Suspended workers, abortions and fertility*

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Abstract

We investigate the effect of an Italian job suspension 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 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. 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' distribution saw a positive effect on quarterly ARs (between 10-13% the average pre-pandemic rate), compared to those belonging to the lower tail; the impact is mostly driven by industrial suspensions. A non-significant effect is retrieved on births. We employ socio-economic information to inquire about potential mechanisms. Plus, for the first time in the research with the same data, we exploit information on past reproductive behavior of the aborting women. The effect on abortions is driven mostly by married women, not in professional condition. Plus, and more interestingly, by those who previously had pregnancies (1 or 2 children). By contrast, the occupational sector of the aborting women is independent on the sector of the job suspension share, while the industrial sector-driven effect linked to married women OLF hints that, for those who seek for abortion, male partners' work trajectories matter more than theirs in the context of such decision-making process, thus revealing potential mechanisms for the exposure of gender imbalances within the impacted couples.

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

1 Introduction

Along the latest decades, 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 decisions, may lead to major policy implications. These may concern family and childcare subsidization, public and reproductive health, gender-equalizing policies, welfare schemes and the improvement of labor productivity. The topic bears relevance especially in the context of the sharp demographic decline 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 Becker, 1960, who assessed the observed negative relationship between fertility and

*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.

both income and female labor supply. After 2000 there has been a reversal of the pattern, hinted by the positive cross-country association between GDP per capita and fertility, whose major explanations refer to family planning and reproductive health determinants, which are usually related to women's empowerment and improved control of their fertility[1]. Beyond the usual outcomes of a couple's fertility decision (extensive margin - i.e. to have or not a child - and "intensive" margin - i.e. how many kids to have), there is another "negative" 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 embedding the 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 as a resort to terminate an unwanted pregnancy, conditional on an existing one. An abortion requires a faster planning process, as action must be taken before the birth is delivered, *and* before the unvoluntary pregnancy develops beyond gestational limits. 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 shall be naive to trace the fertility decline back to abortion decisions[2]. However, the monitoring of abortion patterns matters to considerations about the "second-step" choice of a fertility decision process, conditional on the first step which is occurrence of an undesired gestation. This shall matter in drawing policy implications related to the interlink between demographics and economic determinants, and also health and gender-related assessments concerning female contraception policies and women's control over their own fertility. 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. Gender equity considerations are also fundamental: it could be topical to understand how many abortions are sought due to economic and/or psychological vulnerability. The latter may stem from fear of motherhood being a source of career costs and/or job displacement, or from the incapacity of controlling one's own fertility because of within-couple vulnerabilities. The aim of the present paper is to study how a public health policy targeting outcomes other to fertility and operating through economic channels, may significantly impact family planning dynamics. The focus is mainly on abortions. We exploit the discontinuity brought about by the Covid-19 pandemic, which caused an unexpected, remarkable breakthrough on multifaceted aspects of 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 crisis, to study its impact on the pattern of voluntary pregnancy terminations of Italian women, following the quarterly evolution of municipal abortion rates (ARs) from 2018 to 2021. We draw this information from the administrative dataset on the universe of Italian abortions, annually collected by the Ministry of Health and managed by ISTAT. 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 the government between the end of March and June 2020, to workers in sectors deemed as "non-essential". While the lockdown, homogeneous across the whole country, triggered an overall drop in abortion rates plausibly due to the reduction in social encounters (see also Trommlerová and González, 2024), such shift was heterogeneous across areas, according to the share of suspended workers in such areas. The first fashion through which the policy might hit differentially abortions is the "exposure" channel, i.e. the more time available to be spent together at home, due to the suspension and to parity of the lock-down. This might have enabled an increase in intercourse between inactive individuals or between inactive ones and their partners, leading to heterogeneous fertility outcomes. Therefore, the differential effect might be driven by an underlying variation in unplanned child-bearings[3]. Concerning the second mechanism, 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 and foremost, compared to municipalities in the

[1] 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), 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).

[2] 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.

[3] The sociological literature points out how increased time within abusive couples raises the exposure to domestic violence, which may be a driver of unplanned pregnancies linked either to direct sexual violence episodes or due to more complex dynamics of imbalances which elapse over time.

lower tail of the distribution, we find that the municipal areas hit more by the pandemic in terms of suspended jobs (i.e. the 4° quartile), saw an increase in quarterly ARs of resident women by slightly more than 10 p.p. Such values amount to more than 10% the average quarterly municipal AR in our data. However, the effect is short-lived, and the differential impacts disappears after 6 months. A major concern to our identification is its integration to the 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, hospital workload and other limitations in reproductive assistance. In this regard, the study is provided with several robustness checks to rule out the channel of supply restrictions. Overall, evidence seems to show the absence of an impact of workers' suspension on the average provision of abortion services. We integrate the abortion analysis in further different directions, by employing the same DiD empirical design, but changing outcomes: we apply the same analysis on the municipal rates of pregnancies culminating, 9 months later, into live births, for which we have administrative data on birth registrations. The aim is to check whether the sudden suspension shock also affected more thoughtful and time-elapsed aspects of family planning. We find no effect on pregnancies resulting into live births. Second, we perform a thorough heterogeneity analysis by making use of detailed demographic and socio-economic information on aborting women, and by differentiating the identification between the suspended share of service workers and that of the industry. We retrieve that results are mostly driven by married women, not in professional condition. Concerning the treatment, the effect seems to be brought about by the suspension of industrial workers, whereas no link seems to subsist between the sectoral share of suspension and the women's economic branch of activity. These results point out to the direction that the policy might affect women mediated by their partner's job trajectories, rather than a direct socio-economic impact of the pandemic insecurity in their field of employment. Third, and for the first time in this strand of literature (in our knowledge at least), we explore the information on previous pregnancies of aborting women.. 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 had aborted at most once in the past. Such outcomes may leave room to the hypothesis of socio-economic insecurity being part of the general explanation of the findings, and as a plausible argument in favor of female vulnerability or lack of independence with respect to male bread. This also provides with relevant insights on how Italian couple may respond to exogenous shocks by adjusting their involuntary fertility decisions. 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" (i.e., more time available together leading to episodes of domestic abuse, Dugan et al., 1999). Our findings show that this may possibly not be the case in the present context in terms of reported violence episodes, as we find no 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, the paper can be numbered among those in the literature that analyzes how socio-economic shocks affect fertility patterns, by adding relatively unexplored elements other than the mere hypothesis of resource constraint being caused by income or job loss: first, exposure due to unemployment/job suspension, second, economic uncertainty in a broader sense and third, past reproductive behavior. Concerning unemployment shocks, 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, mostly for high-skilled women working in career-oriented jobs .[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 income fluctuations (Schaller, 2016; Schaller et al., 2020). Demographic works 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 too (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 pattern. 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

[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, Core, 2024.

empowerment. 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 socio-economic determinants of the abortion demand has soared, mostly concerning the relationship between income/labor market opportunities and fertility: Herbst, 2011 , for instance, displays how increases in income tax-credits lowered abortions in the U.S. Regarding 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 inquire both that and 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 uses a Bartik IV strategy to find a positive association between provincial unemployment and abortion. Few recent studies are, in additionm González et al., 2023 assess the role of Spanish political partisanship on abortion rates, while the findings of Pieroni, Rossellò Roig, et al., 2023 highlight that 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 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. 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, in terms of fertility and gender disparities. Among 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's restriction policy on Spanish fertility rates, by retrieving a pattern similar to the mentioned ones. In Italy, one of the countries hit the earliest and the hardest, demographic studies underlined the negative impact of 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 women harder than men, compared to previous crises. For the latter reason, many scholars have re-branded the pandemic crisis as a "She-cession". The various 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. 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). Regarding the relationship between fertility and Covid-related remote working (which has the faculty to notably affect households' time consumption patterns), Kurowska et al., 2023 find out how highly tele-workable tasks are negatively associated with fertility intentions, due to the increase in the blurriness of the limits between work and free time once most activities in both contexts were to be performed at home; their claims are not causal though. There is actually some cross-county evidence on the impact of Covid-19 on abortion access, although they focus mostly on the supply of pregnancy interruption services rather than on the demand side (Bojovic et al., 2021, Ong et al., 2023). The medical paper by Thacher et al., 2024 uses Swedish data to assess the impact of the pandemic on deliveries and induced abortions through the age channel. In the attempt to fit into the literature, we reckon some papers as more similar to ours. In terms of the covered subject, we mention Trommlerová and González, 2024, who study the negative impact of the lock-down on abortion patterns, observed in Spain due to the decrease in social interactions, although their methodology relies on a temporal discontinuity which does not account for other forms of territorial heterogeneity. 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 (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[5]. Plus, we try to uncover the potential asymmetric channels operating through the job trajectories of different genders within couples. 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 the distribution of suspended workers: Borri et al., 2021, who compare municipality above/below the median of said distribution to assess the effect of “non-essential” sectors on mortality; 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[6]. Our study is flawed by a major drawback: the decision of terminating a pregnancy is extremely endogenous per se, and given that data are drawn from the Italian universe of abortions, women are already selected into the sample, since the observation is conditional on the abortion having occurred. The absence of an alternative realized outcome coming from the same source of data (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[7]; in any case, the set of robustness checks 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 Covid-19 may 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 degree of exogeneity which is usually absent in other quasi-experimental studies. The work is structured as follows: after the introduction, which 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 Section 4 describes the data. In Section Section 5 we present the empirical strategy, whose results are reported in Section 6. Section 7 is dedicated to robustness checks, to internally validate our estimates. In Section 8 we perform hetereogeneity analyses to better dwell into our findings, while in (Section 9), the same is done through some ancillary evidence explored via other data sources (live births, domestic violence, contraception). After a brief section on feasible research implications (Section 10), concluding remarks are reported in Section 11.

2 Institutional Background

2.1 Abortion in Italy

The Italian National Healthcare Service (*Servizio Sanitario Nazionale*, or *SSN*) is a public, tax-funded system which offers universal coverage for a broad set of services. As a matter of fact, the Voluntary Pregnancy Termination (VPT, in Italian *Interruzione Volontaria di Gravidanza*, IVG) is provided by the SSN free of charge since 1978, when it was made legal by L. no. 194 1978 (usually referred as “Law 194”). 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 enables any woman who demands the abortion service within the specified terms to interrupt her pregnancy, setting abortion as a woman’s legal right. After 90 days, a pregnancy can be interrupted only when the 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, and her potential partner’s consent. 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

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

[6] 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

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

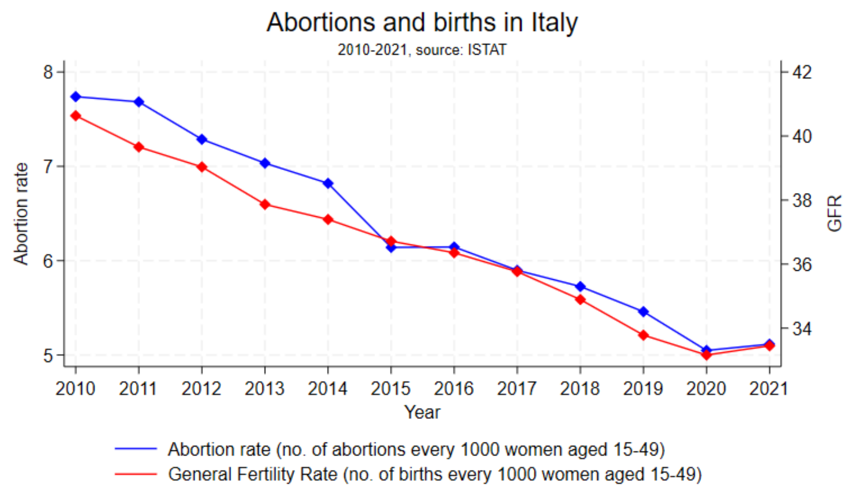
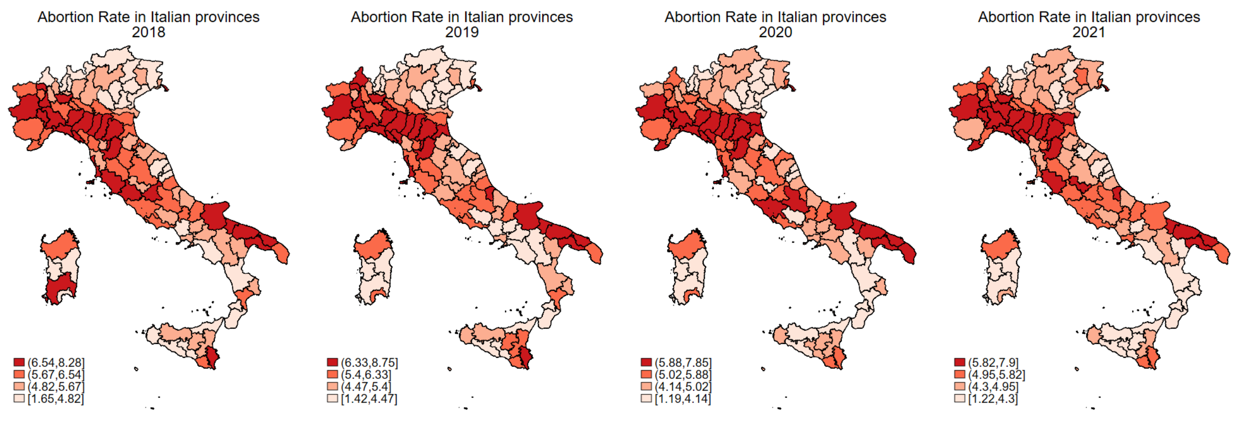


Figure 1: Source: ISTAT

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 cooperation system between the Ministry of Health, the ISS, the National Institute of Statistics (ISTAT) and the regions and autonomous provinces, involves the obligation for Regions to transmit the annual data on abortions to the Ministry of Health, which stores and manage them thanks to the support of ISTAT. The Minister of Health then annually reports to the Parliament the relevant facts and data related to the application of Law 194, and assesses whether conscientious objection looms as a setback to the right to abort. Official data (Figure 1) show a persistent falling trend in the abortion rate (AR - i.e. the number of VPTs every 1000 women aged between 15 and 49 years) over the last decades. Demographically speaking, the General Fertility Rate (GFR, 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 pattern for abortions results 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. 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 characterized 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 shown 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 to undertake an abortion. 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: after collecting data on objection at provincial level, she retrieves a detrimental positive correlation between objection and illegal terminations of pregnancy, "hidden" by miscarriage data.



(a) (b) (c) (d)

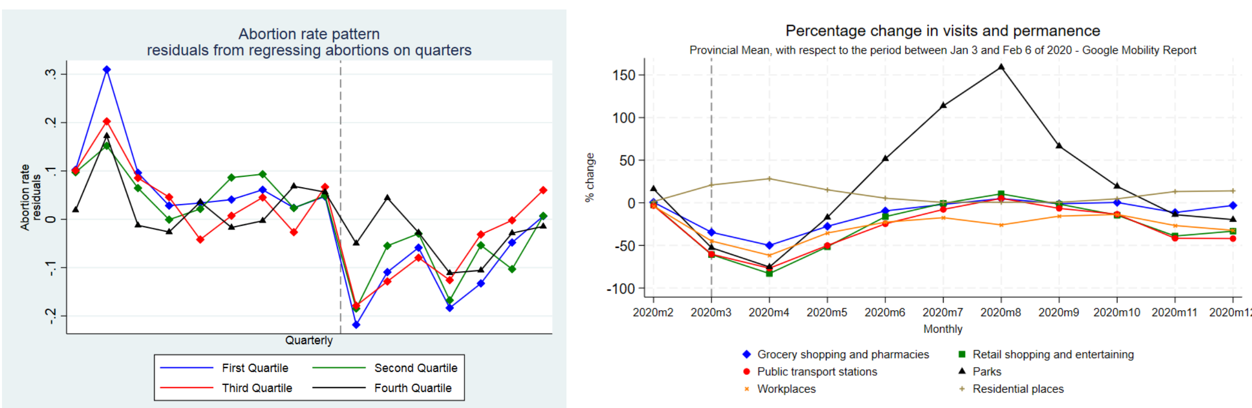
Figure 2: Provincial abortion rates, 2018-2021 (source: ISTAT)

2.2 The COVID-19 Pandemic in Italy

As of the beginning of 2024, Italy results as the 8^{th} Country in the world for total cases of Covid-19 (see Worldometer); in fact, 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 in 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 D1 in Appendix D). Being the first European Country having to deal with such a fast spread of contagions, Italy was also the first one to undertake strict measures; after applying some mobility restrictions to the early affected areas, 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) imposed the suspension of common retail and schooling activities, the closing of restaurants and the ban on meetings in public spaces. 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 all the related enterprises and affiliated workers with them. In the meantime (starting from 17^{th} March with the legislative decree *Cura Italia*, i.e. *Cure Italy*), the government forbade layoffs (*firing freeze*) and house ejectments (*eviction freeze*), and also a loan standstill for SMEs and free-lance professionals (*moratorium*). Such measures (differently from the lock-down and work suspension, aimed at preventing further infections), aimed at protecting the most vulnerable citizens and workers in a period of high economic uncertainty, were planned as momentary interventions meant to last for few months, but they ended up being periodically renewed and prolonged in their terms all over 2020 and until the end of 2021. On the other hand, the national lock-down lasted until 4^{th} May 2020, while economic closures of non-essential activities started being loosened gradually; the process lasted as far as the summer, when most businesses 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 until 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. Notwithstanding some commercial and labor restrictions imposed to enterprises (like opening curfews and workers' safeguards), the performance of all economic activities would never be shut down again. After some further restrictions between the end of 2021 and the beginning of 2022 due to a new wave of cases, the emergency state, initially declared on 31^{st} January 2020, ceased on 22^{nd} April 2022.

