The Role of Crisis Pregnancy Centers in Fertility Decisions

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Abstract

The “pro-life” movement has sought to end the practice of abortion in the United States for the past 50 years. Crisis Pregnancy Centers (CPCs) are an integral part of this effort, and provide counseling services from an anti-abortion perspective. I study the location choice of CPCs and the impact of CPCs on fertility outcomes. CPCs lower the local abortion rate by 9.6 percent, with larger effects among teenagers and young women. I also show that the presence of CPCs leads to an increase in birth rates.

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1 Introduction

The federal legalization of induced abortion in the United States in 1973 fundamentally changed women's ability to make reproductive choices. For pregnant women, abortion became another family planning tool, a societal shift that prompted the founding of the first Crisis Pregnancy Centers (CPCs) (Care Net 2022). Since then, activists in the "pro-life" movement, rooted in Christian religious beliefs, have opened CPCs to lower the incidence of abortions in communities across the country. CPCs focus on reaching young women who experience an unplanned or unwanted pregnancy, and, by nature of their mission, compete with reproductive healthcare and abortion providers.[1] In addition to advocating against abortion, CPCs seek to reverse the liberalization of social norms around sex and relationships, for example, by providing sexual abstinence education to teenagers. Thus far, there is no evidence that CPCs achieve their goal of reducing the incidence of abortion. However, CPCs claim to have reduced the number of abortions by 10 percent in the United States between 2008 and 2017.[2] In this paper, I provide evidence that CPCs are effectively lowering local abortion rates.

There are between 2,500 and 4,500 CPCs across the United States and more than half of women of reproductive age live closer to a CPC than an abortion provider (Jones & Jerman, 2017; McVeigh, Crubaugh, & Estep, 2017; Swartzendruber & Lambert, 2020; Thomsen, Baker, & Levitt, 2022). CPCs are present in all U.S. states and, in the 2021/22 Fiscal Year, $89 million in federal and state funding has been allocated to CPCs across a dozen states (Kruesi, 2022). There is some research on who visits CPCs. Rice, Chakraborty, Keder, Turner, and Gallo (2021) found that 13.5 percent of surveyed women in Ohio had ever visited a CPC. CPC attendance was higher among black women, women with lower incomes and women without college degrees. Cartwright, Tumlinson, and Upadhyay (2021) found that 13.1 percent of women searching for abortion services online visited a CPC during their pregnancy. This study also found that living closer to a CPC is also associated with greater odds of visiting a CPC and women who had visited a CPC are 21 percentage points less

[1] According to a survey reported in Finer and Zolna (2016), 45 percent of all pregnancies were reported mistimed or unwanted and 42 percent of these pregnancies result in abortion.

[2] According to a survey by the umbrella organization Care Net, their 1100 affiliated CPCs prevented 677,248 abortions between 2008 and 2017, or about 1 in 10 abortions (Care Net, 2018). Care Net sources this figure as follows: "Number based on data collected between 2008-2017 from Care Net's network of affiliated pregnancy centers. Lives saved based on last stated intent of clients visiting centers (Care Net, 2018)."

likely to have had an abortion. A strand of the literature explores CPC service provision and advertising, with several studies showing that CPCs misrepresent their services, mimic medical providers, and provide misleading and false medical information (Lin and Dailard 2002; Rosen 2012; Swartzendruber et al. 2018; Waxman 2006). Concerns that online searches for abortion services direct users to CPCs have recently attracted interest from lawmakers (Bellware, 2022).

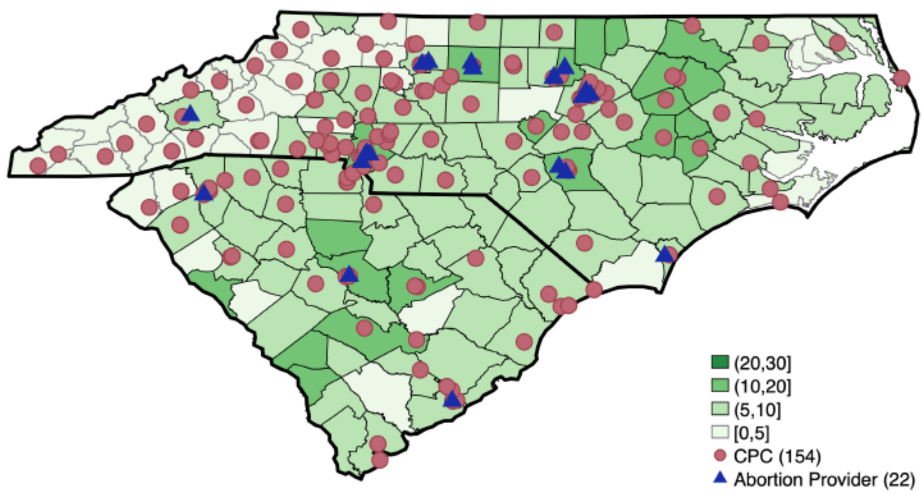


Figure 1: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2019

Sources: The CPC data was compiled by the author, annual county-level population estimates were obtained from the U.S. Census Bureau (2019), and abortion counts were obtained from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control (2020).

I use a generalized difference-in-differences approach to show that CPCs lower the county-level (log) abortion rate by 9.6 percent. This effect is concentrated among teenagers and young women. The analyses build on a unique, 30-year panel of CPCs, abortion providers, and vital statistics records from North Carolina and South Carolina.[3] The robustness of the main result is validated using alternative specifications that take into account CPC revenues, the driving distance to a CPC, age-specific heterogeneity, and the latest difference-in-differences literature (see De Chaisemartin & d'Haultfoeuille, 2022b). An important identification challenge stems from the CPC location choice, which may be informed by unobserved community characteristics that also shape fertility outcomes. To better understand this potential endogeneity concern, I construct a logit model of the CPC location choice. To

[3] "Abortion providers" includes clinics, for example Planned Parenthood clinic locations, that do not offer abortion services but refer patients to other clinics.

assuage potential endogeneity concerns due to placement of CPCs, I devise a data-driven instrumental variables approach, which uses to the prediction from logit model to construct instruments, and estimate a dynamic panel model.

This paper contributes to the literature on abortion access by providing causal evidence that Crisis Pregnancy Centers decrease the local abortion rate. To date, there have been descriptive analyses of the location choice of CPCs, service provision of CPCs, and the competition between CPCs and abortion providers (Cartwright et al., 2021; Swartzendruber, Solsman, & Lambert, 2021; Yuengert & Fetzer, 2010). In a separate strand of the literature, several authors showed the importance of travel distance to abortion providers. Lindo, Myers, Schlosser, and Cunningham (2020), for example, find that policy-induced clinic closures in Texas reduced the abortion rate. My findings expand our understanding of pregnancy counseling services and fertility outcomes. I show that CPCs cause a significant reduction in abortion rates, a result that is distinct from the reduction in abortion rates due to restrictions on abortion providers. This is plausibly explained by CPCs reaching young women that seek pregnancy counseling and support near their home, without having to travel long distances to a healthcare provider.

