Abortivity ratio	(2) Abortivity ratio	(3) Abortivity ratio	(4) Abortivity ratio	(5) Abortivity ratio	(6) Abortivity ratio
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	11.06531*	10.26344*	11.20935*	10.42181*	6.88156	6.81692
	[6.03860]	[5.63701]	[6.04102]	[5.64457]	[6.71017]	[6.28474]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	3.22136	2.21137	3.39440	2.40031	0.34136	-0.27634
	[5.56678]	[5.13370]	[5.57498]	[5.14596]	[5.81824]	[5.37480]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.06919	0.29399	0.23400	0.46207	-2.09225	-1.56822
	[0.11916]	[0.09300]	[0.11930]	[0.09318]	[0.12193]	[0.09547]
Observations	86,216	86,216	86,216	86,216	86,216	86,216
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Population weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	117.9	117.9	117.9	117.9	117.9	117.9

*** p<0.01, ** p<0.05, * p<0.1

Table K4: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Pregnancy rate (Single)	(2) Pregnancy rate (Married or in civil union)	(3) Pregnancy rate (Divorced or separated)	(4) Pregnancy rate (Widow)	(5) Pregnancy rate (Single)	(6) Pregnancy rate (Married or in civil union)	(7) Pregnancy rate (Divorced or separated)	(8) Pregnancy rate (Widow)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.02728	-0.00948	0.01379	0.00449	0.03302	-0.00340	0.03525	0.07689
				*				**
	[0.07717]	[0.09427]	[0.01178]	[0.00229]	[0.07913]	[0.09309]	[0.02414]	[0.03169]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	-0.01102	0.02078	0.02121	0.00286	-0.00469	0.02426	0.05365	0.03324
			*				**	
	[0.08329]	[0.10440]	[0.01235]	[0.00342]	[0.08366]	[0.10483]	[0.02572]	[0.04003]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.17972	-0.00920	0.00444	-0.00039	0.16801	-0.00531	0.01671	-0.02350
	[0.11375]	[0.12561]	[0.01608]	[0.00261]	[0.10398]	[0.13006]	[0.03168]	[0.04980]
Observations	102,739	102,739	102,739	102,739	99,073	100,646	53,295	7,761
R-squared	0.12967	0.14508	0.09098	0.08720				
Policy covariates	X	X	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML
Mean	2.814	4.563	0.138	0.00815	2.814	4.563	0.138	0.00815

*** p<0.01, ** p<0.05, * p<0.1

Table K5: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) Pregnancy rate (with 1 minor in the family already)	(2) Pregnancy rate (with no minor in the family already)	(3) Pregnancy rate (with more than 1 minor in the family)	(4) Pregnancy rate (with 1 minor in the family already)	(5) Pregnancy rate (with no minor in the family already)	(6) Pregnancy rate (with more than 1 minor in the family)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.08043	-0.03657	-0.02557	0.08527	-0.03071	-0.02786
	[0.07219]	[0.08965]	[0.04105]	[0.07312]	[0.08872]	[0.04615]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.08673	-0.10174	0.03708	0.08836	-0.09353	0.04328
	[0.07804]	[0.09648]	[0.04430]	[0.07934]	[0.09501]	[0.04962]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	0.04504	0.12412	0.00417	0.04748	0.11070	0.00609
	[0.09393]	[0.13213]	[0.05715]	[0.09768]	[0.12317]	[0.06291]
Observations	102,739	102,739	102,739	99,086	100,581	91,247
R-squared	0.10669	0.10427	0.13050			
Policy covariates	X	X	X	X	X	X
Municipal FE	X	X	X	X	X	X
Month−year FE	X	X	X	X	X	X
Province x Quarter˙year FE	X	X	X	X	X	X
Method	OLS	OLS	OLS	PPML	PPML	PPML
Mean	2.813	3.595	1.166	2.813	3.595	1.166

*** p<0.01, ** p<0.05, * p<0.1

Table K6: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

L Contraception

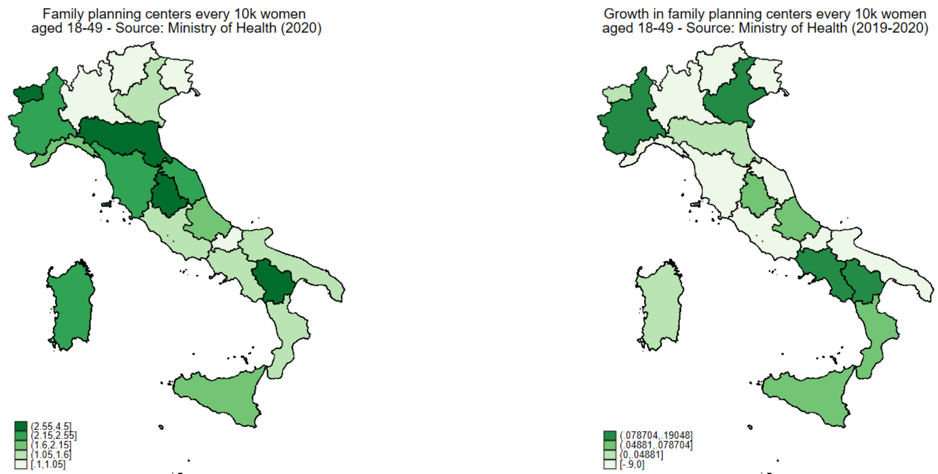


Figure L1: Family planning centres in Italy in 2020. Left panel: number of family planning centres every 10,000 women aged between 18 and 49 in 2020. Right panel: growth in family planning centres every 10,000 women aged between 18 and 49 between 2019 and 2020. Source: Ministry of Health