3 Conceptual framework

While the aim is to try and assess whether work suspension from the governmental policy has a differential impact on abortion decisions, we reckon how, after the implementation of the policy, abortion rates substantially dropped all over the sample (Graph (a) in Figure 3). At the beginning of Section 7, we argue and try to empirically validate the finding that the observed difference between the municipalities in the 4° quartile of the distribution and the others is not driven by reasons linked to the healthcare supply contraction; however, it is worth to understand why a decrease in VPTs is seen in the available data, in the period involving the lock-down. Trommlerová and González, 2024, similarly observe a relevant drop in abortion rates in Spain just simultaneously with the lock-down implementation. While the channels at work may be several, they argue that the major cause of such decrease is to be credited to an overall reduction of social interactions, rather than on supply-side factors. Their evidence can be easily extended, anecdotally, to the Italian case, as they are indeed characterized by similar cultural and economic features. Among the other things, they display rates amongst the lowest within European Union (1.16 in Spain, 1.24 in Italy, Eurostat, 2024), and conscientious objection is legal in both countries (Bojovic et al., 2021). Furthermore and almost concurrently, both countries adopted a similar package or very restrictive policies. Such involved a sudden lock-down, followed by a sudden suspension of non-essential workers, which were both gradually loosened at the beginning of the Summer. It is then reasonable to believe, in such regards, that the overall drop in Italian VPTs was due to the lock-down likewise, which worsened the likelihood of social interactions, thence sexual intercourse among non-cohabiting people and, by consequence, unintended pregnancies. Graph (b) of Figure 3 shows how this could be sensibly consistent with the Italian case, as movements towards the most relevant places of aggregation followed a decreasing pattern during the lock-down, before recovering starting from Summer 2020. With respect to the possibility of a VPT reduction due to access restriction, according to the Italian ISS the public supply of abortion services was not hindered by the pandemic (INIH, 2022). However, both credible anecdotal press evidence (Muratori and Di Tommaso, 2020, Torrisi, 2021) and some healthcare research studies (Ong et al., 2023) contradicted such claims, due to hospital excess workload and epidemiological concerns. The latter brought however a relaxation of usual abortion constraints (Bojovic et al., 2021); plus, in our first and main robustness check in Section 7, we address this issue.



(a)

(b)

Figure 3: (a) 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. The vertical dashed line is set between Q1 and Q2 of 2020. (b) Mean percentage provincial monthly variation, with respect to the period between Jan 3 and Feb 6 of 2020, of visits to and permanence in different kind of places.

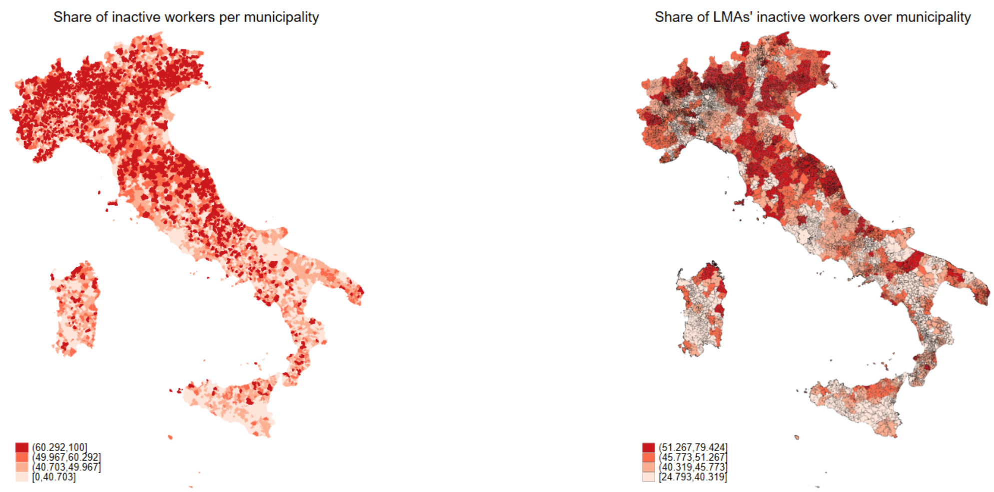
As a matter of fact, the general drop in induced abortion rates notwithstanding, a visible difference in the patterns is observed across quartiles of the suspended workers' share distribution. We pin down the most plausible mechanisms through which the effect might have deployed: 1) **Unplanned fertility: increase in unplanned pregnancies** (*irrespective of economic insecurity*): due to nationally homogeneous shelter-in-home policies and the heterogeneous work suspension distribution, unwanted pregnancies could rise because of couples having more available time together ("exposure"). Exposure may affect non-voluntary pregnancies either by means of increased consensual and unprotected intercourse, or by increased in unintented intercourse tied to abusive within-couple dynamics leading women not to be in control of their own fertility, potentially including psychological or sexual IPV. Note that, beyond exposure, domestic sexual violence may also increase due to the escalation of income or unemployment-related stressful situations (Card and Dahl, 2011, Diaz and Saldarriaga, 2023), or due to the worsening of female bargaining power given a detrimental shock to the labor market (Aizer, 2010). Data report indeed a 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)[8]. However, the role of the topic's salience might have played a major role in shifting numbers: Colagrossi et al., 2022 highlight indeed how the governmental domestic violence-related sensitisation policy put in place at the beginning of the pandemic was the driver of the increased reports, rather than assaults themselves. 2) **Planned fertility: sudden economic vulnerability** *(to parity of given occurred pregnancies)*: since not only individual negative income shocks and job displacement may affect individual fertility outcomes, but also macroeconomic downturns and overall socio-economic insecurity, we reckon how the pandemic mostly resulted in the increase in unemployment in given service sectors (Bluedorn et al., 2023). In these sectors, the share of employed women was higher; as also confirmed by Casarico and Lattanzio, 2022. The temporary inactivity of workers caused by the pandemic may represent a reasonable proxy of the unexpected perceived vulnerability for the future embedded by the shock, as it could allow to capture certain dynamics at municipal level which are not incorporated in provincial employment statistics. Bordignon et al., 2023 utilize survey data to observe how the condition of temporary inactivity was able indeed to shift the vote preferences of the sampled citizens, due to uncertainty for the future. Therefore, to parity of unplanned pregnancies, the abrupt shift in the economic situation might have led to a jump in VPT decisions for women not willing to carry on the occurred conceptions in future, unforeseeable and bleak prospects, postponing their fertility; 3) **Unplanned (1°) + planned (2°) fertility: sudden economic vulnerability** (*with increased unplanned pregnancies*): holding the latter considerations as fair, economic uncertainty may also make less affordable an unplanned fertility (i.e., carrying over an unexpected pregnancy); 4) **Limited access to abortion supply** (*irrespective of pregnancies*): the rapid spread of the virus brought about a burden on Italian hospitals. Plus, mobility restrictions may have caused a setback to people moving across areas seeking for healthcare, while clogged institutes due to the treating of large numbers of infected people may have been delayed in the undertaking of VPTs (Bojovic et al., 2021), especially those with many objectors; longer waiting times might also lead women to overcome the eligibility time threshold. In such case, we would observe a supply-driven decrease in abortion rates in areas hit harder by the pandemic in epidemiological terms.[9].

We exploit a policy variation to assess said 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. Such suspension lasted from March to middle June (for some activities even later), with the end of the lock-down happening on May 4. Thanks to ISTAT, we recovered the share of suspended workers across Italian municipalities during the national lock-down (Figure 4). The exploitation of the heterogeneity of such share as means of identification is not novel in the Italian economic literature (Borri et al., 2021, Di Porto et al., 2022, Bordignon et al., 2023). 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 impact on the labor market[10]. By comparing outcomes (VPTs, births) before and after the second quarter of 2020, over the distribution of inactive workers across Italian municipalities (or Local Market Areas), we can observe the effect of the local economic change on aggregate abortion decisions, by ruling out the explanations due to lock-down, as the whole Country was under such 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 higher prevalence of non-essential workers staying home with their partners might be linked to more unplanned pregnancies.

[8]Early estimates displayed 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 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 linked to a raise in actual violence.

[9]Women may also be discouraged to access hospitals in areas where it was more likely to contract the virus.

[10]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).



(a) (b)

Figure 4: Municipal share of suspended, non-essential workers during the Italian national lock-down. The (a) 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 (b) 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.

We explore such possibilities by examining pregnancies resulting in live births and through heterogeneity analyses also. We illustrate the identification strategy for our main outcome (the VPTs) by means of two Dyrected Acyclic Graphs (DAG), reported in Appendix C. In Figure C2, we observe the phenomena 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 deployed almost concurrently (the time dimension is thus neglected). In the DAG, we stress how they may have reasonably affected the same channels in the same direction before reverberating on the VPTs (except for the negative, confounding mechanism of reduced social interaction, caused by the lock-down); as a matter of fact, the outcome of both policies was the same, i.e. to stay at 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 of them were affected to the same extent. By contrast, the distribution of the suspended workers was strongly heterogeneous. The second DAG (Figure C3) displays what changes in the identification of the effects after introducing such empirical device (indicated as "inactive share" in the picture). By means of the inactive share, we place into the framework a further dimension of variability, which adds up to the homogeneous shift caused by the 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 operating channels. Plus, it must be also clear 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 fixed effects, while including interacted province by time fixed effects allows to a better degree of control to such extent.

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 considered time), regarding their revenues, value added, workers and employees, and the ATECO-5 digit sector within wich they perform their activity. The sectoral share of workers refers to the local units in 2017 (the most recent one before 2020), confirming that the distribution of the working population was orthogonal to the pandemic outbreak[11]. ISTAT matched such data with information on the suspended sectors during the lock-down, enabling a detailed estimate of the number of inactive workers at municipal level after the economic closures, and their share over total working population[12]. 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 does not have information on people 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. Concerning the outcomes, annual cross-sections on all Italian abortions are yearly collected by ISTAT, as envisaged by the epidemiological surveillance system on Italian VPTs. They 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 Italy 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, at monthly frequency; in our design however, we collapse them at quarterly frequency[13]. From these observations, we remove about 8500 observations with relevant missing information or including women residing abroad. 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 an interesting information contained in the data, never exploited in previous research. There are also details on the VPT procedure (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:

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

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 birth is daily, and we can recover all 1,664,972 births registered in Italy in the four-year period of interest, with information on the birth date of registered children, their municipality of residence and that of birth; plus, we know their parents' marital status and the number of minor kids in the household of the head of the family. 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 locate the hospitals where abortions are performed, we match the medical facilities' codes reported in the VPT information with the official dataset on healthcare institutions recovered from the open data of the Ministry of Health, in order to know the municipalities, provinces, local health authorities and regions where the VPTs are undergone. Since hospitals are not present in all municipalities, the quarterly longitudinal hospital panel contains fewer observations: 5,492. To conclude this section, we report that starting from November 2020,

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

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

[13] We prefer to collapse the variable at the quarterly level for the following reasons: 1) given the high seasonality of abortion trends, which follow sexual conception patterns, such 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 zeros. This places a heavy weight on the extensive margin of the phenomenon, which is partly offset by adopting the quarterly frequency; 3) the policy was introduced on 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 (except, of course, the those few VPTs performed in the very weeks between the end of March and the beginning of April which had been conceived prior to the closures). Thereby, we can reasonably consider treated areas as such from 20202Q2. To give credibility and robustness to our design though, we perform the same analysis by adopting different frequencies, including the monthly one, as shown in Section 7.

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 period of "coloring zones" (in ascending order depending on restrictions' severity: white, yellow, orange and red) might have brought about confounding effects in terms of exposure. To account for that, we add up to the model some covariates, which proxy 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 indicators devised by Conteduca and Borin, 2022, better explained in Appendix D. Together with this set of policy covariates, we add data on municipal excess mortality, aggregated at quarterly frequency, as provided by ISTAT with the official and publicly available dataset about causes of mortality in Italy. However, such regressors do not really condition for unobservable confounders; indeed, as these are all post-treatment variables, time-varying omitted heterogeneities related to the pandemic policies may not be captured. We add them up to the specification to assess whether the outcome somehow follows the epidemiological pattern of the pandemic anyway, similarly to Franzoni et al., 2024. Descriptive information about the abortion dataset 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 excess mortality (since 2020)	0.441	1.1869	-14.067	75.133	1.006	7.402	-145.667	684.933
Obs.				31616				948328

Table 1: Descriptive statistics of the variables used in the present work. The definition *Treated municipalities/provinces* involves units part of the 4° quartile of the suspended workers' share distribution. The definition *Non-treated municipalities/provinces* involves the other units.

5 Empirical Strategy

To assess the effect of the work suspensions on Italian VPTs, we estimate via OLS a TWFE Difference-in-Differences model, in the form as such:

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

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 accounts for both health providers' excessive workload and for a higher perception of epidemiological risk. Again, such post-treatment covariates allow to track whether the phenomenon follows the epidemiological evolution of the pandemic, although they cannot really help us conditioning for other time-varying observables related to the infection. 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. It represents the ITT (Intention-to-Treat) of suspending higher shares of workers in given municipalities (taking the fourth quartile as the portion defining the treatment), on the resulting abortion rate. Since the distinction between treated and controlled units is not neat, as also lower parts of the distribution are affected by the policy, we cannot consider the first quartiles of the distribution as a clear-cut control group[14]. 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 1° 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 "municipality 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 benchmark 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.

$$
\begin{aligned}
&E(AR_{mpt}|Post_t,\ Inactive\ Share_{q2/2020},\ X'_{mt},\ \tau_i,\ \gamma_t, \delta_{p,t}) = \\
&\qquad = exp(\ \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(Inactive\ Share_{q2/2020} \in Q_k) + X'_{mt}\beta + \tau_i + \gamma_t + \delta_{p,t})
\end{aligned}
\tag{3}
$$

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

6 Baseline Results

The estimates (reported in Table 2 - OLS - and Table 3 - PPML) display how belonging to the higher tails of the inactive share distribution has a positive impact on the municipal AR. However, only the dummy for the 4° quartile (our treatment) is statistically significant in both specifications. Column (1) of both tables reports the baseline model results without policy restriction covariates. In Column (3) covariates are added,; in Column (5) the model is integrated by 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[15]. Most of the coefficients of interest are significant at 1% level, with Column (5) of Table 1 being significant at 5% level (i.e., the unweighted OLS specification with provincial interactions). Estimates are comparable between the two different methods, as the PPML results table presents the Marginal Effects. All statistics range between 11 and 14.6 p.p., meaning that municipalities which were part of the 4° 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 in absolute terms, appear more relevant when compared to the mean value of the municipal AR of treated units pre-treatment, as they range between 10% and 13% of the number of abortions every 1000 women in fertile age residing in Italy.
Since the design is based on a Difference-in-Differences methodology, in order for the estimates to hold robustly, the parallel trend assumption needs to be met. That means, in absence of the treatment (i.e. the

[14] More on Difference-in-Differences designs with continuous treatment can be found in Callaway et al., 2021.
[15] Following the same approach as Pieroni, Rosselló Roig, and Salmasi, 2023.

repercussions triggered by Covid-related closures), the treated and non-treated units would evolve following their pre-existing path. 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 work suspension never occurred.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13134***	0.11340***	0.12879***	0.11133***	0.13168**	0.11087***
	[0.04565]	[0.03563]	[0.4587]	[0.03585]	[0.05185]	[0.04061]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05711	0.04825	0.05570	0.04698	0.06342	0.05119
	[0.04266]	[0.03300]	[0.04276]	[0.03311]	[0.04501]	[0.03488]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13978***	0.11324***	0.13676***	0.11082***	0.14560***	0.11515***
	[0.05105]	[0.03904]	[0.05119]	[0.03919]	[0.05580]	[0.04335]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.06016	0.04614	0.05855	0.04471	0.07307	0.05239
	[0.04669]	[0.03527]	[0.04697]	[0.03537]	[0.04834]	[0.03685]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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.

In order to perform such robustness check, we estimate an event-study equation as follows:

$$AR_{mpt} = \beta_0 + \sum_{j=2}^{J} \beta_j (Lead\ j)_{mt} + \sum_{k=1}^{K} \beta_k (Lag\ k)_{mt} + X'_{mt}\beta + \tau_m + \gamma_t + \delta_{p,t} + \varepsilon_{mt} \quad (4)$$

The equation above shall be interpreted on the basis of the event of interest, which is of course $Event_t :=$ $Q2$ 2020. As in Equation (3), 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 and 0 otherwise (leads, indeed), with

$(Lead\ j)_{mt} = 1[t = Event_t - j]\ for\ j \in \{1, ..., J\}$. 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 $(Lag\ k)_{mt} = 1[t = Event_t + k]\ for\ k \in \{1, ..., K\}$. $(Lead\ 1)_{mt}$ 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 interaction dummies for Province x Quarter and Year FEs as well. The coefficients of the event study are estimated both via OLS (Figure 5), and Poisson (the latter mirroring Equation 7; its MEs are reported in Figure E1 in Appendix E). 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 pregnancies) seems not having been fully removed from the quarterly-frequency aggregation. In general, 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 September), before turning back to be statistically similar to zero at 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 after 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 tied to the presence of informal/precarious contracts and remote working, coupled with the period of summer holidays. At the beginning of 2021, the effect seemed to be already fully re-absorbed. 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). Accounting for a hypothetical violation of common trends, we follow the so-called "honest" approach developed by Rambachan and Roth, 2023, which enable us to perform inference and sensitivity even in presence of (small) deviation from parallel trends[16]. Their methodology is based on bounds on relative magnitude: we replicate it 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.