In section 2, I describe the mission of CPCs, funding sources, and the policy landscape. Section 3 describes data sources. In section 4, I explain the model of CPC location choice. In 5, I describe the empirical strategy to identify the effect of CPCs on fertility outcomes. Section 6 presents the results and section 7 concludes.

2 Background

2A. Crisis Pregnancy Centers

CPCs offer services relating to sexual behavior, pregnancy and relationships. Pregnancy counseling, by volunteers or staff, is a core service. Typically, counseling is offered in conjunction with additional services, such as free over-the-counter pregnancy tests (Swartzendruber et al., 2018). When a pregnancy is confirmed, many CPCs offer limited ultrasounds

[4] The provision of ultrasound services does not necessarily imply that the CPC offers comprehensive medical examinations. Review of CPC websites indicates that only some CPCs have staff who are certified as as Registered Diagnostic Medical Sonographers and that a small share of CPCs employs registered nurses, OBGYNs and other medical professionals. Further, some CPCs have partnerships with off-site physicians.

intended to inform about the gestational age, heartbeat, and viability of the pregnancy.[4] CPCs also offer material aid, like baby clothes, cribs, diapers, as well as direct financial assistance. Some CPCs provide abstinence education or "sexual integrity" classes. Sexual abstinence education is aimed at teenagers and takes place either at the CPC or in schools.

CPCs are relatively small non-profit organizations. On average, the organizations in the analysis sample had annual revenues of $230,275 in 2018. Some of this funding comes from the federal government and state governments. In the 2021/22 Fiscal Year, $89 million of federal and state funding has been allocated to CPCs across a dozen states (Kruesi, 2022). Historically, CPCs primarily received public funding in their role of providers of sexual abstinence education programs. Over the past decade, CPCs have received increasing amounts of Temporary Assistance for Needy Families (TANF) funding and, for a some years, Title X funding for the provision of reproductive healthcare. North Carolina and South Carolina, the two states in the sample, provide some state funding in addition to distributing federal funds. In North Carolina, state and federal grants have been provided to the umbrella organization Carolina Pregnancy Care Fellowship, which directs funds to over 70 affiliated CPCs.[5] South Carolina's Department of Motor Vehicles, like most state motor vehicle departments, sells "Choose Life" license plates, with proceeds being allocated to CPCs.

Systematic evidence on the information content of CPC counseling is lacking but public health researchers have analyzed the information that CPCs provide online, which is indicative of counseling content. Swartzendruber et al. (2018) find that CPC websites contain false and misleading health information and the advertised services do not align with prevailing medical guidelines. Some of these findings are corroborated by Rosen (2012), who identified that CPC websites commonly provide inaccurate information on the medical risks of abortions. Moreover, according to Swartzendruber et al. (2018), 58 percent of CPC websites do not indicate that they do not provide abortion services or refer clients to an abortion provider. Similarly, Cartwright et al. (2021) report that some CPC clients are not aware of the "pro-life" mission and are, in fact, seeking abortion services. A survey conducted in the

[5]Federal funds were first used in the Fiscal Year 2014 and have been supplemented by state funding since 2018 (see Table 7). The North Carolina General Assembly started to designate money from the Title V Maternal and Child Health Block Grant (MCHBG) for the Carolina Pregnancy Care Fellowship in FY2013-14. The goal of MCHBG grants is to support the health and well-being of mothers, children, and families.

State of Georgia, indicates that most adults who had visited a CPC held misconceptions about CPC policies and practices (Swartzendruber et al., 2021).

CPCs are almost universally unregulated. Most CPCs are not licensed medical facilities, which means medical ethics rules and patient privacy laws are not applicable. In instances where women felt misled by CPCs, state attorneys have mostly declined to open investigations because CPCs do not charge a fee for their services (Office of the Attorney General, New York, 2002). The most consequential attempt at regulating CPCs is the California Reproductive Freedom, Accountability, Comprehensive Care, and Transparency Act (FACT Act; CA AB 775), which was passed in 2015. This legislation intended to limit CPC practices that were deemed deceptive, particularly in regard to anti-abortion counseling.[6] In the 2018 decision *National Institute of Family & Life Advocates v. Becerra*, the Supreme Court of the United States deemed the FACT Act unconstitutional on the grounds that it violates the First Amendment, which protects free speech.

2B. Abortion Access

In North Carolina and South Carolina abortion was legal during the entire period under consideration. Over time, state laws placed restrictions on abortion providers, required waiting periods, and ruled out health insurance reimbursement for abortion services.[7] In North Carolina, a 1973 law legalized abortion up to 20 weeks of gestation (N.S. G.S. 14-45.1). Since 2011, abortion providers in North Carolina are required to consult with each patient at least 72 hours before an abortion procedure and to provide certain information that is specified in law as part of the informed consent process. They also require the physical presence of the physician for both surgical and medical abortions (N.C. G.S. Ch. 90, Art. 1I.). In 2023, outside of the study period, legal abortion was limited to 12 weeks gestation, except under specified circumstances (N.C. G.S. 90-21.81B). In South Carolina, a 1974 law

[6] Under the law, unlicensed CPCs would have had to disclose to their clients in writing, or post a sign, that the center is not a licensed medical facility and has no medical staff to provide services. The disclosure requirement extended to advertising. Some CPCs in California are, however, licensed as medical providers. The FACT Act required licensed CPCs, who do not provide a full range of reproductive care, to post a sign informing clients that the state provides free or low-cost access to reproductive care, including abortions.

[7] As a result of the Hyde Amendment in 1977, certain federal funds, including Medicaid funding, cannot be used to pay for pregnancy termination except in cases of rape, incest, and life threatening health conditions of the pregnant woman. Both North Carolina and South Carolina implemented these restriction in state law. Federal Title X funds can also not be used to pay for abortion services.

broadly legalizes abortion up to 24 weeks of gestation and under specified circumstances beyond 24 weeks of gestation (S.C. Code Ann. §§ 44-41-20). In 1995, state law was revised so that any health care provider that performs at least five abortions a month must be licensed as an abortion clinic, subject to new regulations and inspection at any time (S.C. Code Ann. §§ 44-41-75). In 2010, Sec. 44-41-330 is amended to include a mandatory 24-hour waiting period following an abortion consultation. In sum, although abortion access became more restrictive over time, gestational limits for abortion remained unchanged between 1990 and 2019. There is also no indication of widespread clinic closures as a result of state policy, as was observed in Texas and elsewhere. Several recent studies showed that increased travel distances to abortion clinics, due to closures, reduce the abortion rate (Fischer, Royer, & White, 2018; Lindo et al., 2020; Quast, Gonzalez, & Ziemba, 2017). Further, increases in travel distances to abortion providers increases the birth rate (Lu & Slusky, 2019). As barriers to abortion access are mounting, with several U.S. states having banned the practice, the role of CPCs may continue to evolve. CPCs do not face any of these restrictions to providing their services, which could mean that more women are looking for abortion counseling outside of the healthcare system.