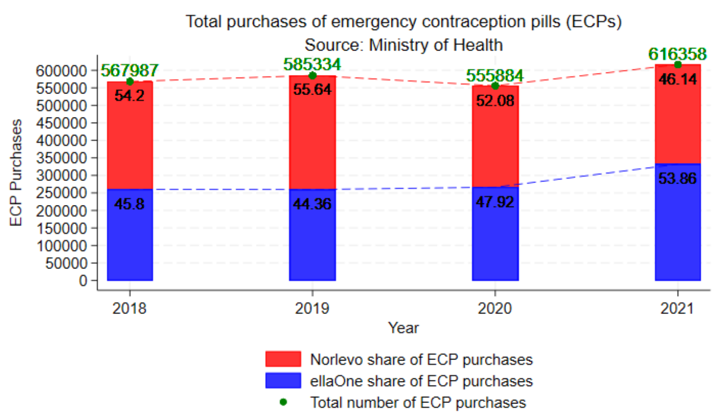


Figure L2: ECP sales in Italy between 2018 and 2021. Source: Ministry of Health.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

	(1) AR (minors)	(2) AR (minors)	(3) AR (minors)	(4) AR (minors)	(5) AR (minors)	(6) AR (minors)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.00882	0.00513	0.00864	0.00498	0.01316	0.00848
	[0.00918]	[0.00655]	[0.00904]	[0.00648]	[0.01091]	[0.00776]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.00636	0.00400	0.00630	0.00393	0.00933	0.00615
	[0.00692]	[0.00535]	[0.00690]	[0.00534]	[0.00755]	[0.00583]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.00347	-0.00357	-0.00344	-0.00360	-0.00326	-0.00370
	[0.00443]	[0.00380]	[0.00443]	[0.00380]	[0.00467]	[0.00393]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.06461	0.06524	0.06462	0.06525	0.07395	0.07377
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Pop. weight		X		X		X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.098	1.098	1.098	1.098	1.098	1.098

*** p<0.01, ** p<0.05, * p<0.1

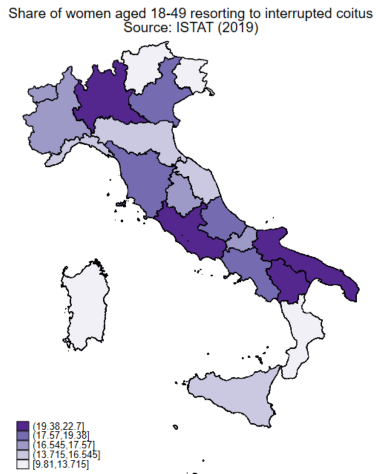
Table L1: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

OLS results - Pregnancies resulting into live births - SEs clustered at municipal level

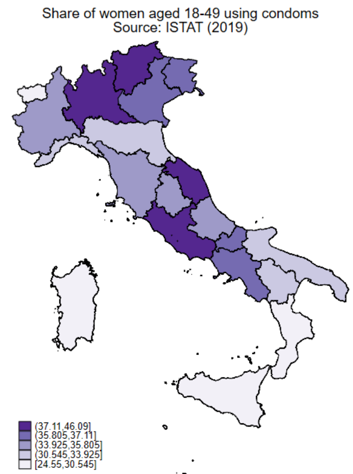
	(1) AR (minors)	(2) AR (minors)	(3) AR (minors)	(4) AR (minors)	(5) AR (minors)	(6) AR (minors)
$Post * 1(Inactive\ Share_{q2/2020} \in Q_4)$	0.03421	0.01806	0.03430	0.01787	0.05223 *	0.03286
	[0.03219]	[0.02180]	[0.03187]	[0.02162]	[0.02964]	[0.00000]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_3)$	0.02138	0.01196	0.02072	0.01130	0.01326	0.00847
	[0.02315]	[0.01613]	[0.02329]	[0.01618]	[0.02432]	[0.00000]
$Post * 1(Inactive\ Share_{q2/2020} \in Q_2)$	-0.01500	-0.01307	-0.01480	-0.01315	-0.01683	-0.01471
	[0.01949]	[0.01376]	[0.01947]	[0.01376]	[0.02091]	[0.00000]
Observations	32,208	32,208	32,208	32,208	29,024	29,024
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Quarter−year FE	X	X	X	X	X	X
Province x Quarter˙year FE					X	X
Pop. weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.098	1.098	1.098	1.098	1.098	1.098

*** p<0.01, ** p<0.05, * p<0.1

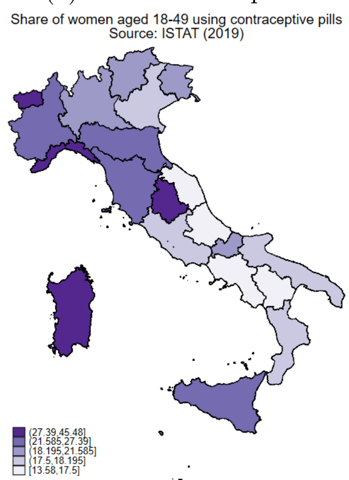
Table L2: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.



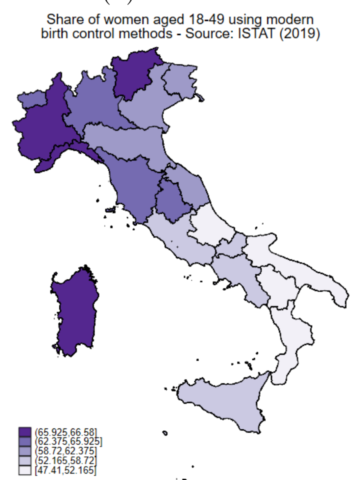
(a) Coitus interruptus.



(b) Condoms.



(c) Contraceptive pills.



(d) Modern birth control methods.

Figure L3: Share of women aged 18-49 using different methods of contraception in 2019. Source: ISTAT

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