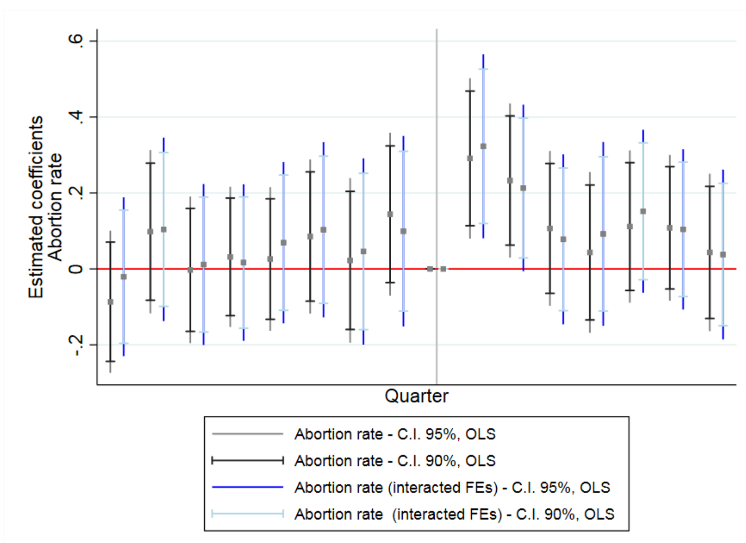


Figure 5: OLS Event-study estimates. The figure reports the coefficient on temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The x-axis 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.

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. Graphs (a) and (b) in Figure E2 and 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

[16]One of the major reasons for which they introduced such methodology of checking involves the (usually) low power of basic pre-trend testings due to few observations. However, in the present case, this does not constitute an issue, given the length and frequency of the timespan.

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

7.1 Abortion mobility

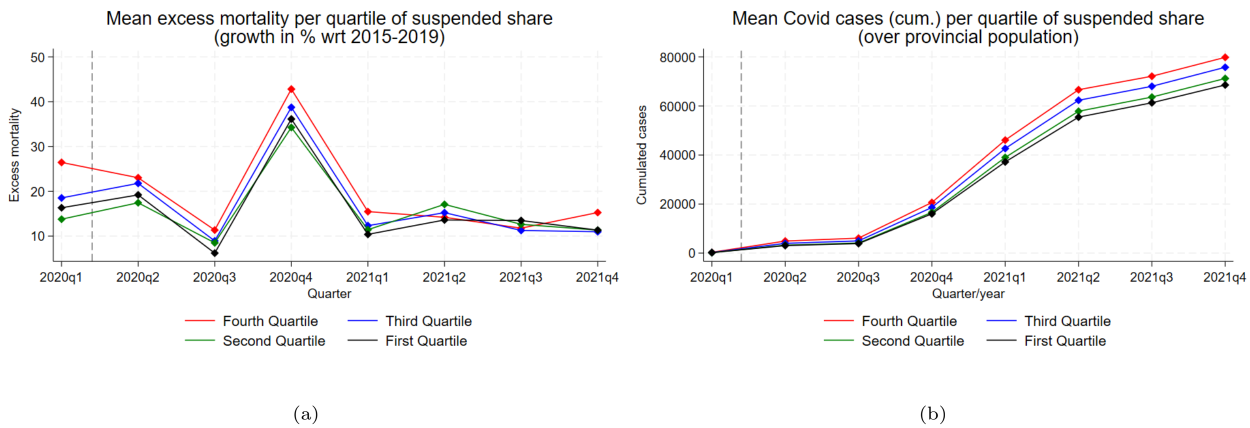


Figure 6: Quarterly municipal excess mortality (a) and Covid-19 provincial cumulated cases (b) per quartile of the inactive shares' distribution over 2020-2021.

To strengthen the conclusion that a supply shortage of abortion services is not mattering in our baseline estimates, we follow up on our work with the robustness checks in the present 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 behavior of healthcare 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, and most importantly, if areas with lower inactive share worsened their supply of VPT services, that conduct could discourage women to abort in their very same municipalities. Thus, our effect would be almost entirely driven by the reduction in abortion supply in areas less affected by the treatment, but more affected by the epidemic (as shown in Borri et al., 2021 and Di Porto et al., 2022). This would constitute a serious issue to the credibility of our results. First, we plot some descriptive evidence (Figure 6), to observe how mean excess mortality (computed as percentage change in quarterly municipal mortality in 2020-2021 compared to the 2015-2019 average of the same variable) and the cumulated sum of provincial covid-cases, normalized by provincial population, were not substantially differing across the inactive share distribution in the quarters interested by the effect. We further prove the low relevance of supply proceeding in two steps: first, we provide with further anecdotal evidence of the fact that a higher inactive share is not linked to a greater supply of VPTs, by aggregating the abortions at the hospital level and evaluating the treatment in correspondence of the municipality where the abortion is performed, rather than that where women live; second (and most importantly), we estimate, by means of a Diff-in-Diff designed at the individual level, an OLS LPM equation using, as outcome, the likelihood of seeking for an abortion in areas which differ from that of one's residence[17]. The latter analysis is called upon by the fact that 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, characterized by a high number of mobility restrictions. Concerning the first check, the methodology slightly varies when we aggregate at 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. The empirical model mirrors that of Equation

[17]By "area" we mean either a different municipality or LMA, as we estimate two separate models.

3, with slight differences:

$$AR_{hlmt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(I.\ S._{q2/20} \in Q_k) + X'_{mt}\beta + \rho_h + \gamma_t + \lambda_{l,t} + \varepsilon_{ht} \tag{5}$$

The outcome of interest is AR_{hmlt}, the VPT rate performed in hospital h within municipality m (irrespective of the municipalities of residence of the aborting women), managed by Local Health Authority l, in quarter-year t[18]. The inactive share-related treatment terms and the policy covariates in the RHS do not change with respect to the previous model, although referring to the hospital municipality as unit of measure. In turns, in addition to time 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[19]. Results are reported in Tables (a) and (b) of Figure H1, in Appendix H. All coefficients on the inactive share quartiles are non-significant. In addition, the direction of such non-significant effect is always negative when looking at the 4° quartile[20]. Such descriptive results hints that the work suspension are affecting women rather than healthcare management in explaining the observed effect. A further, more robust validation, is yielded by our second estimation, as in the individual-level "abortion mobility" DiD. In such case, we keep the sample without municipalities where no abortion is performed [21]. We aim indeed at 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. As a matter of fact, if the increase in abortion was driven by supply reductions in areas with lower inactive share, then we would plausibly 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 to seek for the VPT. In our restricted samples, we count 304 municipalities where VPTs are performed (3.8% of the total number of Italian municipalities), involving 118,351 individual observations; then, we count 251 LMAs where VPTs are performed, which amount to 41% of the 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. 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:

$$\begin{aligned} Y_{imt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(I.\ S._{q2/20} \in Q_k) + X1'_{it}\beta + X2'_{it}\beta + X3'_{mt}\beta + \\ + \tau_m + \theta_{m(VPT)} + \eta_h + \gamma_t + \delta_{p,t} + \varepsilon_{imt} \end{aligned} \tag{6}$$

The outcome is Y_{imt}, a dummy variable equaling 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

[18] Note that the denominator of the outcome is the municipal population of women aged 15-49, which does not coincide with the population with such features in the hospital's catchment area, for which data were not available; hence the anecdotal nature of the estimates, for which no robust causal claim can be drawn.

[19] The coefficients of interest are, again, β_2, β_3 and β_4; in addition, a specular PPML panel regression model is estimated with the same inputs.

[20] There is one significant estimate at 10% (Column (2) of Table (a) in Figure H1), i.e. the OLS specification with policy covariates and weighted by population, of negative sign too.

[21] In the second situation, that of LMAs, we discard all municipalities that are part of LMAs which do not include any municipality where VPTs are performed

$X2'_{it}$ 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_{imst}, a dummy variable equalling 1 if woman i residing in municipality m, part of LMA s undergoes an abortion in quarter-year t in a LMA which is different from s ($m \in s \wedge m(VPT) \notin s$), which we call inter-LMA abortion mobility. The treatment is applied at the LMA level in this case[22].

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE							X	X
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 4: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

Table 4 and 5 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 validity: we observe that, mobility restrictions notwithstanding, women were moving across areas to abort. 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 both coefficients on the 3° and 4° quartile of the distribution of the inactive share to be significant and positive. Estimates range between 5.3 and 8.7 p.p for the coefficients on the 3° quartile, depending on the specification; such values amount to 12-22% of the mean of the treated pre-treatment. Concerning the 4° quartile, estimates range between 4.7 and 9.7 p.p. (the latter being 25% of the mean), at a lower degree 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 4° quartile matters, with values ranging between 3.1 and 4.4 p.p, 8-11% of the mean value of the treated units pre-treatment circa[23]. The latter analyses seem to confirm that the inactive share does not play a role in shifting the supply of VPT services in directions which could potentially bias the baseline estimates. The results show that women seeking for abortion were able to move across municipalities or even LMAs to undergo a VPT anyway. This

[22] In the first model, SEs are clustered at municipal level; in the second model, at the LMA level.
[23] Although the highest coefficients are only significant at 10%

is consistent with our initial findings, which show quarterly abortion rates of municipalities hit the most by the workers' suspension greater by 10% circa[24]

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.03187 *** [0.01026]	0.03224 *** [0.01037]	0.03476 *** [0.01074]	0.03099 *** [0.01015]	0.03120 *** [0.01027]	0.03429 *** [0.01056]	0.04420 * [0.02464]	0.04236 * [0.02468]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.00914 [0.00920]	0.00944 [0.00937]	0.01180 [0.00950]	0.00769 [0.00855]	0.00796 [0.00876]	0.01081 [0.00879]	0.03764 [0.02397]	0.03939 [0.02397]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-0.00056 [0.00851]	-0.00032 [0.00878]	0.00222 [0.00926]	-0.00111 [0.00777]	-0.00096 [0.00806]	0.00211 [0.00851]	-0.02996 [0.03203]	-0.03278 [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
Prov. x Quarterly FE					X	X		
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 5: SEs clustered at LMA level. *Mean* reports the mean of the treated units pre-treatment.

7.2 Sensitivity analysis

To assess the validity of the 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 semestral models, 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 latter regression lagged by one period, to account for the unfolding of their heterogeneous impact on the abortion decisions with some delay (X'_{mt-1}). All OLS and PPML estimates at the annual, semestral, and monthly frequency can be looked at in the Appendix E. Results are consistent with the baseline model. Coherently with expectations, in absolute values the monthly coefficients on the 4° quartile are lower in magnitude than the quarterly ones (ranging between 3.5 and 4.4 p.p); however, relative to the mean, the monthly results are slightly lower than our benchmark estimates, amounting to 9.5%-11.9% of the mean AR circa (Figure E2, Tables (a) and (b)). Consistently, the coefficients for the annual (Figure E1) and semestral specifications (Figure E3) are magnified in absolute sizes, although their relative values are alike. In both cases though, the 3° quartile of the distribution obtains a degree of significance in some of the adopted specifications (at 10%). After that, 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 2° and the 3° tercile (the 1° tercile being the reference category). We also estimate a DiD with continuous treatment, following Di Porto et al., 2022 and Bordignon et al., 2023. The estimates in Tables (a) and (b) of Figure F1 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 of the 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 accounting for continuous treatment,

[24] The event-study graphs of both inter-municipal and inter-LMA mobility are represented in Figure E1 in Appendix E.

as specified by Equation 7. However, we do not identify the treated units through quartiles, but we apply the continuous treatment specification, which cannot be subject to arbitrary threshold manipulations (Figure 7. 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, even though this loss occurs for the OLS coefficients only, not for the PPML ones (Figure F1). However, the first lag after 2020 Q1 still results significant at both 90% and 95% level. In addition to that, the coefficient dynamics and their confidence intervals display 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 viable to be biasing the results, for both the estimated event-studies. 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 undertaken after the gestational limit (90 days) unless the woman's health is endangered, we discard all VPTs performed after 90 days, as they shall be credited to health-related necessities rather than to voluntary fertility; 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 Italian biggest cities[25]. 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.

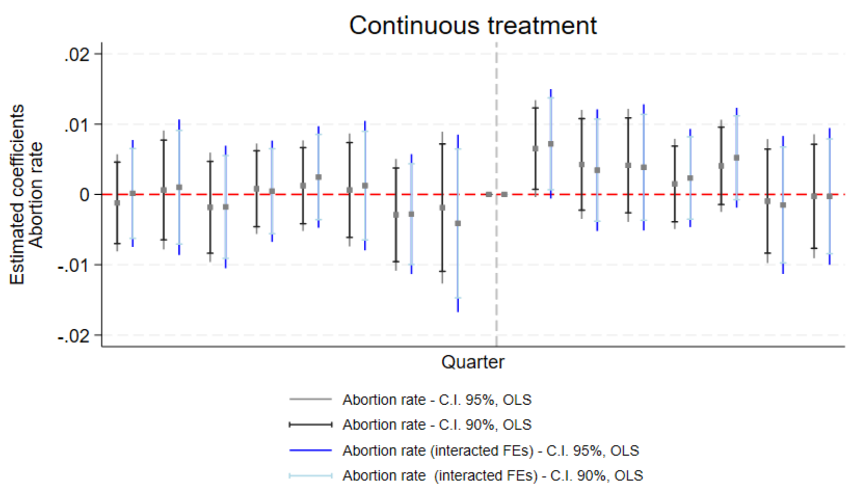


Figure 7: OLS Event-study estimates, as in dynamic specification of Equation 3 with the continuous treatment specification. The figure reports the coefficient on temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies 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.

The results of these three estimations are reported, respectively, in the tables of Figure F3, F4, and F5. While the specifications estimated in the first two sub-samples are strongly consistent with the baseline, in the tables of Figure F5 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 Graphs (a) and (b) of Figure F6. The graphs prove for the

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

non-randomness of our findings, as our estimated coefficient (the red vertical line at the extreme right of the graph) lies way rightwards of the sampled distribution from the randomization inference procedure, in both specifications with and without interacted provincial FEs.

7.3 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 cyclicality, which is not definitely removed from our quarterly aggregation. Second, the identification of the effect is visibly re-absorbed 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 estimate the same models in various time-spans, always around the seasonal temporal discontinuity of the second quarter, although in different years[26]. Estimates are performed by employing both the OLS and the PPML specifications (PPML estimates in Appendix E, Table E1). The considered treatment is always a dummy equal to 1 if the municipality belongs to the 4° quartile of the inactive share distribution, 0 otherwise. The time placebo in Table 7 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 effect on ARs in municipalities with higher share of suspended workers is plausibly driven by the Covid-related repercussions, and not by some seasonal pattern due to a relation with sexual behavior between April 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 suggestion to the re-absorption 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 starting from the second quarter of 2020 only, even when we use year 2020 alone as the sample of our model, corroborates our conclusion.

7.4 Local Market Areas

It must be noted that the municipal level of aggregation of the inactive workers' share may result restrictive for the present impact evaluation: indeed, people living in a given municipality may be commuters, and thus being affected by work suspension of bordering or close municipalities, as in the one where they are actually employed. In such case, we may be violating the stable unit value assumption (SUTVA). We therefore undertake two sets of estimations: 1) a robust clustering of the standard errors at the LMA level rather than municipal, both for OLS and PPML estimates, to account for the possibility of VPT rates to be independently distributed within local labor markets due to workers' cross-municipal commuting[27]; 2) secondly, we directly apply the treatment at the LMA level, hypothesizing that the overall shock to the industry area 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 aggregation of the outcome remains the municipality. In both hypotheses, the yielded estimates are consistent with the ones obtained at the municipal level; they are all reported in Table G1 of Appendix G. In the case of clustering only, the values do not change at all, as only SEs do, and not enough to compromise significance. When the treatment is considered at LMA level, coefficients on the 4° quartile of the inactive share shift down on average by few p.p. compared to the baseline, although their magnitude is clearly comparable; the only exceptions are the estimates involving provincial trends. 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 Prov. x Quarterly FE indeed.

[26]The restricted samples, with their relative treatment discontinuity, are the following: 1) from 2018 to 2021 excluding 2020, with Q2 2018 as treatment threshold; 2) 2018 only, with Q2 2018 as threshold; 3) 2018-2019 only, with Q2 2018 as threshold; 4) 2018-2019 only, with Q2 2019 as threshold; 5) from 2018 to 2021 excluding 2020, with Q2 2019 as threshold; 6) 2019 only, with Q2 2019 as threshold; 7) 2019-2020 only, with Q2 2019 as threshold; 8) from 2018 to 2020, with Q2 2020 as threshold; 9) 2019-2020 only, with Q2 2020 as threshold; 10) 2020 only, with Q2 2020 as treatment threshold; 11) 2020-2021 only, with Q2 2020 as threshold; 12) from 2018 to 2021 excluding 2020, with Q2 2021 as threshold; 13) 2021 only, with Q2 2021 as threshold; 14) 2020-2021 only, with Q2 2021 as threshold; 15) from 2018 to 2021, with Q2 2021 as threshold

[27]In the wording of ISTAT, LMAs are "610 sub-regional areas where the bulk of the labour force lives and works, where establishments find the main part of the labour force (...), defined on a functional basis, the key criterion being the proportion of commuters who cross the LMA boundary on to work.".

7.5 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 6 shows how the results are clearly driven by the Northern municipalities, as the suspended workers share has a significant impact in the Northern Italian sub-sample 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 3° 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. Therefore, the response in abortion rates might have been more "elastic" to the crisis. No significant effect seems to loom within the Southern and Central areas' sub-samples.

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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.19098***	0.16360***	0.00555	0.03342	0.03087	0.01954
	[0.06749]	[0.05401]	[0.17073]	[0.12425]	[0.07455]	[0.06002]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.14382**	0.12009***	0.18416	0.14645	0.03211	0.02817
	[0.05869]	[0.04581]	[0.14595]	[0.10643]	[0.06254]	[0.05065]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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	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 6: 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.