3 Data

I study the location choice of CPCs and the effect of CPCs on the abortion rate. These analyses requires detailed longitudinal data on CPCs, specifically the geographic location and timing of opening. Second, outcome measures of abortions and births are needed. These fertility rates are constructed from vital statistics and Census data. Third, data on county characteristics (including unemployment, election vote shares, religiosity) are required. I focus on North Carolina and South Carolina for several reasons. These states, unlike many others, provide fertility counts by age, ethnicity and county of residence starting in the year 1990, allowing me to study CPC openings and the fertility outcomes of females by age group over a long time horizon. In addition, North Carolina and South Carolina counties are of relatively small and homogenous size, which allows me to provide plausible travel distance estimates from counties of residence to CPCs. Summary statistics of the variables used in the analysis for the first and last year of the sample are reported in Table 1.

Table 1: Summary Statistics

	1990-2019		1990		2019	
	Mean	SD	Mean	SD	Mean	SD
Abortion rate (per 1,000 women)						
Total	11.07	(4.90)	16.82	(5.95)	8.63	(3.14)
Age 10-19	7.86	(5.36)	19.04	(6.55)	2.91	(0.99)
Birth rate (per 1,000 women)						
Total	45.87	(15.03)	49.44	(13.40)	42.03	(13.44)
Age 10-19	22.04	(10.26)	34.08	(8.87)	9.73	(3.63)
Crisis Pregnancy Centers						
No. of CPCs	2.15	(2.46)	1.12	(1.40)	2.81	(2.80)
No. of CPCs (per 1,000)	0.35	(0.39)	0.20	(0.30)	0.41	(0.42)
Nearest CPC (in miles)	11.61	(14.24)	20.39	(20.77)	7.65	(9.28)
Annual CPC revenue (in $1,000s)	463.75	(1,013.43)	.	(.)	799.81	(1,312.50)
County Characteristics						
Female Population Age 10-44	67,469	(69,970)	48,311	(42,283)	88,652	(92,893)
Non-white share	0.32	(0.15)	0.29	(0.15)	0.34	(0.15)
Share age 10-19	0.27	(0.03)	0.26	(0.03)	0.28	(0.02)
Nearest abortion clinic (in miles)	27.91	(26.11)	32.70	(29.63)	29.31	(23.91)
Unemployment rate	5.94	(2.66)	4.35	(1.54)	3.56	(0.79)
House Price Index	158	(40)	100	(0)	220	(42)
U.S. House GOP vote share	0.53	(0.20)	0.45	(0.24)	0.52	(0.18)
Mainline protestant share	0.21	(0.07)	0.19	(0.07)	0.20	(0.07)
Evangelical protestant share	0.28	(0.10)	0.29	(0.12)	0.28	(0.09)
Catholic share	0.04	(0.03)	0.02	(0.02)	0.04	(0.03)
Black protestant share	0.05	(0.06)	0.12	(0.07)	0.03	(0.03)
No. of county-level obs.	4,320		144		144	

Sources: The CPC operation data was compiled by the author, annual county-level population estimates from the U.S. Census Bureau (2019), and abortion counts from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control.

Notes: Population-weighted summary statistics calculated for the year 2019. Fertility rates are calculated using population of women in the age bracket 10-44 (10-19) as denominator.

3A. CPC and Clinic Data

The longitudinal registry of CPCs is an important contribution of this paper. I construct a data set of addresses of CPCs and abortion clinics, as well as information on the dates of their operation. The dataset contains 288 CPC locations (addresses) associated with 138 CPC organizations, and 43 abortion provider locations (and referrers). This data is the backbone for the study of how CPCs affect local abortions. I thus observe the opening of CPCs in North and South Carolina between 1990 and 2019, the period for which fertility data is available. Figures 4 to 7 show CPCs and abortion providers over time, overlayed on a map of county-level abortion rates in N.C. and S.C. To extend the analysis to the financial strength of CPCs I add information from tax filings for years 1996-2018.[8]

Data on abortion clinics (and referrers) is sourced from records of Title X grant recipients, which includes many abortion providers, is was provided by the United States Department of Health and Human Services (HHS) for the years 2013 to present. I categorize some clinics as "referrers" if they do not provide abortion services but have provided them at some point in time or are part of a network, such as Planned Parenthood, of abortion providers.

Further, I obtain state licensing information on abortion clinics in N.C. and S.C. I cross-check this information with the provider list of the National Abortion Federation, Planned Parenthood, and generic online search of newspaper reports. The resulting data set provides the precise geographic location of each facility and allows me to track at what point in time facilities open and close.

3B. Fertility Rates

The primary outcome of interest is the (Log) abortion rate in a county, which is constructed using the abortion count per 1,000 females, in years 1990 to 2019.[9] Abortion and birth counts were obtained from administrative and vital records provided by vital statistics offices

[8]The number of locations exceeds the number of CPC organizations because some organizations operate at multiple facilities and because address changes are tracked. For a given CPC organization, a relocation ("move") is defined as the closure of a facility at one address and the opening of a facility at a location in the same county within a year. I validate the CPC data by comparing four sources: (1) A database maintained by the umbrella organization Birthright that contains the majority of CPCs, both its affiliates and independent CPCs. (2) Tax filings to the Internal Revenue Service. (3) CPC websites. (4) Yellow pages entries. In the case of CPCs, I also can observe some address changes and closures in financial fillings from news articles too.

[9]Birth rates, used in additional analyses, are constructed in the same way and birth count data is sourced from birth certificates. In robustness checks I also study the pregnancy rate. The number of pregnancies is defined as the sum of births, abortions and fetal deaths.

in North Carolina and South Carolina. Pregnancy outcome data was provided by county of residence of the women, aggregated by age groups and ethnicity (white/non-white). In most states, including North Carolina and South Carolina, abortion providers are required to submit regular and confidential reports, on the number of abortions performed, to the state. The analysis sample is restricted to the following age-groups: 10-19, 20-24, 25-29, 30-34, 35-44. All males are excluded from the analysis.[10] Rates are constructed by combining fertility rates with Census data of demographic information on age groups, ethnicity, and county of residence. The result is a repeated cross-section of fertility rates by age-ethnicity group by county of residence. This implies that at the county-level, the data has a balanced panel structure.[11] Analyses are conducted both at the county-level and at the age-ethnicity-group-level.

4 The Location Choice of Crisis Pregnancy Centers

The non-profit sector is primarily community-based and locally operated, where needs and resources in a particular region determine the number of non-profit organizations (Bielefeld & Murdoch, 2004; Wolpert, 1993). Analogously, the CPCs in this study are independent organizations, founded by local community members. Where do people choose to open a CPC? Existing evidence suggests that CPCs compete with abortion providers for women who are likely to seek abortion services. The umbrella organization Care Net reportedly entered into "bidding wars" with abortion providers over sponsored-link placements on online search engines when someone searches for abortion services (Gibbs, 2007). Two cross-sectional studies investigated whether CPC location is related to the prevailing religious affiliation of a local population. Yuengert and Fetzer (2010) found that CPC locate near population centers and in counties with a high share of Catholics, whereas McVeigh et al. (2017) found

[10]The total number of pregnancies is an undercount, because a significant share of pregnancies go unreported, for example due to miscarriage, which occurs in approximately 13 percent of all pregnancies (Andersen, Wohlfahrt, Christens, Olsen, & Melbye, 2000).

[11]In the case of North Carolina, resident abortion data includes abortions that occur in any state. In the case of South Carolina, resident abortion data are limited to abortions that occur in South Carolina, North Carolina or Georgia to South Carolina residents. The analysis in this study only uses fertility outcomes of women that reside in North Carolina and South Carolina. The analysis is conducted at the level of the county of residence of the pregnant woman, which means fertility of out-of-state women are not represented in the analysis data–a boon to this analysis. Residents of of North Carolina or South Carolina that sought abortion services in another state are also not included in this data, a limitation of this analysis.

that CPC location is associated with the share of evangelical and catholics in a county. What we lack to date is evidence from longitudinal data on the location choice of CPCs.

The location choice problem is motivated in terms of community support for the opening of a CPC and demand for CPC services. Should CPC open in areas with high demand and low community support or in areas with lower demand and high community support? Areas with potentially high demand are urban centers with abortion providers but lower shares of conservative Christians. In contrast, low demand communities with high support are rural communities with higher shares of conservative Christians. The need for a new CPC depends on the number of people already served and the overall population in the area. The county population and the abortion rate proxy local demand for a CPC. The number of existing CPCs in county and the distance from a population center to the nearest existing CPC is a measure of existing supply. If people have to travel farther to a CPC, there is a greater incentive to open a new CPC. Community support is proxied by the share of religious adherents of christian denominations that reject abortion in principle (for example, evangelicals, catholics), and the share of votes for the Republican Party, which has advanced policies to limit abortion access, in federal elections.

CPCs, like any other organization, operate under cost constraints. Thus, I conceive of CPCs as independent, utility maximizing entities that choose locations under a cost constraint. The stated goal of CPCs is to lower the local abortion rate and provide social services. Intuitively, we can think of the utility as increasing with the number of clients served. I use a logit model to explain the location choice of a CPC (McFadden et al., 1973).[12] The opening decision is made within each county and every year between 1990 and 2019.[13] The utility of the CPC consists of observable and unobservable components. Observable attributes of the choice alternatives include county characteristics, such as the presence of existing CPCs, the abortion rate, and local operating costs. Labor cost is proxied by the wage cost of similar social service non-profits in the area in which a CPC is locating. Finally, CPCs compete with existing abortion providers, so the distance of a CPC location to the

[12]In the standard choice model, U_{ij} represents the value or utility of the $j-th$ choice to the $i-th$ individual. U_{ij} is treated as independent random variables with a systematic component η_{ij} and a random component ϵ_{ij} such that $U_{ij} = \eta_{ij} + \epsilon_{ij}$.

[13]For simplicity, the board of directors that choose a CPC location and the resulting organization ("CPC") are treated as the same entity.

nearest abortion clinic enters the model.[14] It is assumed that the observed part of the utility of opening a CPC is a linear function of observed attributes and that the unobserved part is random. The unobserved component of the utility of opening a CPC varies over counties, depending on benefits and costs of opening a CPC. For example, the individuals that open a CPC observe, to some extent, the unmet demand for abortions (this is unobserved to the researcher). In some counties and years the utility of opening a CPC is greater than the alternative, in others it is not.

More than one CPC can choose to locate in a given county. Therefore, I model CPC openings in a county as a repeated hazard (renewal process). Following Mroz (2012), I estimate the count of CPCs with a hazard model decomposition, extended to a renewal framework. The decomposition of the outcome distribution implies that each of its components can be described as a binary event independent of all of the other elements in the decomposition. This means that the use of a logit model is appropriate, regardless of the true process generating the counts (Mroz, 2012).

The probability of a CPC opening in county c in year t is determined by estimating the following logistic regression equation using maximum likelihood:

$$Logit(p) = ln\left(\frac{p}{1-p}\right) = \tag{1}$$

$$= \beta_0 + \beta_1 CPC_{ct-1} + \beta_2 Dist_{ct-1} + \beta_3 AR_{ct-1} + \beta_4 X_{ct-1} + \gamma_s + \gamma_c + \alpha TimeTrend$$

The outcome variable is binary, indicating the opening of a new CPC in a given county and year. Relocations within a county are excluded. CPC_{ct-1} (the number of CPCs in a county), $Dist_{ct-1}$ (the distance to the nearest CPC), and AR_{ct-1} (the local abortion rate) are key factors hypothesized to be relevant for the opening of a new CPC, as explained above. X_{ct-1} contains a series of county characteristics, such as the unemployment rate, federal election vote shares, urban/rural categorization, and the prevailing wage at similar non-profits. X_{ct-1} also contains the distance from a given county centroid to the nearest abortion provider (or referrer). Because opening a CPC requires time to plan and prepare, the predictors of a CPC opening are set to $t-1$. γ_c is a county fixed effect. Including county

[14] The driving distance was obtained from the HERE geolocation and routing service. Since routing is only available for the 2021 road network, the shortest route in previous years may have been different from the calculated route.

fixed effects in the logit model implies that if a county did not open a CPC over the sample period of 30 years, the probability of a CPC opening is zero (and the county is dropped from the estimation sample).

5 The Impact of CPCs on the Abortion Rate

CPCs primarily seek to prevent abortions by providing pregnancy counseling. This counseling may include an ultrasound, a referral to an adoption agency and offers of further counseling and material support during the pregnancy. A CPC visit may alter a woman's preferences sufficiently to not seek abortion services or cause a delay sufficient to prevent her receiving abortion care within the gestational time limit set by law. It is plausible that women who are certain that they want to carry to term are neither targeted by CPCs nor going to alter their decision as a result of a CPC visit. Changes in local abortion rates are thus hypothesized to be driven by two groups of women. First, CPCs are plausibly affecting the decision of a woman who is on the margin, that is, uncertain whether to have a child or terminate the pregnancy. This is a potentially large share of women, because 45 percent of all pregnancies are reportedly mistimed or unwanted (Finer & Zolna, 2016). The second group of women who are expected to be more likely to visit a CPC are those facing substantial barriers, for example a great travel distance, to access abortion services from a medical provider. They may be looking for any available support or mistake a CPC as an organization that provides abortion services.