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
$Post\ March\ 2018 * 1(I.\ S._{q2/20} \in Q_4)$	0.09653	0.06472	0.08486												
	[0.07505]	[0.08175]	[0.07739]												
$Post\ March\ 2019 * 1(I.\ S._{q2/20} \in Q_4)$				0.05436	0.01368	0.04662	0.05396								
				[0.05313]	[0.09276]	[0.06974]	[0.08085]								
$Post\ March\ 2020 * 1(I.\ S._{q2/20} \in Q_4)$								0.20488 **	0.15689 ***	0.14117 **		0.14289			
								[0.09449]	[0.05250]	[0.05838]		[0.08823]			
$Post\ March\ 2021 * 1(I.\ S._{q2/20} \in Q_4)$											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
Prov. x Quarterly 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
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 7: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

8 Heterogeneity analysis

8.1 Sectoral heterogeneity

We already highlighted how the explanation linked to economic insecurity does not 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 in a straightforward fashion (i.e., directly affecting women's profession), we would be led to believe that a higher share of inactive workers in the service sectors, featured by a higher prevalence of women (Casarico and Lattanzio, 2022), would be the determinant factor in explaining the response in ARs. However, if we differentiate the distribution between that of suspended workers in the industrial sector and that of suspended workers in the service one, as we did in Table 8, we reckon how only suspensions in the industrial sectors matter in explaining our results.

OLS results - By municipality of residence

	Industry Share			Service Share		
	(1)	(2)	(3)	(4)	(5)	(6)
	AR	AR	AR	AR	AR	AR
$Post * I.S._{q2/2020} \in Q_4$ $(Industry)$	0.11880	0.11528	0.12829			
	***	**	**			
	[0.04568]	[0.04623]	[0.05384]			
$Post * I.S._{q2/2020} \in Q_3$ $(Industry)$	0.02693	0.02427	0.03758			
	[0.04599]	[0.04634]	[0.05003]			
$Post * I.S._{q2/2020} \in Q_2$ $(Industry)$	0.01450	0.01393	0.01966			
	[0.04355]	[0.04364]	[0.04408]			
$Post * I.S._{q2/2020} \in Q_4$ $(Services)$				-0.01773	-0.01388	-0.01645
				[0.04775]	[0.04807]	[0.05077]
$Post * I.S._{q2/2020} \in Q_3$ $(Services)$				-0.04640	-0.04235	-0.03867
				[0.04026]	[0.04041]	[0.04178]
$Post * I.S._{q2/2020} \in Q_2$ $(Services)$				-0.05198	-0.04960	-0.05771
				[0.03983]	[0.03989]	[0.04034]
Observations	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.10042	0.10045	0.11223	0.10036	0.10039	0.11218
Policy Controls	NO	X	X	NO	X	X
Municipal FE	X	X	X	X	X	X
Quarter_year FE	X	X	X	X	X	X
Province x Quarter_year FE	NO	NO	X	NO	NO	X
Method	OLS	OLS	OLS	OLS	OLS	OLS
Mean	1.087	1.087	1.087	1.172	1.172	1.172

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

Table 8: 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.

As the industrial workers' suspended share is more correlated with male employment, it is reasonable to believe that the effect on abortions that we observe depends more upon the job trajectories (in this case, temporary inactivity) of males than that women. If the effect is more significant on married women, as it shown later in the paper, that would consistently mean that the suspension of plausibly male partners is driving the effect. In addition, if a direct link between women's work suspension and abortion existed, 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[28]. 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, or an overall bleak prospect for future development in that given sector. The sectorally-differentiated inactive share distribution affects differently the abortion rates of women who are, in order, not in professional

[28]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.

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. We exclude women active in agriculture, hunting and fishing and those on whom we do not have professional information from the analysis.

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

	Industry Share				Service Share			
	(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
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00888	-0.01529	0.01282	0.00827				
	[0.03517]	[0.02728]	[0.01148]	[0.01118]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	-0.01111	-0.02795	0.01076	0.00897				
	[0.03013]	[0.02217]	[0.01027]	[0.00729]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.03148	-0.01314	0.00714	0.00893				
	[0.02931]	[0.02264]	[0.00957]	[0.00718]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.07977 **	0.04531	-0.00052	0.00780
					[0.03712]	[0.02958]	[0.01460]	[0.00917]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.03449	0.00661	-0.00830	0.0150
					[0.03519]	[0.02689]	[0.01157]	[0.01012]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					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
Prov. x Quarterly 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 9: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

The estimates in Table 9 seem not to be any sensitive to the professional branch of the aborting women, thus suggesting the branch of activity not to be influencing the VPT decision. Actually, the only significant estimates for the abortion rates' heterogeneity by branch of activity, are the coefficients on the 4° quartile of the distribution (at 5%) for women not in professional condition, whose AR is greater by 15.5% the mean if residing in a municipality of the 4° quartile. As expected, civil servants' municipal ARs do not respond to treatment. In addition, although the coefficient is 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. Such considerations may highlight a plausible higher responsiveness in terms of abortion decisions by women in a pre-existing condition of vulnerability within couple arrangements, if really the effect on ARs of women out of the labor force (OLF) was driven by their partners' suspension[29]. 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 women who are out of the labor force (OLF), may suggest abortion decisions not to be directly influenced by a shift in economic insecurity related to women's career.

8.2 Marital Status

Irrespective of the mechanisms, to corroborate further the male partner's job trajectory hypothesis, we heterogeneize the outcome by women's marital status, and assess how it is impacted by the treatment. As

[29]The estimates for the AR of women differentiated by professional branch of activity with respect to the overall inactive share are reported in the Appendix I (Table I1), together with the PPML version of Table 9 (Table I2).

the effect observed is concentrated along the quarters immediately after the lock-down, we would expect a higher effect amongst married/cohabiting couples, as unplanned pregnancies were way more unlikely to occur among non-cohabiting partners (actually being 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE	X	X	X	X	X	X	X	X
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 10: 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 10[30] shows that the coefficients on the 4° 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 8.5 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; note that the latter result may sensibly be driven by cohabiting but unmarried couples. Such results are consistent with the fact that, differentiating by age class (Table I5, the effect is significant among older women, more likely to cohabit with their partner. A quite counterintuitive result is observed when heterogeneizing by educational attainment (Table I6). As a matter of fact, significant coefficients are found for women with university degree, which is indeed consistent with the finding concerning age and marital status (being graduates older on average, and thus more likely to be married), although colliding with the results observed with regards to women OLF. One would expect indeed that, once observed the findings about professional condition, VPTs would display a differential shift mostly for women with a lower degree. The set of evidence gathered so far does not actually prevent us from deeming economic insecurity as a potential channel; what is suggested is that, plausibly, such mechanism does not work directly through women, as most are not in professional condition. Nevertheless, due to the conclusions drawn from the analysis on marital status and seeing how the effect is driven from the industry sector, we acknowledge that the choice to undertake an abortion, for those who are locally affected by the policy, may be compellingly dependent upon the partner's work trajectories more than on their own jobs. And while this may be significantly consistent with the hypothesis of more exposure, nothing leads to conclude that economic insecurity may not be affecting fertility choices through the male partner's job suspension. This is sensible, even though Bordignon et al., 2023 showed already how the sampled workers in their research who were more likely to be negatively affected by such notion of economic insecurity, were the ones with precarious contracts active in the service sector, whereas in our settings is the industry who carries over the results. To further argue either towards or against this conjectural direction, we would ostensibly need suspended workers' data disaggregated by gender at the municipal level; which, unfortunately, we do not. The Eurostat *Labor Force Survey* contains, on the other side, provincial representative survey statistics on employment, heterogeneized by gender, although the sectoral subdivision is not granular enough to allow the matching

[30] Estimates differentiated by industrial and service share are reported in Appendix I, Tables I3 and I4

with the ISTAT database on suspended activities. We also reckon, from existing literature (Kurowska et al., 2023), how teleworkable jobs' activities, whose use has been plenty made during the pandemic, might be held responsible in shifting potential parents' birth intentions. We make use of the 2019's *Labor Force Survey* provincial information to deep the issue a little further. First, we recover the provincial distribution of male workers active in the industrial sector in 2019, and check whether there is at least a correlation with the provincial share of suspended workers during the lock-down. Second, following the work by Barbieri et al., 2022, we built a provincial, sectoral *Working From Remote* (WFR) index. Such index has been developed by assigning a given score from 1 to 100 to each ateco 2-digit sector, according to the relative portion of tasks that could be performed at home prior to the pandemic, as the reference base is, again, the 2019 LFS. We weight such sectoral score at provincial level by the share of employees in the private sector occupied in the sector itself, and assess the overall distribution. Then, again, we look at potential correlation with the suspended workers' share, in overall terms and for males only. In this regard, we can even assess whether, at least in anecdotal terms, the possibility to already be able to work from remote before the pandemic might have played a role in shaping our results. As it is displayed by the maps (a) and (b) in Figure 8, the provincial distribution of the share of industrial workers relative to the total workers can be fairly overlapped to the distribution of industrial workers relative to male workers only, and both can be quite overlapped to the map of the provincial share of industrial male workers active in Italy in 2019 (Figure 8, map (c)), with areas reporting higher shares of industrial male workers located in Central-Northern Italy. On the other side, the distribution of the *WFR* index computed over male workers looks more heterogeneous across provinces, even though the variability of such index is not quite substantial over the Italian territory (Map (a) of Figure I1, Appendix I).[31] Such suggestions could be corroborated by looking at Table (a) in Figure I3. The latter displays the outcomes of some rough OLS regressions, to show unconditional correlations between the suspended workers share (dependent variable), and a set of different regressors: the overall *WFR* index (scoring 1-100) (1), the *WFR* index computed on males only (2), the provincial share of industrial workers (3), the provincial share of male industrial workers over the total active individuals in the private sector (4), and the provincial share of male industrial workers over the total active males in the private sector (5). There exists a strongly significant correlation between the inactive share and the share of active industrial workers in 2019, whose coefficient gets slightly significantly higher when considering the males' share (4). Concerning the *WFR* index, the link, albeit positive, does not differ from zero in general terms (1), while it positively dors for the men-only based measure (second column, at 5%). The matter holds similarly if we look at the graphic evidence in Graph (b) of Figure I3 and Graphs (a) and (b) of Figure I4, which sum up the issues discussed so far. Again, these make up for simple correlational evidence, thus no causal claim can ever be drawn from the exercise. To conclude, we highlight that the partner's job suspension trajectory is likely to play a more relevant role than that of the aborting woman in the finalization of the VPT decision itself, given the relevant link between male industrial 2019 workers' share and the inactive share in 2020. This seems to have brought about the effect led by industrial suspension mostly. This means that, while we can still embrace the possibility of economic insecurity affecting our outcomes, we most certainly can keep track of such hypothesis only accounting for the mechanism operating through the male partners' industrial jobs. By contrast, the role of remote working does not seem to play a major role in our framework, given the available data: this is consistent with our main results, i.e. a significant effect during the previous phase of the pandemic only (in correspondence of the actual job suspension, with the following social distancing policy measures not mattering at all), during which the faculty to perform teleworkable activities did not have any significance as long as one's job was legally suspended.[32]

8.3 Fertility

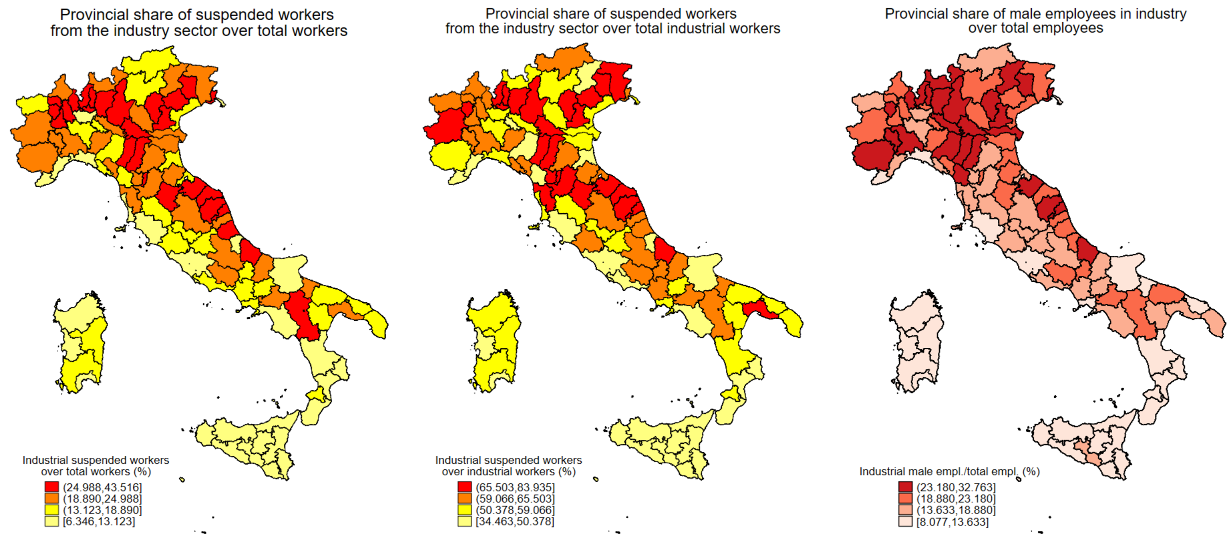
8.3.1 Extensive margin

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

[31] The maps on the provincial share of total industry workers and on the WFR computed on total workers, rather than males ones, are reported in Figure I2, in Appendix I.

[32] The WFR index does not indeed mirror, territorially, the industrial share distribution; yet it has higher values in the Center-North. As our results is ostensibly driven by the North, teleworkable jobs may actually intrinsically be a down-shifting force for the abortion demand, in terms of time availability. Jobs whose activities were already being performed remotely prior to Covid, the relative shift in time due to suspension might have a less significant impact on the possible intercourse during the lockdown, compared to pre-pandemic times. And yet Northern areas, with higher likely presence of telework, drive up the numbers, which may suggest that telework matters little in our context.

how the effect is significant and positive for women not in professional condition and for married women.



(a) (b) (c)

Figure 8: Maps (a) and (b) represent the provincial share of suspended workers from the industrial sector. Map (a) displays the share relative to the total number of private sector workers; map (b) displays the share relative to the number of industry-only private sector workers. Map (c) represents the provincial share of active male workers in the private industrial sector,by using data from the *LFS* 2019.

We would expect that women having had previous pregnancies already would be the ones driving the results in response to the treatment. We can distinguish between live births, stillbirths, miscarriages and previous voluntary abortions. We differentiate municipal abortion rates across 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), those with *at least* one previous abortion (miscarriages+VPTs) (Columns (1)-(4) of Table 11. Then, we differentiate the outcome according to the extensive margin of each type of previous pregnancy (Columns (5)-(8)). We therefore flag women with dummy indicators equal to 1 if they report the mentioned of such characteristics and 0 otherwise, without accounting for the actual number of pregnancies[33]. The findings of Table 11 show that the coefficients on ARs for women with previous pregnancies and previous deliveries (which is a subset of pregnancies) are positive for municipalities in the upper three quartiles reported in the table, relative to the reference category, (Col. (1) and (3)). In this case, the differences between the upper quartile, which we assumed to be the treatment in the baseline DiD specification, and the other two are not so clear-cut, and a valid different size is plausibly disproved by the SEs. This notwithstanding, the statistical significance is definitely increasing in the inactive share portions of the municipal distribution, at least for AR of women with any kind of previous pregnancy. On the other side, we observe no effect for women with no previous pregnancies before the current abortion (Col. (2)) or with previous abortions as a whole, i.e. including both miscarriages and VPTs (Col. (4)). The latter imprecise estimation is plausibly led by the negative, albeit insignificant, effect of women with previous involuntary abortions, with the PPML estimates displaying even a slightly significant 13% positive effect of being a municipality in the 4° quartile of the inactive share of the distribution and the abortion rate of women with any type of previous abortion (Table J1). With regards to the heterogeneity by type, coefficients on AR of women who delivered alive newborns in the past are significant at 5% in both quartiles of the right tail, amounting to 9.7 p.p. at the 4° (15% of the mean, Col. (1)), and 6.6 p.p at the 3° (10%, Col. (5)). Coefficients on stillbirths and miscarriages are non significant, except for the 2° quartile of the estimates in Col. (6), which does not point towards consistent interpretations. 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 only previous VPTs matter in significantly 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 who had voluntary aborted in the past by 5.4 p.p.

[33] PPML estimates and OLS estimates differentiated across industrial and service sectors are reported, respectively, in Table J1, J2, and J3 in Appendix J.

(OLS) at the 5% level, about 25% of the average pre-pandemic rate. The findings 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 in response to the shock. The reason might be twofold: 1) women with previous deliveries are more likely to be mothers already, possibly cohabiting with their partner. Thus, the positive coefficient may be pushed upwards by the larger amount of time spent home by partners during the job suspension, which boosted intercourse; 2) women who become unwillingly pregnant during the pandemic may find fertility less affordable if they have kids already, and they may prefer to pause their fertility in such hard times due to socio-economic considerations, to parity of sexual activity. One fact 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 lock-downs and closures (see Trommlerová and González, 2024; 2) women in a relationship with no 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 find less costly to carry over the pregnancy. Since we cannot distinguish between an increase in sexual activity and the insecurity-related socio-economic considerations, we further explore the heterogeneous results according to the actual number of delivered children or VPTs performed prior to the current abortion, and the overall response of pregnancies resulting into live births in the time-span under consideration.

OLS 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 live births	(6) AR with previous stillbirths	(7) AR with previous miscarriages	(8) AR with previous VPTs
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.10948***	0.02238	0.09800**	0.04712	0.09660**	0.00297	-0.01574	0.05414**
	[0.04144]	[0.03154]	[0.03974]	[0.03186]	[0.03957]	[0.00321]	[0.02222]	[0.02446]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.06753**	-0.00302	0.06796**	0.01226	0.06636**	0.00354	-0.01006	0.01331
	[0.03442]	[0.02778]	[0.03243]	[0.02585]	[0.03236]	[0.00250]	[0.01667]	[0.02181]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	0.05178*	-0.01648	0.04370**	0.02988	0.04171	0.00376*	-0.01272	0.03215
	[0.03132]	[0.02474]	[0.02997]	[0.02366]	[0.02990]	[0.00218]	[0.01554]	[0.01979]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.11128	0.07972	0.10592	0.10431	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
Prov. x Quarterly FE	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.729	0.366	0.650	0.357	0.649	0.00672	0.166	0.227

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

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

8.3.2 Intensive margin

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, and this might hold for the VPTs they undertook in the past too. Those with at least one live birth 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 live birth, 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 children (in times of lock-downs 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. 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, whose results are shown in the same table, we employ a similar set of indicators for the VPTs. In our OLS estimates (Table 12)[34], we observe that the abortion rate for women with 1 previous live birth is significant at 10% at all quartiles of the distribution with respect to the first (amounting to more than 15% of the mean in all cases), while

[34]PPML estimates in Table J4 in Appendix J.

those with 2 previous live births display ARs positive and significant at the 4° quartile at 5 % (21%), and at 10% at the 3°. There is no statistically and positive significant effect on the abortion rate of women with no children, consistently with the results on women without previous pregnancies in Table 11. Concerning VPTs, we reckon that the Italian Ministry of Health highly stressed how 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). Findings in the Cols. (7-11) somehow confirming the Ministry claims, showing that the effect is positive and slightly significant indeed for women with no previous VPTs, who constitute the bulk of the data; the effect amount to about 8.8% of the mean (Col. (7)). However, the impact of being in the upper quartile of the work suspension's distribution on women who had aborted once already is more significant and way greater in magnitude, as it amounts to 26% of the pre-treatment mean (Col. (8)). This notwithstanding, we observe a significant effect of being in the 2° quartile of the distribution. Such fact validates the significant difference from municipalities with the lowest rate of suspension, but it is not fully consistent with our baseline results, which show the highest portion to be mostly mattering. 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 more than one previous VPTs, findings are all negligible taken singularly. 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, being more "prepared" to the occurrence and thus less resistant to undergo a VPT in an altered conditions. We cannot assess whether the non-significant coefficients for higher numbers of previous abortions could be driven by a hypothetical decrease in the drop in disutility of abortion after already having had one, or by the low power of the estimates due to lack of enough data for such women.

9 Ancillary evidence

9.1 Live births

We now explore the impact on pregnancies resulting into live births 9 month later. In doing this, we refer to previous research. 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[35]. 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). On the other side, was it only time exposure, we would instead feasibly observe augmented fertility rates. 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, therefore 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. 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). Results are all positive and never statistically different from zero (Table 13, PPML estimates in the Appendix K, Table K1).

[35] 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.

OLS 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 VPTs	(8) AR with 1 previous VPT	(9) AR with 2 previous VPTs	(10) AR with 3 previous VPTs	(11) AR with at least 4 VPTs
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.03527	0.03973*	0.06118**	-0.00059	-0.00570	0.00179	0.07773*	0.04618**	0.00601	0.00162	0.00014
	[0.03425]	[0.02407]	[0.02716]	[0.01439]	[0.00536]	[0.00430]	[0.04403]	[0.02013]	[0.01618]	[0.00405]	[0.00415]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	-0.00184	0.03932*	0.03557*	-0.00574	-0.00244	-0.00146	0.05121	0.00927	0.00404	0.00001	-0.00110
	[0.02990]	[0.02111]	[0.02097]	[0.01158]	[0.00462]	[0.00417]	[0.03427]	[0.01458]	[0.01296]	[0.00361]	[0.00329]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-0.00640	0.03297*	0.02566	-0.00948	-0.00648	-0.00274	0.00315	0.02862	0.00375	-0.00173	-0.00027
	[0.02644]	[0.01818]	[0.01986]	[0.01122]	[0.00484]	[0.00349]	[0.03427]	[0.01458]**	[0.01296]	[0.00361]	[0.00329]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448	126,448
R-squared	0.08540	0.09021	0.10048	0.08365	0.07765	0.12733	0.09458	0.09009	0.07543	0.07370	0.13794
Policy covariates	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	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
Prov. x Quarterly FE	X	X	X	X	X	X	X	X	X	X	X
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Mean	0.445	0.247	0.287	0.0901	0.0199	0.0140	0.867	0.178	0.0380	0.00733	0.0132

*** 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.

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. Such findings show 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. The non-significance of these results does not help ruling out one explanation or the other: live births stemming from increased exposure may have been offset by the unplanned ones due to economic insecurity/vulnerability. Given the ambiguity, we also perform estimates using the Abortivity Ratio as outcome (instead of the Abortion Rate), which is 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 Tables (a) and (b) of Figure K1 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 is 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.18441	0.09482	0.18762	0.09508	0.19109	0.08248
	[0.15293]	[0.11474]	[0.15364]	[0.11531]	[0.17377]	[0.13211]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.07355	0.05142	0.06774	0.04531	0.04755	0.02530
	[0.12351]	[0.09754]	[0.12426]	[0.09808]	[0.13557]	[0.10721]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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 13: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

9.1.1 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[36]; thus, individual marital status can work in the next heterogeneity

[36]This assumption may bring about few issues: 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, 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 more unlikely that the child has been conceived between two individuals not married with each other. In any case, even when children are born out of wedlock, they usually live with their mothers, especially along the first

analysis, reported in Table 14. 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 K3, Appendix K[37]). The pattern, although coefficients are all statistically close to zero, seems to mirror the one retrieved in the baseline. 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 14, 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 the industry sector suspended share. 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 on affordable fertility (either recreational or aimed at planned fertility) amongst married couples due to closures, which resulted in positive 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 K4).

9.2 Domestic violence

To deepen the role of unplanned pregnancies in explaining the results, we can inquire about whether the heterogeneous shift was led by forced rather than consensual intercoures, as in sexual violence by intimate partners. We reckon indeed how the phone calls to the national public hot-line 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. We hence estimate the following model by OLS:

$$Call\ Rate_{pt} = \beta_1 + \sum_{k=2}^{4} \beta_k Post_t * 1(InactiveShare_{p12/2020} \in Q_k) + X'_{pt}\beta + \tau_p + \gamma_t + \delta_{p,t} + \varepsilon_{mt} \tag{7}$$

Where $Call\ Rate_{pt}$ is the total call to 1522, either by users or victims (a subset of users), 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. All results are displayed Appendix B, the quarterly ones in Table B1 and Table B2, the weekly ones in Table B3 and Table B4.

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.

[37] The table actually shows a surprising positive effect on widowed and separated women, but this does not bring much to the table of our analysis.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pregnancy rate (single)	Pregnancy rate (married or in civil union)	Pregnancy rate (divorced or separated)	Pregnancy rate (widow)	Pregnancy rate (single)	Pregnancy rate (married or in civil union)	Pregnancy rate (divorced or separated)	Pregnancy rate (widow)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13308	0.27145	-0.02234	0.00308				
(*services*)		**						
	[0.11315]	[0.11902]	[0.01722]	[0.00340]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.06007	0.15189	0.00930	-0.00026				
(*services*)	[0.07897]	[0.09768]	[0.01392]	[0.00314]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$	0.01078	0.24291	-0.00146	0.00276				
(*services*)	[0.07624]	[0.09539]	[0.01406]	[0.00278]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$					-0.01129	-0.05927	0.03041	0.00001
(*industry*)							*	
					[0.12338]	[0.12956]	[0.01629]	[0.00263]
$Post * 1(I.\ S._{q2/20} \in Q_3)$					-0.04940	-0.01671	0.02447	0.00216
(*industry*)							*	
					[0.11442]	[0.11609]	[0.01407]	[0.00299]
$Post * 1(I.\ S._{q2/20} \in Q_2)$					-0.02661	-0.05316	0.01628	0.00246
(*industry*)					[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
Prov. x Quarterly 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 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.

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. If anything, the direction of coefficient of upper quartiles is opposite to the one we would expect, as provinces which are part of the 4° quartile of the inactive share's distribution face a differential, imprecisely estimated, negative effect in the 1522 call rate. Weekly frequency regressions lead not to really different conclusions, as shown in Table B3 and B4. 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 B2). This would suggest that the suspension of non-essential workers did not have a significant effect on *reported* DV rates (and when it did, it was negative)[38]. 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[39]. 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 *reported domestic violence*; which appears to be the case. As a matter of fact, the hypothesis of power imbalances within a couple which may lead to abortions may not be so straightforwardly represented by official statistics on domestic violence. There may be more subtle and less explicit way for a male partner to exert control over the woman's fertility, inflict resource deprivation or commit some form of psychological violence that may lead to a VPT (WHO, 2002, 2012, 2014). Such situations, which may me spread in contexts of higher vulnerability for female partners, cannot be disentangled from the available data.

[38] 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.

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

9.3 Contraception

A further channel that may have credibly shifted unwanted conceptions in a heterogenous way, by leaving the patterns of planned pregnancies unchanged could be the access and usage of contraception methods. If there was some impact of the suspension of non-essential workers in the access or employment 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 through which one can disentangle the evolution of contraceptive demand and reproductive care services at such a granular disaggregation as the one we are employing for our analysis. However, we 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 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 (ECP), as in, birth control drugs that can be assumed after an unprotected sexual intercourse. ISTAT platform Health For All collects instead regional data on contraceptive usage in Italy. Concerning the former, family planning centers 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, including sensitisation on prevention. If there was a disruption in the services provided by family planning centres due to the pandemic correlated with the inactive share, the observed increase in VPTs may be linked to a decrease in responsible prevention or to a lack of reproductive care facilities' assistance. Alas, we can only look at the number of yearly family planning centers 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.

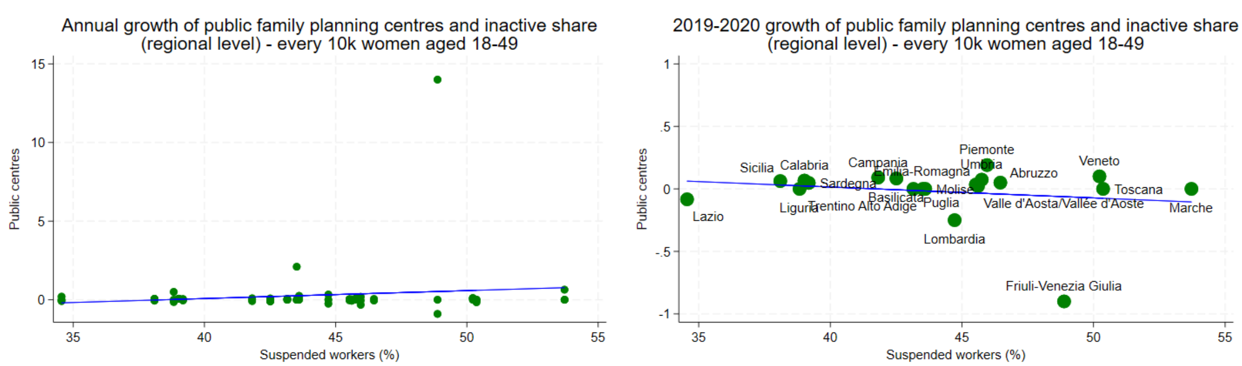


Figure 9: Annual growth of family planning centres in Italy and regional inactive share. Left panel: annual growth of family planning centres every 10,000 women aged between 18 and 49 between 2018 and 2021. Right panel: 2019-2020 growth of family planning centres every 10,000 women aged between 18 and 49 in 2020. Source: Ministry of Health.

Albeit not statistically accurate enough, therefore insufficient to discard the hypothesis, we observe how, in Figure 9, there seems to exists no correlation between the regional suspended workers' share and the growth in reproductive care facilities.

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 intercourse, conditional on assuming them as soon as possible; in any case, they do not constitute an interruption of pregnancy, as they work within a time-frame within which pregnancy has not emerged yet[40]. 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 (which were never suspended) 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.

10 Implications

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 3). 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 average ITT of our estimates,

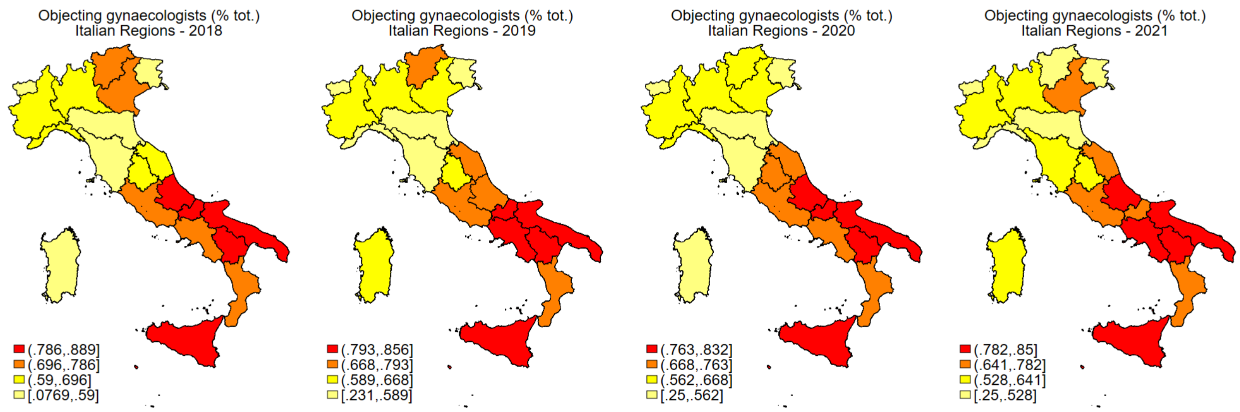
[40] Their effectiveness, however, is reduced at any additional use, and they do not protect from pregnancies if an intercourse happens after their assumption (MoH, 2023)

although we observe that the bulk of the shift in ARs occur in the second and the 3° quarters of 2020, which are the only ones shown by the Event-Study estimates as reporting significant coefficients (Figure 5 and 7). 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. 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; the municipal ARs significantly responding to the exogenous shock are indeed mainly those of women who are not 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 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. 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. Finally, the two most interesting results of our study (not been tackled yet by Italian research on 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 11, Col. (2)), 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 Col. (5) of the same table we observe how 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 not only on the last quartile of the distribution. When looking at the intensive margin, the main non-ambiguous and significant result concerns live birth, from Table 12, tells us that there is positive differential impact on women residing in treated municipalities and with at least one or two children (proxied by previous live births). When looking at previous VPTs, women with either 0 or 1 previous voluntary abortion responding significantly to the treatment, which is pretty intuitive. Although these results alone cannot help us disentangling whether economic insecurity played a major role over time exposure, 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 1 or 2 children or that have at most aborted once are more likely to resort to a VPT. These are however rough considerations, stemming out from indirect interpretation of the ITT results, are intended at corroborating some hypothesis by putting up together all the findings in the work. 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 a previous VPT) 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, the final issue to be addressed is the one vulnerability. An effect driven by the industrial sector on already mothers OLF, likely means that for many women the abortion choice is dependent upon the partner's suspension. This implies the control over fertility for such women is reduced, as they could result more vulnerable in terms of the existing gender balances within couples. This may usher both a policy and research discussion about the issue on how less autonomous women are directly in charge of their own fertility choices contrarily to how such decisions may be relying on the (feasibly male) breadwinners' needs.

11 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 4° 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. We are not able, in conclusion, to distinguish with certainty between the increase in exposure (and consequent intercourse 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, seems to suggest that insecurity could be a channel affecting the decision mostly in terms of male partners' trajectories, thus underlining an issue of potential vulnerability with respect to family control over women's fertility. Such is confirmed but another relevant result of the study, which has to our knowledge never been tackled before, as in the role played by past reproductive behavior of women in shaping the response of abortion patterns to the studied policy: women who had previous children seem to be the ones more likely to be significantly affected by the work suspension policy. 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 couples with children where women are OLF, thus possibly subject to within-family gender imbalances in terms of fertility decisions.

A Conscientious objection



(a) (b) (c) (d)

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

B Domestic Violence

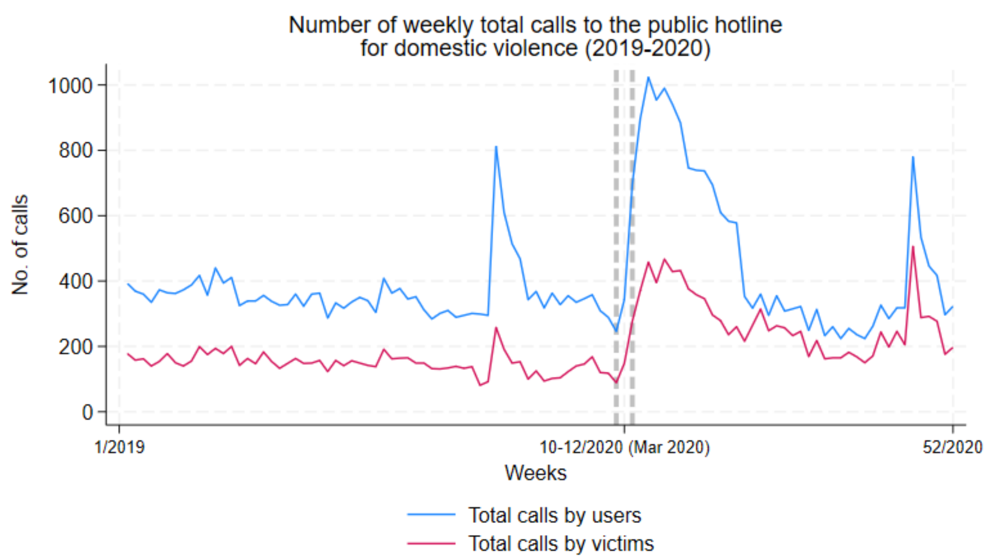


Figure B1: Weekly calls to the Italian public hotline for domestic violence (1522) in 2019 and 2020.