CPCs may also affect the local abortion rate through services for teenagers and young women who are not pregnant. Abstinence education, for instance, teaches teenagers that abstaining from sexual activity is beneficial and sexual abstinence outside marriage is the norm. Preventing abortion is not an explicit goal of sexual abstinence eduction but some abstinence education providers, for instance CPCs, are anti-abortion.[15] If CPCs that provide abstinence education are reducing sexual activity of teenagers, this would mechanically lower both abortion and birth rates. However, existing evidence, with some exceptions, suggests that abstinence education is ineffective at preventing teenage sexual intercourse and pregnancy. For example, Kohler, Manhart, and Lafferty (2008) find abstinence-only edu-

[15] Section 510 (b) of Title V of the Social Security Act, P.L. 104-193 for the federal statutory definition of abstinence education that applies to Title V programs.

cation did not reduce the likelihood of engaging in intercourse. Similarly, Trenholm et al. (2008) find that abstinence education caused no difference in teen sexual activity and no differences in rates of unprotected sex, and Carr and Packham (2017) find that state-level education mandates have no effect on teen birth or abortion rates. In contrast, Cannonier (2012) shows that Title V abstinence-based funding only significantly decreases birth rates for white 15-17-year olds but not other groups. Abortion is also a rarely studied outcome in the abstinence education literature (with the exception of Carr and Packham (2017) and citations therein). In sum, the expected effect of CPC-provided abstinence education on pregnancies, and indirectly abortions, is ambiguous. By providing abstinence education, CPCs may lower or, inadvertently, increase the chance of pregnancy among teenagers and young adults.

5A. Treatment Variable Construction

A researcher in an ideal world would like to answer the following question: Does the presence of CPCs change the probability that a woman receives abortion care? In that world, a woman's place of residence, visits to CPCs, and visits to abortion providers are observable. In practice, there are several data and identification constraints. For example, a woman's place of residence and whether she visits a CPC are unobserved. Given this constraint, proxies of women's exposure to local CPCs are used in the analysis. The first treatment variable is defined as the number of CPCs per 10,000 women of age 10-44 in a county. Adjusting the treatment variable by the population in the service area has precedent in the abortion access literature (see, for example, Lindo et al. 2020). It is a multivalued variable constructed using the information on the number of CPCs in a county and Census population data.[16]

5B. Identification Strategy

The goal is to identify the causal effect of local CPCs on the (log) abortion rate. CPCs are opened in counties at various points in time and some counties receive more than one CPC. Hence, the treatment is conceived as repeated and non-absorbing. To identify the effect of

[16] A typical county in the sample has approximately 10,000 women of childbearing age.

CPCs on the county-level (log) abortion rate, I estimate Equation (2):

$$Y_{ct} = \theta_0 + \theta_1 D_{ct} + \theta_2 \mathbf{X}_{ct} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ct} \tag{2}$$

Y_{ct} represents the (log) abortion rate in county c and year t. D_{ct} is a multivalued treatment variable. $\mathbf{X}_{ct}$ are county characteristics; γ_s, γ_c, and α_t are state-, county-, and year fixed effects, respectively.

5C. Two-way fixed effect estimation

Estimating the effect of CPCs on abortion rate using two-way fixed estimation (TWFE) makes use of within-county variation over time while controlling for aggregate time-varying shocks. Under a set of assumptions described below, the quasi-experimental variation generated by the expansion of CPCs allows me to estimate the causal effect of CPCs on the local abortion rate. The strategy compares the before-after difference in outcomes between women in counties where a CPC opened and women in counties that did not have an additional CPC between the two time periods.

TWFE estimates are weighted sums of treatment effects in each county-year unit. A TWFE estimate can be interpreted as the average treatment effect (ATE) of a positive value of the binary treatment variable on the outcome variable in relatively simple settings. The recent literature on difference-in-differences demonstrated that in more complex settings the TWFE estimand does not have always have a straightforward interpretation (see survey by De Chaisemartin and d'Haultfoeuille (2022b)). This literature shows that, to interpret the TWFE estimand as an ATE, one needs to ensure both parallel trends between control and treated counties and constant treatment effects across counties and periods (

To investigate the validity of the parallel trends assumption I conduct event studies and develop a data-driven instrumental variable strategy that makes use of the CPC location choice, thus explicitly accounting for a potentially endogenous CPC location (see Appendix 8F.). An additional potential concern is that the parallel trends assumption can be sensitive to the chosen functional form (see Roth and Sant'Anna 2023). To investigate how sensitive the main results are two alternative specifications, I also study the effect of CPCs on the untransformed abortion rate using both OLS and Poisson regression (see Appendix Table

11).

5D. Robust Difference-in-Differences

Given the limits of TWFE to recover treatment effects in complex settings, I turn towards difference-in-differences estimation procedures that are robust to heterogeneous treatment effects. The recent difference-in-differences literature proposes several estimators that are robust to heterogenous effects in a multi-period setting (Callaway, Goodman-Bacon, and Sant'Anna 2021; De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). Most of these estimators are however only valid in the context of staggered designs, where the unit of observations, i.e. counties, are treated once and remain treated. The De Chaisemartin and d'Haultfoeuille (2022a)'s DID_l estimator is robust to heterogeneous treatment effects when the treatment is non-absorbing, which means in the context of this paper that CPCs are permitted to sequentially open in a county and remain open.

The De Chaisemartin and d'Haultfoeuille (2022a) DID_l estimator compares the outcome evolution between counties where a CPC opens at a given time-period and counties with the same treatment level, whose treatment, in the relevant time period, has not changed yet. Comparing switchers (counties where a CPC opens) and non-switchers with different period-one treatments relies on a parallel-trends assumption that rules out time-varying treatment effects and effects of the lagged treatments on the outcome. Using De Chaisemartin and d'Haultfoeuille (2022a)'s DID_l estimator I estimate a dynamic version of Equation (2). The idea behind the DID_l estimator is to estimate separately the dynamic treatment effects for counties switching "in" and for those switching "out" of treatment for each county-year pair (year of first switch times period after first switch) and to aggregate them afterwards. The DID_l estimates capture the effect of being exposed to a (weakly) larger treatment for l periods compared to the baseline treatment. The estimator relies on a weaker parallel-trends assumption that can be tested using placebo estimators comparing the outcome trends of switchers and non-switchers with the same period-one treatment, before switchers switch. If the parallel trend assumption holds, this estimator is an unbiased measure of the effect of CPCs openings (counties switching into treatment). In addition to estimate dynamic treatment effects, De Chaisemartin and d'Haultfoeuille (2022a) propose an additional estimation procedure that provides weights to aggregate the time-to-treatment estimands into a single coefficient that reflects the average "total effect" per unit of treatment. Given that the "total effect" refers to the sum of all the instantaneous and dynamic treatment effects, the interpretation of the parameter of interest is a close approximation to the usual interpretation of the TWFE estimand. However, as noted above, the DID_l estimator is robust to dynamic and heterogeneous effects.