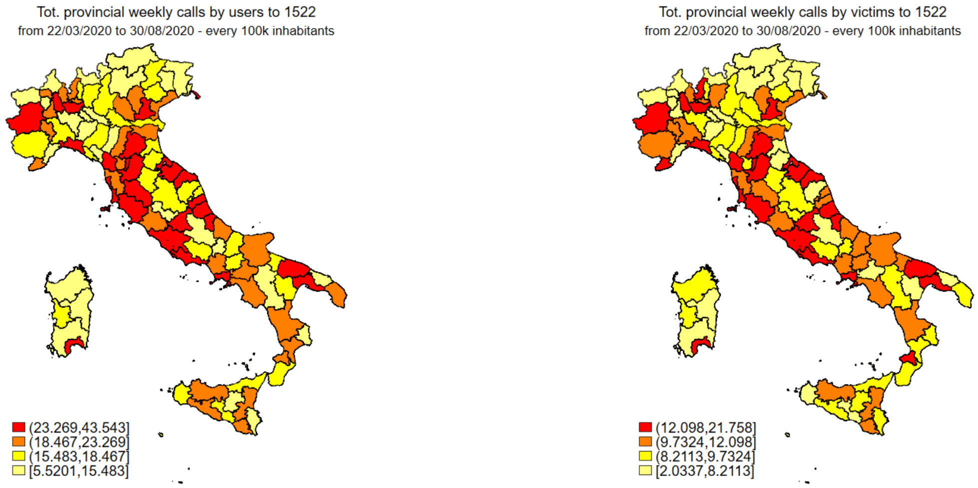


Figure B2: Total calls to 1522 over provincial population, from the week of closures in March 2020, to the last week of August 2020. Left panel reports the heat map for calls by all users, whereas the right panel reports the heat map for the calls by victims only. Calls with missing provenience are discarded.

SEs clustered at provincial level; 2018-2021

	(1) 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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 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) 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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 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.

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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 B3: 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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 B4: 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 Identification strategy

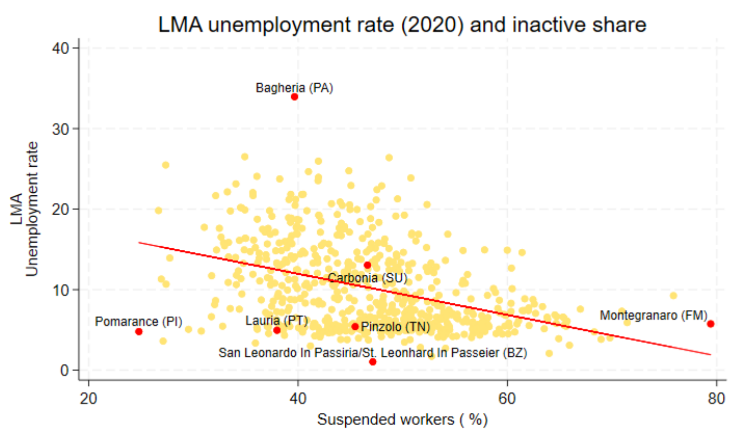


Figure C1: Predicted values between Local Market Areas' unemployment rate (2020, left panel) and suspended workers' share. The highlighted LMAs correspond to the ones having the maximum/minimum 2020's unemployment rate and inactive share. Carbonia (SU) has the median value of the inactive share.

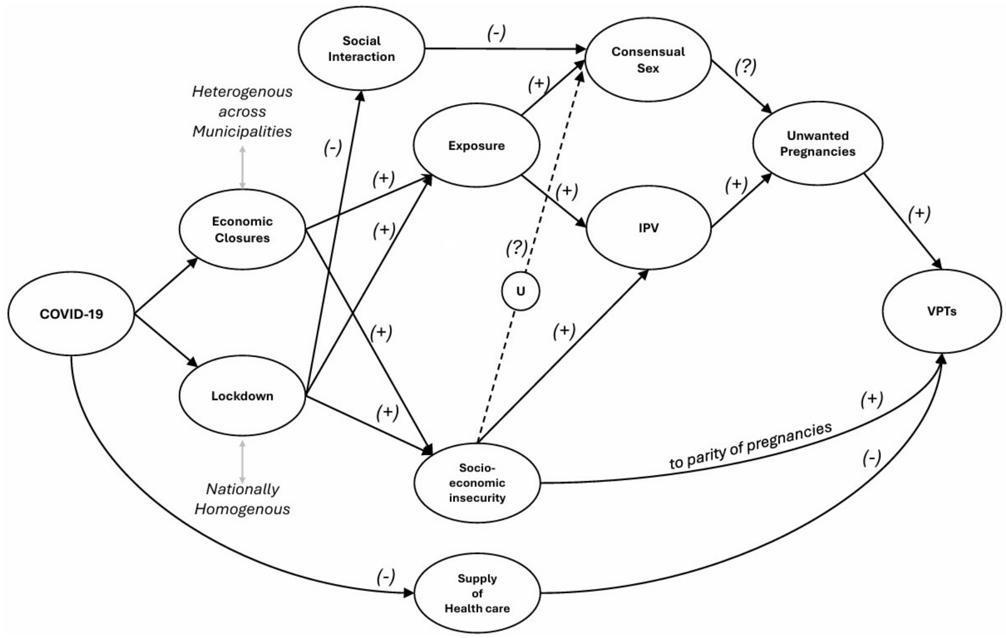


Figure C2: Supposed phenomena in action starting from the Covid pandemic: before the identification strategy.

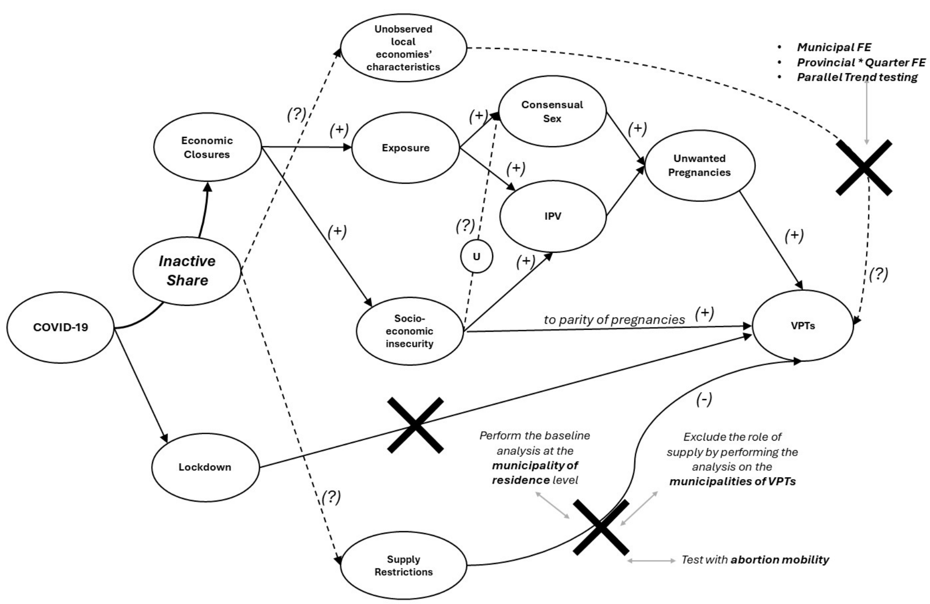


Figure C3: Identification strategy.

D Covid-19 data

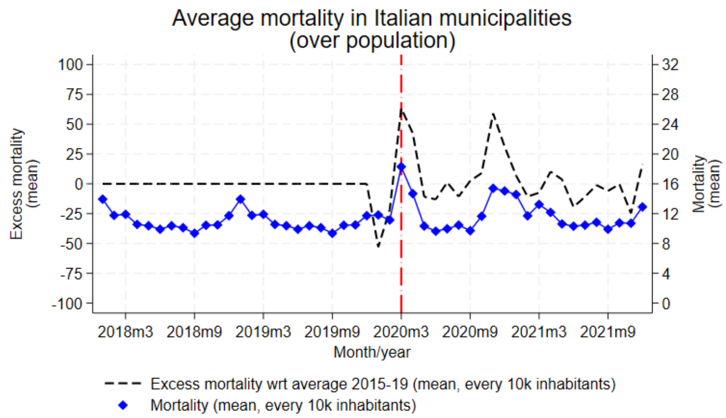


Figure D1: Path of municipal excess mortality in Italy between 2018 and 2021.

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:

$$I_{mti} = 100 * \frac{v_{mti}}{V_i} \tag{8}$$

- 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:

$$I_{mti} = 100 * \frac{\sigma^g_{mt} v^g_{mti} + (1 - \sigma^g_{mt}) v^{ng}_{mti}}{V_i} \tag{9}$$

- 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:

$$ItSI_{mt} = \sum_i w_i I_{mti} \tag{10}$$

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

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

(a)

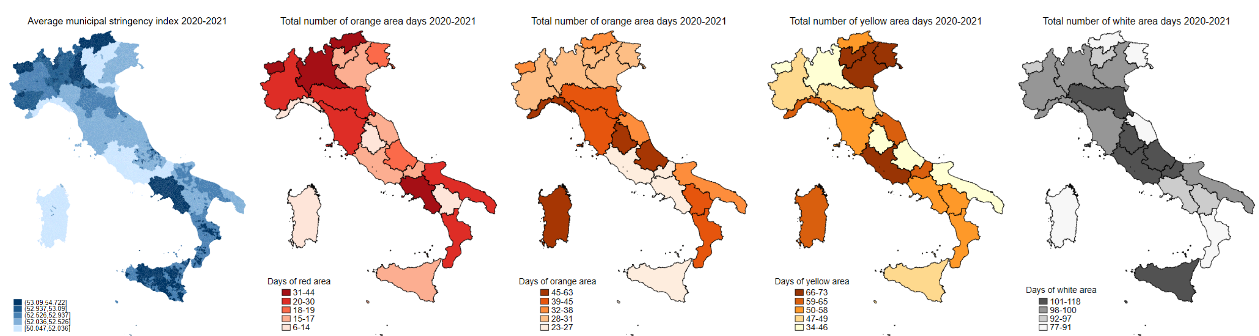
Table 1 continued

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

(b)

Figure D2: Source: Conteduca and Borin, 2022.



(a) Avg municipal stringency index. (b) Red days (c) Orange days (d) Yellow days (e) White days

Figure D3: Elaboration on the data by Conteduca and Borin, 2022

E Temporal sensitivity

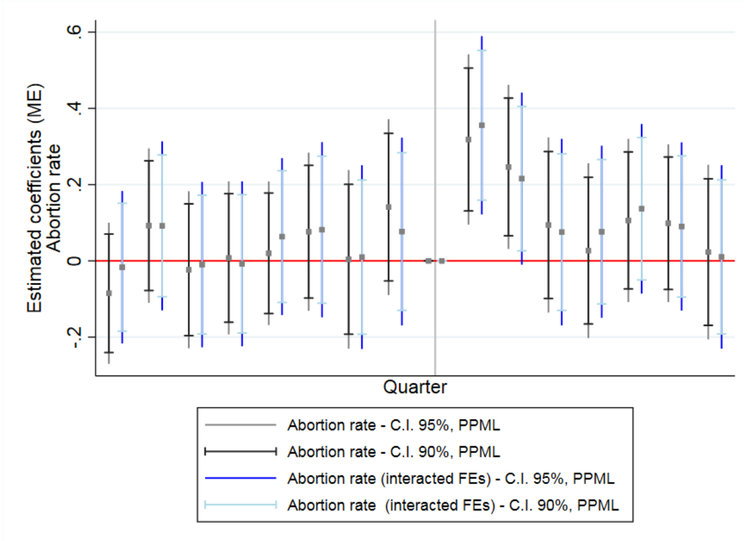
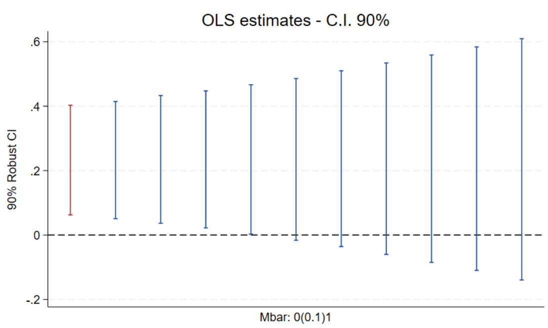
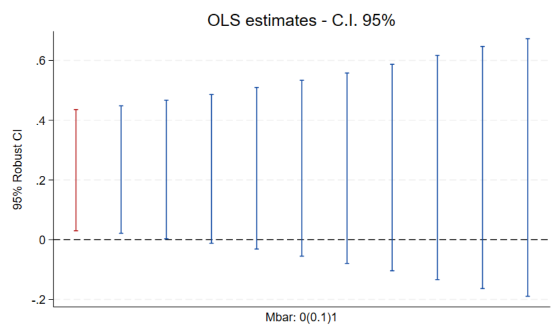


Figure E1: PPML Event-study estimates. The figure reports the marginal effects of temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence intervals are reported at both 90% and 95% The 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.



(a)



(b)

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 90% (a), 95% (b). 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%.

OLS results - By municipality of residence - Annual specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{2020} \in Q_4)$	0.45936***	0.40473***	0.44251**	0.38749***	0.46248**	0.40370**
	[0.18155]	[0.14232]	[0.18278]	[0.14344]	[0.20957]	[0.16431]
$Post * 1(I.\ S._{2020} \in Q_3)$	0.027750	0.22828*	0.27461	0.22259*	0.30372*	0.24423*
	[0.17144]	[0.13291]	[0.17227]	[0.13375]	[0.18107]	[0.14047]
$Post * 1(I.\ S._{2020} \in Q_2)$	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
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

(a) Annual Specification (OLS)

PPML results - By municipality of residence - Annual specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{2020} \in Q_4)$	0.48261**	0.40296***	0.46742**	0.38752**	0.54760**	0.42632**
	[0.19869]	[0.15296]	[0.20052]	[0.15456]	[0.22249]	[0.17294]
$Post * 1(I.\ S._{2020} \in Q_3)$	0.29128	0.22390	0.29055	0.22038	0.35035*	0.25932*
	[0.18411]	[0.13928]	[0.18542]	[0.14043]	[0.19054]	[0.14573]
$Post * 1(I.\ S._{2020} \in Q_2)$	0.16671	0.13396	0.17390	0.13784	0.19209	0.14084
	[0.17143]	[0.12889]	[0.17192]	[0.12965]	[0.17193]	[0.13113]
Observations	29,048	29,048	29,048	29,048	29,048	29,048
Policy covariates			X	X	X	X
Municipal FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Prov. x Year FE					X	X
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

(b) Annual Specification (PPML)

Figure E3: SEs clustered at municipal level. *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
$Post * 1(I.\ S._{03/2020} \in Q_4)$	0.04378***	0.03780***	0.04125***	0.03556***	0.04285**	0.03628***
	[0.01522]	[0.01188]	[0.01530]	[0.01194]	[0.01736]	[0.01356]
$Post * 1(I.\ S._{03/2020} \in Q_3)$	0.01904	0.01608	0.01989	0.01666	0.02235	0.01811
	[0.01422]	[0.01100]	[0.01414]	[0.01093]	[0.01495]	[0.01157]
$Post * 1(I.\ S._{03/2020} \in Q_2)$	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
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

(a) Monthly Specification (OLS)

PPML results - By municipality of residence - Monthly specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{03/2020} \in Q_4)$	0.04659***	0.03775***	0.04413***	0.03568***	0.04807**	0.03810***
	[0.01702]	[0.01301]	[0.01708]	[0.01305]	[0.01865]	[0.01446]
$Post * 1(I.\ S._{03/2020} \in Q_3)$	0.02005	0.01358	0.02110	0.01617	0.02566	0.01866
	[0.01563]	[0.01176]	[0.01556]	[0.01170]	[0.01606]	[0.01224]
$Post * 1(I.\ S._{03/2020} \in Q_2)$	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
Prov. x Month˙year FE					X	X
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

(b) Monthly Specification (PPML)

Figure E4: SEs clustered at municipal level. *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
$Post * 1(I.\ S._{03/2020} \in Q_4)$	0.22968	0.20237	0.22546	0.19714	0.23061	0.20126
	**	***	**	***	**	**
	[0.09077]	[0.07116]	[0.09114]	[0.07150]	[0.10459]	[0.08196]
$Post * 1(I.\ S._{03/2020} \in Q_3)$	0.13875	0.11414	0.13668	0.11126	0.15137	0.12155
		*		*	*	*
	[0.08572]	[0.06646]	[0.08600]	[0.06675]	[0.09039]	[0.07009]
$Post * 1(I.\ S._{03/2020} \in Q_2)$	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
Prov. x Semester˙year FE					X	X
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

(a) Semestral Specification (OLS)

OLS results - By municipality of residence - Semestral specification

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{03/2020} \in Q_4)$	0.24131	0.20148	0.23656	0.19705	0.25776	0.21183
	**	***	**	**	**	**
	[0.09935]	[0.07648]	[0.09988]	[0.07695]	[0.11101]	[0.08623]
$Post * 1(I.\ S._{03/2020} \in Q_3)$	0.14565	0.11195	0.14389	0.10965	0.17412	0.12821
					*	*
	[0.09220]	[0.06964]	[0.09258]	[0.07004]	[0.09504]	[0.07263]
$Post * 1(I.\ S._{03/2020} \in Q_2)$	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
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

(b) Semestral Specification (PPML)