5E. Instrumental Variables

In the fertility model, the main identification challenge stems from the joint endogeneity of CPCs and the abortion rate. This implies that the strict exogeneity assumption, necessary for consistent fixed effects estimation, may not hold. To assess the robustness of the fixed effect estimation, I use a dynamic panel model that relaxes the strict exogeneity assumption. Bhargava (1991) provides fairly weak sufficient conditions for the identification of dynamic models containing endogenous regressors in a panel data context. My identification strategy exploits that the impact of a lagged exogenous variable on a current endogenous variable depends on the entire time series of all exogenous variables prior to the current time period. A similar identification strategy, in the context of a nonlinear dynamic model, has been used by (Liu, Mroz, & Van der Klaauw, 2010). In Appendix 8F. I explain how I construct instrumental variables to estimate this dynamic model using two-stage least squares.

5F. Further Analyses

5F..1 Heterogeneity by Age

A central proposition of this paper is that CPCs try to reach girls and young women. To investigate heterogenous treatment effects by age, In subsection Y, I estimate variations of Equation (2) using both interaction effects and subsample analyses. I estimate the coefficient on the number of CPCs per 10,000 women age 10-44 in a county, and θ_3, associated with the interaction of the number of CPCs and one of the five age groups. The vector of dummy variables represented by Age_{ict} captures these age groups.

[17] A small share of the population groups in some counties and years have an abortion rate of zero. To account for zero values, an inverse hyperbolic sine transformation is applied to the abortion, birth and pregnancy rates. The inverse hyperbolic sine function is defined at zero. This function closely approximates the natural log transform (except near zero).

$$
\begin{aligned}
Y_{ict} = \theta_0 + \theta_1 D_{ct} + \theta_2 Age_{ict} + \theta_3 D_{ct} \times Age_{ict} + \\
+ \theta_4 DistClinic_{ct} + \theta_5 X_{ict} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ict}
\end{aligned} \tag{3}
$$

Y_{ict} represents the (IHS) abortion rate.[17] The unit of observation is a demographic age-ethnicity group i in county c in year t. The effect of CPCs on the abortion rate Y_{ict} is given by the coefficients θ_1, the coefficient on the number of CPCs per 10,000 women age 10-44 in a county, and θ_3, associated with the interaction of the number of CPCs and one of the five age groups. The age groups are women age 10-19, 24-29, 30-34, and 35-44, for whites and non-whites. The vector of dummy variables represented by Age_{ict} captures these age groups. $NonWhite_{ict}$ is an indicator variable that takes value zero if the population group is white and value 1 if the group is not white. There are a total of 10 age-ethnicity groups. I also apply the DID_l estimator to the demographic group-level data set.

5F..2 CPC Revenues

The main treatment variable, the number of CPCs per 10,000 women, sums the number of CPCs in a county without accounting for potential differences in service capacity of these facilities. I thus construct a second treatment variable using revenue data, a proxy for CPC service capacity. This variable is defined as the total annual CPC revenue (in $1,000s) per 1,000 women in a county. I re-estimate Equation (2) using this alternative treatment measure to study if CPC revenues are an important mechanism that drives the effect of CPCs on the local abortion rate.[18]

5F..3 The Role of Distance

Equation (2) relies on the assumption that CPCs only serve women in the county where the CPC is located. This is a reasonable assumption because CPCs focus on serving a local population. A potential concern are spillovers, whereby women visit a CPC in a county other than their county of residence. The "no spillovers" assumption is relaxed in Section 6B..5 in two ways. First I estimate Equation (3), which replaces the CPC per capita measure with a treatment variable that measures the driving distance from the population-weighted county

[18]CPC tax filing data is only available from 1997 onwards, resulting in a shorter timeseries.

centroid to the nearest CPC, as well as squared and cubed distance terms.

$$Y_{ct} = \theta_0 + \theta_1 CPCDist. + \theta_2 CPCDist.^2 + \theta_3 CPCDist.^3 + \theta_4 \mathbf{X}_{ct} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ct} \quad (4)$$

Finally, I add the CPC per capita measure to Equation 4, and estimate the joint effect of CPC exposure in a county and the distance to the nearest CPC.[19]

6 Results

6A. CPC Location Decision

The results from the logit model of CPC location choice are in Table 2. I focus on the results in column (1), which are used to construct the instrumental variables discussed in Appendix 8F. The main result is that an existing CPC reduces the probability of additional CPC openings in the same county by 5.0 percent. This is also indicated by the CPC distance coefficient that implies that a 10 mile increase in the driving distance to the nearest CPC increases the probability of a new CPC opening by 1 percent. The coefficient of the variable measuring the distance from a CPC to the nearest abortion provider is close to zero, indicating that CPCs do not open in a location to reduce the distance between existing abortion providers and CPCs. However, this is potentially misleading because in 1990, at the beginning of the time period under consideration, all but one county with an abortion provider already had a CPC nearby. Thus, locating near abortion providers was likely a top priority for the first CPCs that opened prior to 1990. It is also plausible that CPCs are more likely to open in a county with a greater share of teenagers, the target demographic. A surprising result is that a higher vote share of the GOP in elections to the U.S. House of Representatives is associated with a lower probability of a CPC opening, because GOP policies align with CPC values and goals. Similarly, it is surprising that there is no clear pattern of CPC location choice in response to religious affiliations in a community.

[19] The driving distance was obtained from the HERE geolocation and routing service.

Table 2: Predicting the Opening of Crisis Pregnancy Centers

	(1)	(2)
No. of CPCs (lagged)	-0.050	-0.057
	(0.017)	(0.016)
Nearest CPC (lagged)	0.001	0.001
	(0.001)	(0.001)
Nearest Clinic (Lagged)	-0.000	-0.000
	(0.000)	(0.000)
Abortion rate 1000 women 10-44 (lagged)	0.001	-0.001
	(0.003)	(0.004)
Population (lagged)	0.000	0.000
	(0.000)	(0.000)
Pop. share age 10-19 (lagged)	0.072	0.018
	(0.553)	(0.603)
Non-white share (lagged)	0.186	0.386
	(0.554)	(0.605)
Unemployment rate (lagged)	0.001	0.004
	(0.003)	(0.006)
U.S. GOP vote share (lagged)	-0.068	-0.076
	(0.037)	(0.038)
Protestant share (lagged)	0.113	0.174
	(0.224)	(0.187)
Catholic share (lagged)	-0.197	0.717
	(0.816)	(1.025)
No religion share (lagged)	0.134	0.236
	(0.150)	(0.169)
N	2,129	1,987
State FE	Yes	Yes
County FE	Yes	Yes
Time Trend	Yes	No
Year FE	No	Yes

Notes: This table shows the estimates of the renewal model of CPC location choice. All independent variables are lagged by one time period. Each county characteristic in the model makes the opening of a new CPC more or less likely. Average marginal effects were derived using the delta method and each coefficient can be interpreted as a percentage. Standard errors are in parentheses.

Taken together, there is no evidence for the community support hypothesis that CPCs locate in counties with a high share of christian denominations that reject abortion in principle, as well as a grater share of conservative voters. However, it is clear that CPCs are focused on locating in counties without existing CPCs and in counties with a greater share of teenagers, who constitute potential clients. This suggests that CPCs do not compete with other CPCs in a Hotelling-style competition. Rather this pattern is consistent with central planning to maximize the number of clients served.

6B. Fertility Outcomes

6B..1 Two-way Fixed Effect Estimation

The primary goal of this paper is to estimate the causal effect of CPCs on local abortion rates. The main results are in Table 3, with the preferred specification in column (2) discussed here. In Panel 1, increasing the number of CPCs per 10,000 women by one, decreases the abortion rate by 10.0 percent. This is an average of the effect of a first (second, third, ...) CPC opening. Given an average abortion rate of 11 per 1,000 women of childbearing age, this means that CPCs prevent approximately 1 in 10 abortions. However, a one unit change in the treatment variable is relatively large, and corresponds to a first CPC opening in a small county. A change more representative of subsequent CPC openings in larger counties is a 0.2 unit change, which is approximately one third of the standard deviation in the number of CPCs per 10,000 women.

Table 3: Effect of CPCs on the Abortion Rate

	TWFE			DID_l
	(1)	(2)	(3)	(4)
No. of CPCs (per 10,000)	-0.113	-0.100	-0.0860	-0.095
	(0.0272)	(0.0301)	(0.0315)	(0.0367)
N	4376	4376	4376	2734
Control Vars.	No	Yes	Yes	Yes
Pop. weighted	No	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Notes: This table shows the percent change in the abortion rate as a result of an additional CPC per 10,000 women age 10-44. Column (1)-(3) shows two-way fixed effect estimates. Column (4) shows the estimates from the heterogeneity robust DID_l estimator. Robust standard errors are in parentheses.

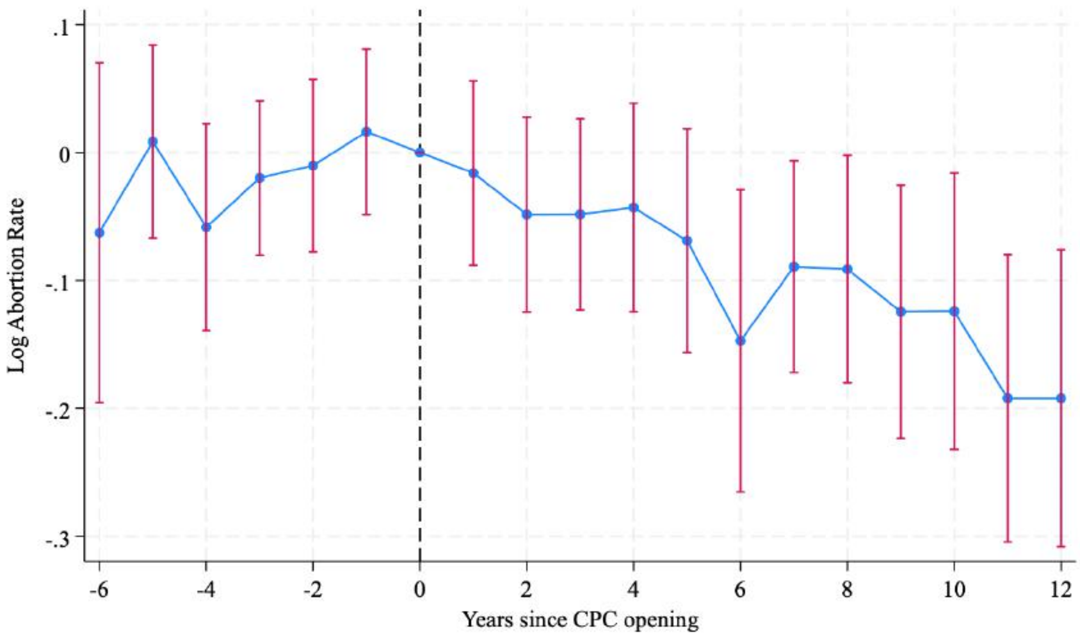
6B..2 Robust Difference-in-Differences

Column (4) of Table 3 shows the average total effects estimated using the heterogeneity-robust DID_l estimator. This point-estimate is obtained by aggregating the period-specific treatment effects from a dynamic specification. Each period-specific effect is weighted by the intensity of the corresponding treatment change. The DID_l coefficient of -0.95 is close to the estimate from the preferred TWFE specification (-0.10). To investigate the validity of the DID_l estimator, I study if key assumptions (parallel trends, no anticipation) are met. To this end, I present Figure 2, which shows the dynamic effects of the number of CPCs per 10,000 women on the (log) abortion rate estimated using the DID_l estimator of De Chaisemartin and d'Haultfoeuille (2022a). The blue line depicts the effect size over time. The red lines plot the 95% confidence intervals.

None of the estimates from pre-period shows a statistically significant difference between the treated and non-treated counties. This suggests that there is no differential trend in the (log) abortion rate, supporting the notion that the parallel trends and no anticipation assumptions holds. This is confirmed by the result of the joint significance test that all the six pre-treatment estimates are null (p=0.11).

The event-study effects in Figure 2 are average effects of having been exposed to a weakly higher treatment dose for l periods. Only counties whose treatments have not changed from period 1 to t are used as controls, resulting in a smaller analysis sample. In Figure 2, the effect

Figure 2: Event Study of CPC Openings



Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line on the figure shows the DID_l estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. To the left of zero, the blue line shows the DID_lplacebo estimates. At t=0, the placebo is normalized to 0.

at t=1 is the instantaneous effect of a CPC opening. The effect at t=2 is the treatment change that happened 1 time periods ago, telling us the effect of a CPC opening that happened t=1 periods ago on the (log) abortion rate. The event study estimates in Figure 2 do not reflect the intensity of the treatment, i.e. if a new CPC opened in a county with a small or large population. In Figure 11 (Appendix 8D.), I also show the normalized event-study estimators DID_{nl}, that normalize DID_l by the average total incremental treatment dose received by switchers with respect to their baseline treatment. This normalization ensures that DID_{nl} estimates a weighted average of effects of the current treatment and of its l-1 first lags on the (log) abortion rate.

6B..3 Age-specific Hetereogeneity

CPCs are trying to reach teenagers and young women. Are there larger reductions in the abortion rate of young women? Estimating Equation (3), which includes interactions of the CPC variable and age groups reveals age-specific difference. The results in Table 4 show large negative effects for teenagers and women under 30. In contrast effects among women older than 30 are not distinguishable from zero. In Appendix Table 9 I show results from estimating Equation (2) separately for each of the five age groups under consideration which also shows larger effects for younger women compared to older women. The DID_1 estimates for teenagers and younger women in Figure 12 also show a clear reduction in the abortion rate as a result of CPC openings. In contrast, Figure 9 reveals no clear effect among older women. In sum, CPCs are effectively reaching teenagers and young women.