Figure E5: 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	(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 $*1(I.\ S._{q2/20} \in Q_4)$	0.07931	0.06583	0.07583												
	[0.07533)	[0.10626]	[0.08493]												
Post March 2019 $*1(I.\ S._{q2/20} \in Q_4)$				0.04414	-0.00377	0.04229	0.04748								
				[0.05396]	[0.11132]	[0.07427]	[0.08611]								
Post March 2020 $*1(I.\ S._{q2/20} \in Q_4)$								0.27922	0.19013	0.18673		0.14851			
								**	***	***		*			
								[0.11336]	[0.06092]	[0.06854]		[0.08940]			
Post March 2021 $*1(I.\ S._{q2/20} \in Q_4)$											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 E1: 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
$Post * 1(I.\ S._{q2/20})$ (*continuous*)	0.00325 ** [0.00141]			0.00327 ** [0.00158]		
$Post * 1(I.\ S._{q2/20} \geq median)$		0.07450 *** [0.02858]			0.07678 ** [0.03177]	
$Post * 1(I.\ S._{q2/20} \in Tercile_3)$			0.10914 *** [0.03744]			0.11317 *** [0.04301]
$Post * 1(I.\ S._{q2/20} \in Tercile_2)$			0.01415 [0.03371]			0.02023 [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
Prov. x Quarterly 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

(a) OLS

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{q2/20})$ (*continuous*)	0.00360 ** [0.00161]			0.00388 ** [0.00174]		
$Post * 1(I.\ S._{q2/20} \geq median)$		0.07825 *** [0.03170]			0.08517 ** [0.03428]	
$Post * 1(I.\ S._{q2/20} \in Tercile_3)$			0.11610 *** [0.04193]			0.12601 *** [0.04647]
$Post * 1(I.\ S._{q2/20} \in Tercile_2)$			0.01754 [0.03694]			0.02838 [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
Prov. x Quarterly 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

(b) PPML

Figure F1: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

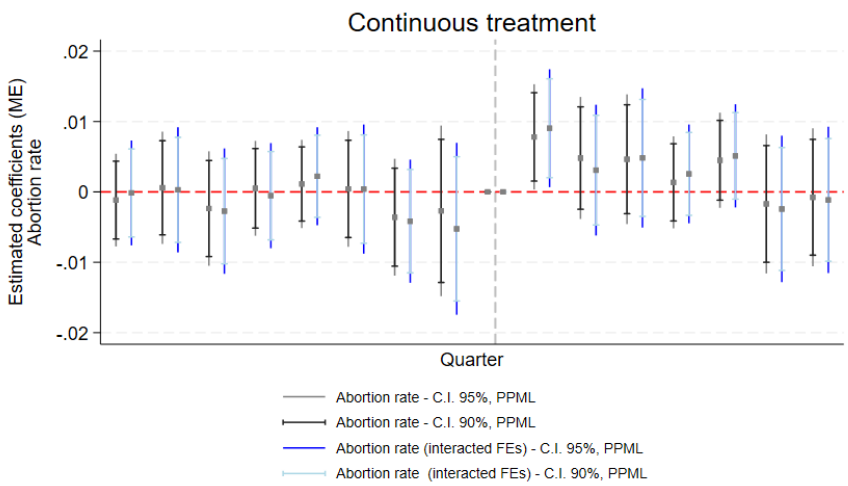


Figure F2: PPML Event-study estimates with the continuous treatment specification. The figure reports the marginal effects of temporal units and their confidence intervals, both for the baseline specification and the one with interaction FEs between province dummies and quarterly dummies. Confidence 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.

OLS results - By municipality of residence

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.12711	0.10910	0.12504	0.10737	0.12628	0.10531
	***	***	***	***	**	***
	[0.04446]	[0.03469]	[0.04469]	[0.03492]	[0.05043]	[0.03949]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05544	0.04717	0.05413	0.04595	0.05906	0.04760
	[0.04168]	[0.03228]	[0.04177]	[0.03238]	[0.04397]	[0.03411]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(a) OLS

OLS results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13487	0.10765	0.13240	0.10562	0.13769	0.10738
	***	***	***	***	**	***
	[0.05016]	[0.03829]	[0.05031]	[0.03844]	[0.05461]	[0.04238]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05787	0.04417	0.05639	0.04282	0.06745	0.04757
	[0.04611]	[0.03468]	[0.04619]	[0.03476]	[0.04750]	[0.03620]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(b) PPML

Figure F3: 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13125	0.11333	0.12888	0.11156	0.13183	0.11136
	***	***	***	***	***	***
	[0.04576]	[0.03580]	[0.04598]	[0.03602]	[0.05200]	[0.04082]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05615	0.04712	0.05482	0.04603	0.06231	0.05009
	[0.04276]	[0.03316]	[0.04284]	[0.03325]	[0.04513]	[0.03506]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(a) OLS

PPML results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.14015	0.11406	0.13732	0.11191	0.14597	0.11630
	***	***	***	***	***	***
	[0.05119]	[0.03925]	[0.05133]	[0.03938]	[0.05596]	[0.04358]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05962	0.04587	0.05798	0.04450	0.07222	0.05199
	[0.04703]	[0.03549]	[0.04708]	[0.03554]	[0.04847]	[0.03707]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(b) PPML

Figure F4: 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.09557 **	0.08961 ***	0.08975 **	0.08505 ***	0.07036	0.06337 *
	[0.03902]	[0.03069]	[0.03938]	[0.03097]	[0.04490]	[0.03524]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.05835	0.05018 *	0.05477	0.04720 *	0.04516	0.03498
	[0.03581]	[0.02812]	[0.03599]	[0.02827]	[0.03789]	[0.02973]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(a) OLS

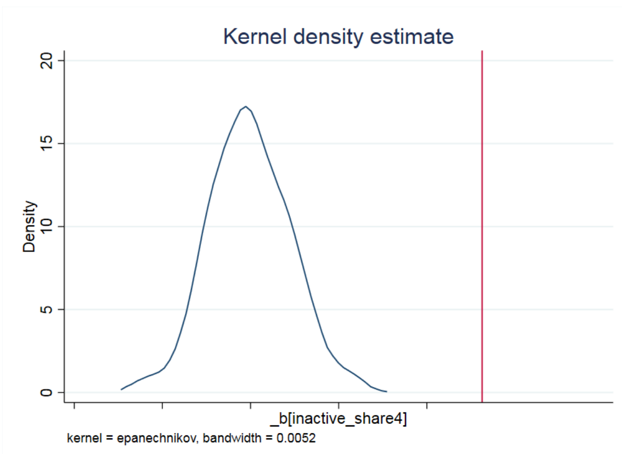
PPML results - By municipality of residence

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.10303 **	0.08936 ***	0.09639 **	0.08429 **	0.07855	0.06404 *
	[0.04473]	[0.03432]	[0.04508]	[0.03457]	[0.04910]	[0.03829]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.06003	0.04651	0.05595	0.04327	0.04834	0.03193
	[0.04066]	[0.03089]	[0.04088]	[0.03104]	[0.04140]	[0.03198]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
Weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	1.103	1.103	1.103	1.103	1.103	1.103

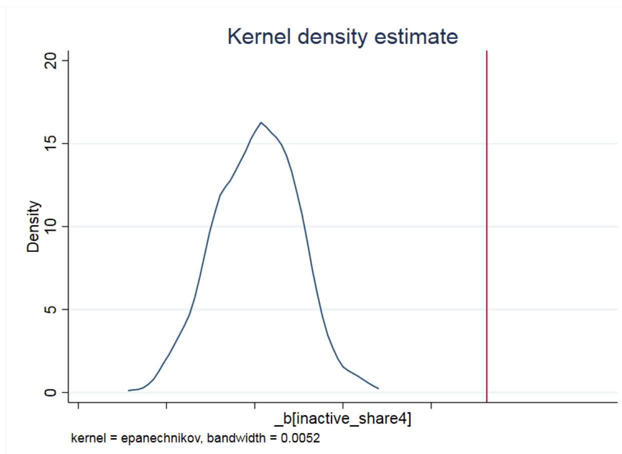
*** p<0.01, ** p<0.05, * p<0.1

(b) PPML

Figure F5: 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.



(a)



(b)

Figure F6: 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 in (a), while it includes them in (b). The actual estimated baseline coefficient is the red line at the extreme right of the distribution.

G Labor Market Areas

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR
Treatment at municipal level, SEs clustered at LMA level												
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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]
Treatment at LMA level, SEs clustered at LMA level												
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Provincial x Quarter˙year FE					X	X					X	X
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 of residence of the women. *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

OLS results - By hospital

	(1) AR	(2) AR	(3) AR	(4) AR	(5) AR	(6) AR
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-1.34072	-1.50525*	-1.20354	-1.39824	-1.15342	-1.67544
	[1.13140]	[0.87256]	[1.16186]	[0.088944]	[2.71143]	[2.21840]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.04345	-0.23301	-0.18356	-0.12472	0.78914	0.25097
	[0.80849]	[0.54258]	[0.86028]	[0.57442]	[2.75011]	[2.22934]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
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

(a) OLS

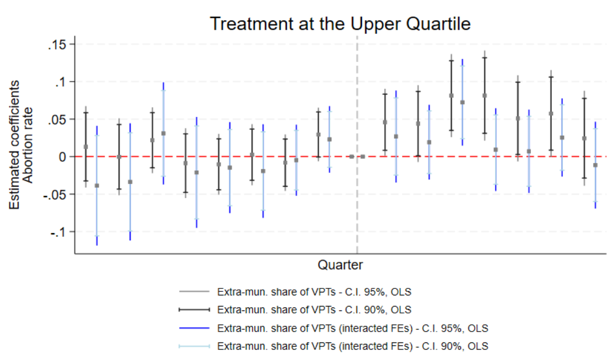
PPML results - By hospital

	(1) AR (ME)	(2) AR (ME)	(3) AR (ME)	(4) AR (ME)	(5) AR (ME)	(6) AR (ME)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-0.34996	-0.34081	-0.31330	-0.31080	-0.71250	-0.76142
	[0.71949]	[0.58730]	[0.71348]	[0.58216]	[1.02622]	[0.84359]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.27605	0.18864	0.29475	0.20608	-0.91513	-0.79908
	[0.52626]	[0.45530]	[0.52362]	[0.45498]	[0.99737]	[0.82143]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Weight		X		X		X
Method	PPML	PPML	PPML	PPML	PPML	PPML
Mean	9.640	9.640	9.640	9.640	9.640	9.640

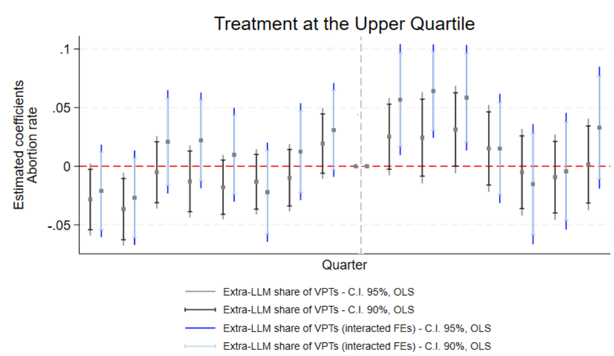
*** p<0.01, ** p<0.05, * p<0.1

(b) PPML

Figure H1: 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.



(a)



(b)

Figure H2: OLS Event-study estimates (dynamic specification of Equation 6) for the inter-municipal (a) and inter-LMA (b) abortion mobility analysis. 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.

	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.

I Socio-economic Information

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly 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 I1: 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

	Industry Share				Service Share			
	(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
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00316	-0.00961	0.01335	0.00681				
	[0.04292]	[0.03474]	[0.03339]	[0.02680]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	-0.01117	-0.02102	0.04114*	0.01872				
	[0.03472]	[0.02914]	[0.02401]	[0.02135]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.03788	-0.00893	0.03069	0.01074				
	[0.03450]	[0.03017]	[0.02013]	[0.02015]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.10119**	0.05653	0.03940	0.01968
					[0.04326]	[0.03707]	[0.03877]	[0.02661]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.03869	0.00980	0.01252	0.02236
					[0.03911]	[0.03381]	[0.03643]	[0.02447]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					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
Prov. x Quarterly 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 I2: 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 results - By municipality of residence - SEs clustered at municipal level

	Industry Share				Service Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR	AR	AR	AR	AR	AR	AR	AR
	single	married	separated	widow	single	married	separated	widow
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00107	-0.02319	0.00026	0.00941				
	[0.04030]	[0.02880]	[0.00432]	[0.00767]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	-0.01561	-0.02276	0.00061	-0.00599				
	[0.02999]	[0.02681]	[0.00371]	[0.00553]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.02311	-0.03385	0.00303	0.00048				
	[0.03611]	[0.02929]	[0.04846]	[0.02652]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.08384*	0.03899	0.00360	-0.00737
					[0.04353]	[0.03038]	[0.00470]	[0.00832]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.01386	0.02836	0.00009	-0.01190**
					[0.03960]	[0.02784]	[0.00434]	[0.00566]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					-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
Prov. x Quarterly 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 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

	Industry Share				Service Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR	AR	AR	AR	AR	AR	AR	AR
	single	married	separated	widow	single	married	separated	widow
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00666	-0.05523	-0.03730	0.05348**				
	[0.04582]	[0.03603]	[0.05273]	[0.02684]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	-0.01534	-0.03143	-0.01379	-0.01448				
	[0.03577]	[0.03038]	[0.05832]	[0.02402]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.02515	-0.04631	-0.05966	0.00028				
	[0.03611]	[0.02929]	[0.04846]	[0.02652]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.09310*	0.07597**	0.09492*	-0.06138**
					[0.04874]	[0.03778]	[0.05293]	[0.02603]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.01029	0.05643*	-0.05002	-0.06404***
					[0.04297]	[0.03363]	[0.05082]	[0.02190]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					-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
Prov. x Quarterly 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 I4: SEs clustered at municipal level. *Mean* reports the mean of the treated units pre-treatment.

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

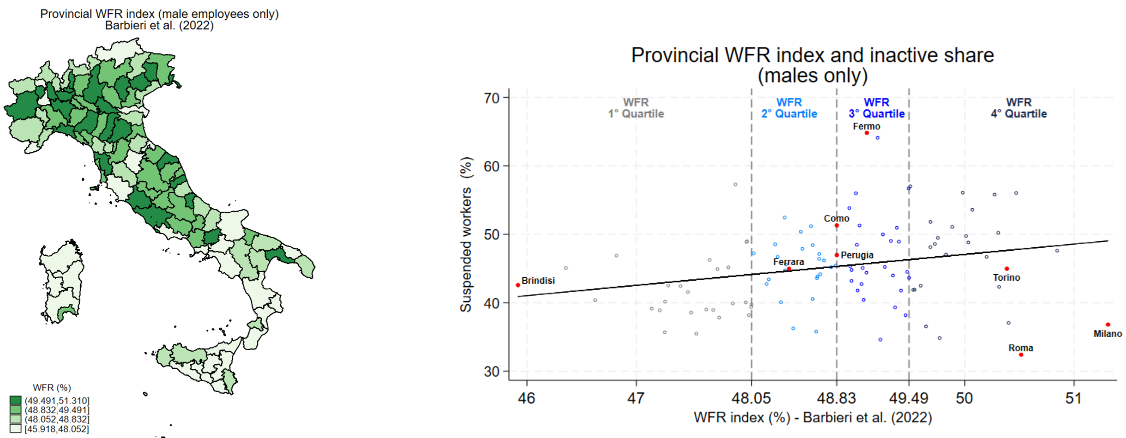
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR	AR
	<14	15–19	20–24	25–29	30–34	35–39	>40	<14	15–19	20–24	25–29	30–34	35–39	>40
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.00185	0.01287	0.02969	0.03175	-0.04616*	0.06145**	0.03969*	0.09436	0.03178	0.03520	0.04410	-0.05819*	0.08383***	0.06247**
	[0.00134]	[0.01252]	[0.02310]	[0.02059]	[0.02697]	[0.02411]	[0.02105]	[0.08622]	[0.02470]	[0.03358]	[0.03035]	[0.03474]	[0.03127]	[0.02773]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.00140	-0.00001	0.01308	0.04123**	-0.03659*	0.01179	0.03267*	0.05178	0.00585	0.01743	0.06142**	-0.05023*	0.01934	0.05139**
	[0.00118]	[0.01002]	[0.02026]	[0.01831]	[0.02212]	[0.01695]	[0.01760]	[0.05173]	[0.02028]	[0.03009]	[0.02550]	[0.02783]	[0.02406]	[0.02284]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	0.00001	-0.01435	0.00803	0.03552**	-0.03641*	0.00652	0.03422**	0.04099	-0.02004	0.01292	0.04680**	-0.05009*	0.01282	0.05424***
	[0.00113]	[0.00882]	[0.01723]	[0.01688]	[0.02085]	[0.01643]	[0.01574]	[0.05545]	[0.01915]	[0.02478]	[0.02378]	[0.02560]	[0.02272]	[0.02089]
Observations	126,448	126,448	126,448	126,448	126,448	126,448	126,448	2,039	55,156	80,005	85,144	89,676	87,596	74,520
R-squared	0.07374	0.07729	0.08903	0.08805	0.08292	0.08008	0.07885							
Policy covariates	X	X	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	X	X
Quarter_year FE	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
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.000861	0.0740	0.177	0.217	0.262	0.233	0.139	0.000861	0.0740	0.177	0.217	0.262	0.233	0.139

Table I5: 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

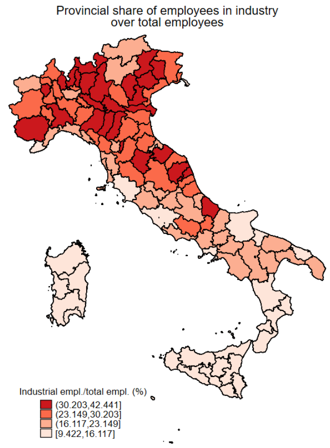
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR	AR	AR	AR	AR	AR	AR	AR
	elementary	middle school	high school	university	elementary	middle school	high school	university
$Post * 1(I.\ S._{q2/20} \in Q_4)$	-0.00208	0.04775 *	0.04389	0.03345	-0.00816	0.06329 **	0.05145	0.05765
	[0.01005]	[0.03215]	[0.03426]	[0.01775]	[0.03454]	[0.03866]	[0.04016]	[0.02826]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.00044	0.01889 *	0.01082	0.02707	0.00177	0.01877 **	0.01242	0.04824
	[0.00603]	[0.02557]	[0.03099]	[0.01449]	[0.02337]	[0.03029]	[0.03605]	[0.02341]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-0.00331	0.01750 *	-0.00418	0.02277	-0.01383	0.02353 *	-0.00438	0.03541
	[0.00645]	[0.02297]	[0.02796]	[0.01326]	[0.02055]	[0.02741]	[0.03237]	[0.02081]
Observations	126,448	126,448	126,448	126,448	35,064	95,980	106,192	74,312
R-squared	0.10851	0.09152	0.08960	0.08042				
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	0.0467	0.376	0.520	0.135	0.0467	0.376	0.520	0.135

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

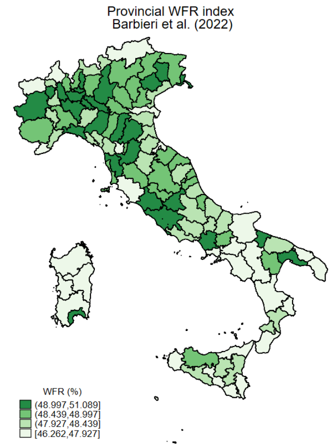


(a) (b)

Figure I1: Map (a): provincial distribution of the weighted average of the *Working From Remote* sectoral index. Graph (b): suspended workers share over the *WFR* index for active males. The black line reports the fitted values from an unconditional regression of former share on the latter. The vertical dashed lines define the 1°, 2° and 3° quartile of the *WFR* distribution. Labeled provinces have the min., max. and median value of both variables. The WFR is built as conceived by Barbieri et al., 2022; the provincial index is then computed by weighing the sectoral values from Barbieri et al., 2022, by the provincial share of sectoral active males.



(a)



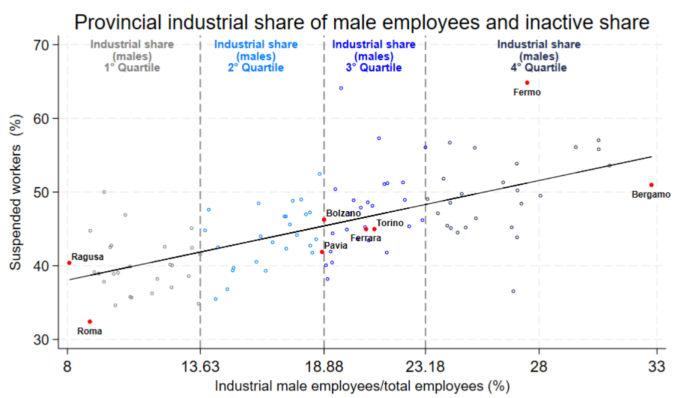
(b)

Figure I2: Industrial sector-related variables from *LFS* 2019. Map (a): provincial share of active workers in the private industrial sector. Map (b): provincial distribution of the weighted average of the *Working From Remote* sectoral index as conceived by Barbieri et al., 2022; the provincial index is computed by weighing the sectoral values from Barbieri et al., 2022, by the provincial share of sectoral active individuals.

	2019; Robust SEs				
	(1) Inactive share (%)	(2) Inactive share (%)	(3) Inactive share (%)	(4) Inactive share (%)	(5) Inactive share (%)
(1) WFR Index	0.85864 [0.76011]				
(2) WFR Index (males)		1.50612 ** [0.59623]			
(3) Industrial share			0.48438 *** [0.05660]		
(4) Industrial share (males/total empl.)				0.67572 *** [0.07827]	
(5) Industrial share (males/males empl.)					0.37001 *** [0.04299]
Observations	107	107	107	107	107
R-squared	0.01481	0.06125	0.48876	0.43047	0.44668
Covariates	NO	NO	NO	NO	NO
Method	OLS	OLS	OLS	OLS	OLS
Mean	45.27	45.27	45.27	45.27	45.27

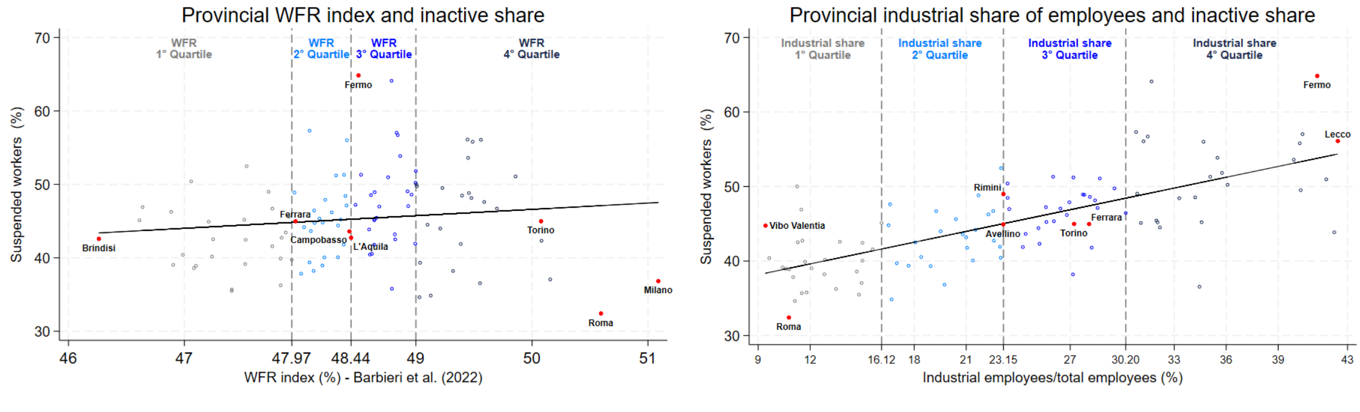
*** p<0.01, ** p<0.05, * p<0.1

(a)



(b)

Figure I3: Table (a): Table of regressions of the provincial inactive share (%) on 1) *WFR Index*; 2) *WFR Index (males)*; 3) *Industrial share* ; 4) *Industrial share (males/tot. employees)*; 5) *Industrial share (males/tot. males employees).Mean* reports the mean of the provincial inactive share in 2020. Graph (b): suspended workers share over the provincial share of industrial active males on total active individuals. The black line reports the fitted values from an unconditional regression of the former share on the latter. The vertical dashed lines define the 1°, 2° and 3° quartile of the latter distribution. Labeled provinces have the min., max. and median value of both variables.



(a) (b)

Figure I4: Graph (a): suspended workers share over the Barbieri et al., 2022's *WFR* index. Graph (b): suspended workers share over the provincial share of industrial active people on total active individuals. The black line reports the fitted values from an unconditional regression of the variable in the y-axis on that on the x-axis. The vertical dashed lines define the 1°, 2° and 3° quartile of the distribution of the x-axis variables. Labeled provinces have the min., max. and median value of both variables.

J Fertility

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 live births	(6) AR with previous stillbirths	(7) AR with previous miscarriages	(8) AR with previous VPTs
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.13273 ***	0.2771	0.12369 ***	0.06329 *	0.12274 ***	0.02151	-0.01620	0.07755 **
	[0.04645]	[0.03877]	[0.04505]	[0.03698]	[0.04481]	[0.03845]	[0.03022]	[0.03266]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.08275 **	-0.00484	0.08565 **	0.01967	0.08431 **	-0.02675	-0.00769	0.01510
	[0.03889]	[0.03327]	[0.03699]	[0.03147]	[0.03690]	[0.03254]	[0.02549]	[0.02880]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	0.07003 *	-0.02193	0.06365 **	0.04790 *	0.06177 *	0.00298	-0.01149	0.04935 *
	[0.03513]	[0.02974]	[0.03390]	[0.02892]	[0.02282]	[0.03003]	[0.02367]	[0.02574]
Observations	109,632	100,112	107,600	95,525	107,552	8,909	77,276	84,020
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
Prov. x Quarterly FE	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.729	0.366	0.650	0.357	0.649	0.00672	0.166	0.227

*** 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.

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00760	-0.00740	0.00939	0.00138				
	[0.01270]	[0.00992]	[0.01220]	[0.00961]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	0.00420	-0.01712 **	0.00718	-0.00038				
	[0.01078]	[0.00767]	[0.01040]	[0.00799]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.00253	-0.01558 **	0.00032	-0.00221				
	[0.01069]	[0.00776]	[0.01030]	[0.00792]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.02952 **	0.00168	0.03140 ***	0.01173
					[0.01270]	[0.00992]	[0.01220]	[0.00961]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.01859	-0.00984	0.01786	0.00274
					[0.01240]	[0.00922]	[0.01168]	[0.00946]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					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
Prov. x Quarterly 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 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.

PPML 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(services)$	0.00810	-0.00836	0.00984	0.00206				
	[0.01512]	[0.01242]	[0.01474]	[0.01316]				
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(services)$	0.00607	-0.02173 **	0.00934	0.00065				
	[0.01237]	[0.01015]	[0.01209]	[0.01064]				
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(services)$	-0.00286	-0.02059 **	0.00027	-0.00286				
	[0.01243]	[0.01040]	[0.01212]	[0.01073]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$ $(industry)$					0.03367 **	0.00090	0.03705 ***	0.01407
					[0.01405]	[0.01187]	[0.01349]	[0.01252]
$Post * 1(I.\ S._{q2/20} \in Q_3)$ $(industry)$					0.02183	-0.01306	0.02187	0.00285
					[0.01430]	[0.01136]	[0.01362]	[0.01235]
$Post * 1(I.\ S._{q2/20} \in Q_2)$ $(industry)$					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
Prov. x Quarterly 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 J3: 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 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 VPTs	(8) AR with 1 previous VPT	(9) AR with 2 previous VPTs	(10) AR with 3 previous VPTs	(11) AR with at least 4 VPTs
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.04195	0.04869	0.09200 **	0.02031	-0.04016	0.00008	0.08889 *	0.07133 **	0.02992	0.03649	0.02478
	[0.04081]	[0.03068]	[0.03624]	[0.02281]	[0.00000]	[0.03769]	[0.04875]	[0.02850]	[0.02747]	[0.03551]	[0.06687]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.04051	0.03069 **	0.05358 **	0.04526	0.06918	0.01153	0.06112	0.01321	0.01946	0.00722	-0.02844
	[0.03539]	[0.02618]	[0.02818]	[0.01953]	[0.00000]	[0.03769]	[0.03756]	[0.02258]	[0.01967]	[0.02191]	[0.04080]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-0.00974	0.04180 *	0.04765 *	-0.00539	-0.02907	-0.06613 *	0.00257	0.05102 **	0.00904	-0.01681	-0.02844
	[0.03137]	[0.02281]	[0.02657]	[0.01871]	[0.00000]	[0.03652]	[0.03756]	[0.02258]	[0.01967]	[0.02191]	[0.04080]
Observations	103,632	86,862	90,721	61,719	25,289	13,717	113,968	78,815	39,447	14,225	11,664
Policy covariates	X	X	X	X	X	X	X	X	X	X	X
Municipal FE	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
Prov. x Quarterly FE	X	X	X	X	X	X	X	X	X	X	X
Method	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Mean	0.445	0.247	0.287	0.0901	0.0199	0.0140	0.867	0.178	0.0380	0.00733	0.0132

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

Table J4: 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.18648	0.09564	0.19157	0.09772	0.19198	0.08489
	[0.15421]	[0.11545]	[0.15473]	[0.11593]	[0.17103]	[0.13174]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.07411	0.05157	0.07043	0.04717	0.05417	0.02808
	[0.12459]	[0.09789]	[0.12520]	[0.09835]	[0.13563]	[0.10705]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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
$Post * 1(I.\ S._{q2/2018} \in Q_4)$	0.14968	0.27593	0.15891								
	[0.23275]	[0.24249]	[0.23310]								
$Post * 1(I.\ S._{q2/2019} \in Q_4)$				0.04109	0.43332*	0.06468	0.48555**				
				[0.13925]	[0.22139]	[0.15492]	[0.20271]				
$Post * 1(I.\ S._{q2/20} \in Q_4)$								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
Prov. x Quarterly 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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	9.80620 **	10.11692 **	9.98114 **	10.31095 **	6.23252	6.83577
	[4.38194]	[4.33384]	[4.38197]	[4.33737]	[4.81508]	[4.80299]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.37257	0.65708	0.58223	0.87678	-1.49803	-1.28786
	[4.41271]	[4.26418]	[4.41333]	[4.26832]	[4.58851]	[4.45510]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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
Prov. x Quarterly FE					X	X
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

(a) OLS

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
$Post * 1(I.\ S._{q2/20} \in Q_4)$	11.06531 *	10.26344 *	11.20935 *	10.42181 *	6.88156	6.81692
	[6.03860]	[5.63701]	[6.04102]	[5.64457]	[6.71017]	[6.28474]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	3.22136	2.21137	3.39440	2.40031	0.34136	-0.27634
	[5.56678]	[5.13370]	[5.57498]	[5.14596]	[5.81824]	[5.37480]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly FE					X	X
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

(b) PPML

Figure 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 (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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	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]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	-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]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly 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 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) 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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.08043	-0.03657	-0.02557	0.08527	-0.03071	-0.02786
	[0.07219]	[0.08965]	[0.04105]	[0.07312]	[0.08872]	[0.04615]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.08673	-0.10174	0.03708	0.08836	-0.09353	0.04328
	[0.07804]	[0.09648]	[0.04430]	[0.07934]	[0.09501]	[0.04962]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	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
Prov. x Quarterly 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 K4: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

L Contraception

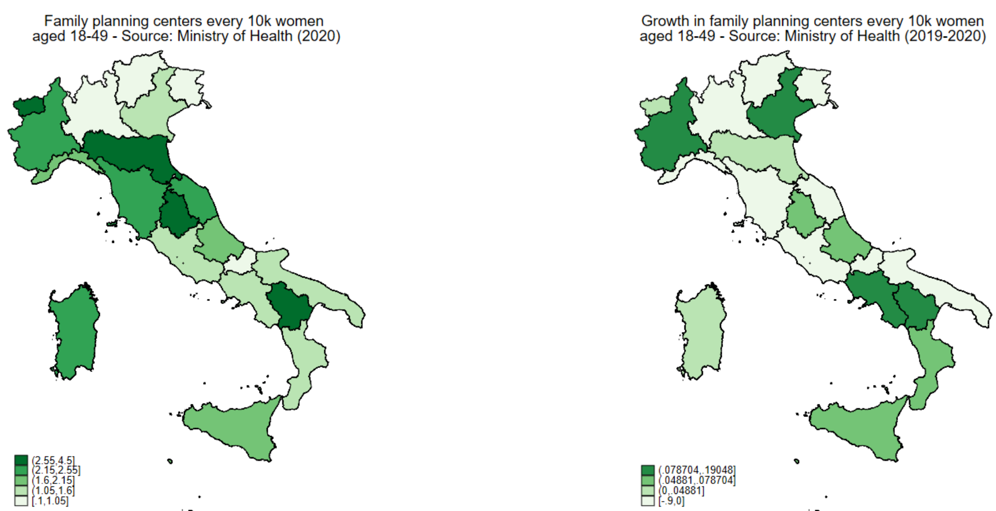


Figure L1: Family planning centres in Italy in 2020. Left panel: number of family planning centres every 10,000 women aged between 18 and 49 in 2020. Right panel: growth in family planning centres every 10,000 women aged between 18 and 49 between 2019 and 2020. Source: Ministry of Health

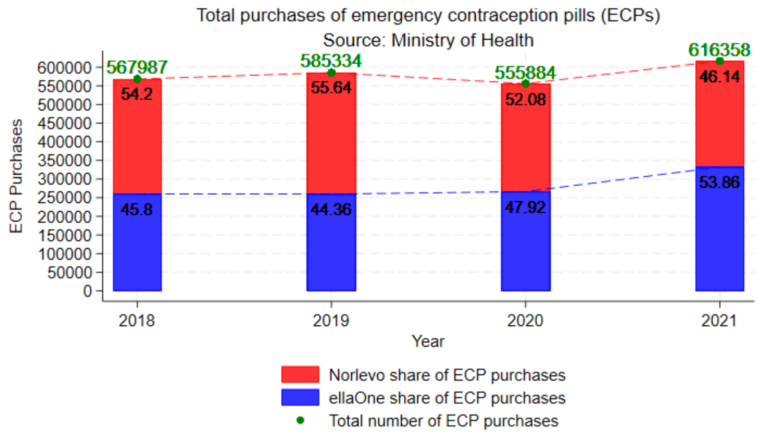


Figure L2: ECP sales in Italy between 2018 and 2021. Source: Ministry of Health.

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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.00882	0.00513	0.00864	0.00498	0.01316	0.00848
	[0.00918]	[0.00655]	[0.00904]	[0.00648]	[0.01091]	[0.00776]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.00636	0.00400	0.00630	0.00393	0.00933	0.00615
	[0.00692]	[0.00535]	[0.00690]	[0.00534]	[0.00755]	[0.00583]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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
Prov. x Quarterly 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

(a) OLS

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)
$Post * 1(I.\ S._{q2/20} \in Q_4)$	0.03421	0.01806	0.03430	0.01787	0.05223 *	0.03286
	[0.03219]	[0.02180]	[0.03187]	[0.02162]	[0.02964]	[0.00000]
$Post * 1(I.\ S._{q2/20} \in Q_3)$	0.02138	0.01196	0.02072	0.01130	0.01326	0.00847
	[0.02315]	[0.01613]	[0.02329]	[0.01618]	[0.02432]	[0.00000]
$Post * 1(I.\ S._{q2/20} \in Q_2)$	-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
Prov. x Quarterly 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

(b)

Figure L3: SEs clustered at municipal level. *Mean* reports the mean value of the treated units pre-treatment.

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