Table 4: CPC Abortion Rate by Age

	(1) CPC X Age
No. of CPCs (per 1,000) X Age 10-19	-0.182
	(0.0570)
No. of CPCs (per 1,000) X Age 20-24	-0.135
	(0.0406)
No. of CPCs (per 1,000) X Age 25-29	-0.0940
	(0.0449)
No. of CPCs (per 1,000) X Age 30-34	-0.0329
	(0.0547)
No. of CPCs (per 1,000) X Age 35-44	-0.0124
	(0.0362)
N	43800
Control Vars.	Yes
Year FE	Yes
County FE	Yes
State FE	Yes

Notes: This table shows the results from estimating this model using OLS: $Y_{ict} = \theta_0 + \theta_1 CPC_{ct} + \theta_2 Age_{ict} + \theta_3 CPC_{ct} \times Age_{ict} + +\theta_8 DistClinic_{ct} + \theta_9 X_{ict} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ict}$. Robust standard errors in parentheses.

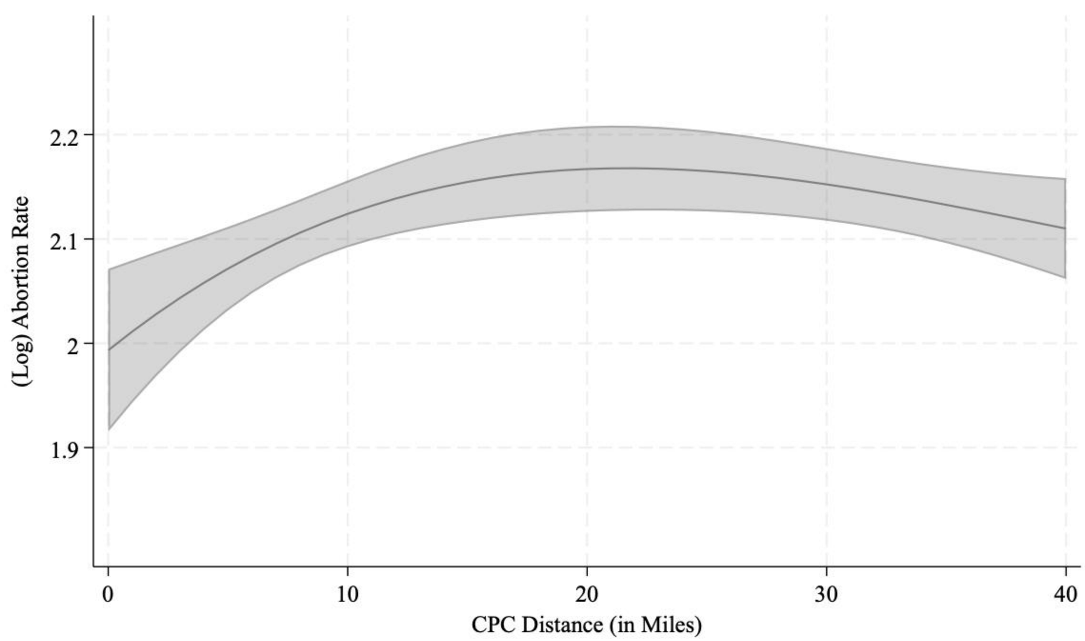
6B..4 CPC Revenues

Table 8C. shows the effect of the CPC revenue per 1,000 women in a county on the log abortion rate. The coefficient -0.0071 in column (2), indicates that an additional $\$1,000$ in CPC revenues per 1,000 women (or \$1 per person) reduces the abortion rate by 0.71 percent. On average, CPCs have revenues of approximately \$3.50 for each woman in a county. Thus, a one unit change represents a 29 percent change in CPC revenues per person. In other words, if CPCs in a county increase their revenues by 29 percent, it results in a eduction of the local abortion rate of 0.71 percent. This effect is small, compared to the main effects in Table 4. CPCs largely rely on volunteer labor and face no regulatory burden, which helps explain that the presence of CPCs (the extensive margin), however small, has a greater impact than funding for staff and service provision (the intensive margin). However, this also means that a small absolute funding increase can substantially amplify the impact of a CPC.

6B..5 Effect of Distance to a CPC

In this section I show that the county-level results discussed in the previous section are robust to distance-based specifications. This is important, because for a woman who experiences a fertility outcome, the nearest CPC may be in a neighboring county. To account for this, the distance specification relaxes the no spillover assumption of Equation (2). Further, I show that the driving distance to the nearest CPC is of minor importance relative to the effect of being exposed to local CPCs.

Figure 3: Avg. Marginal Effects of Distance on the (log) Abortion Rate



Notes: Estimated model: $Y_{ct} = \theta_0 + \theta_1 CPCDist. + \theta_2 CPCDist.^2 + \theta_3 CPCDist.^3 + \theta_4 \mathbf{X}_{ct} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ct}$

Table 5: Distance to the Nearest CPC

	(1)
	(Log) Abortion Rate
No. of CPCs (per 1,000)	-0.1062
	(0.0366)
CPC Distance (in miles)	0.0068
	(0.0051)
CPC Distance Sq.	-0.0004
	(0.0002)
CPC Distance Cube.	0.0000
	(0.0000)
N	4,376
Year FE	Yes
County FE	Yes
State FE	Yes

Marginal Effects

	3 m	6 m	9 m	12 m
Distance	0.0072	0.0089	0.0062	-0.0003
	(0.0068)	(0.0110)	(0.0133)	(0.0141)
CPC + Distance	-0.1144	-0.1162	-0.1135	-0.1070
	(0.0302)	(0.0290)	(0.0277)	(0.0260)

In the analysis sample, 50 percent of the population-weighted driving distances to the nearest CPC are under 18 miles and and 90 percent are under 45 miles. As noted earlier, the community roots of CPCs suggest that they serve very local populations. Figure 3 show a clear increase in the (log) abortion rate for additional miles of driving distance from a population-weighted county center to the nearest CPC, up to approximately 20 miles. This shows that CPCs lower the local abortion rate. Beyond 20 miles, the effect of distance diminishes and turns slightly negative, suggesting that women are not traveling great distances to visit a CPC.

How important is the presence of CPCs in a local community, relative to the distance to the nearest CPC? In Table 5, I present the coefficients of interest and the average marginal effect of the driving distance to the nearest CPC at relevant mile markers and the joint effect of the CPC dose variable and the distance variables. Adding distance variables to the main specification, Equation (2), does not change the coefficient representing the county-wide exposure to CPCs meaningfully. The distance variable coefficients indicates that a one mile increase in driving distance from a CPC increases the abortion rate by 0.68 percent on average. This effect decreases with greater distance up to a point of inversion, suggesting once again that CPCs serve women in a local radius.

The Marginal Effects panel in Table 5 shows that up to a distance of 12 miles between the population center and the nearest CPC, as the distance that women travel to abortion providers the (log) abortion rate increases as well. In other words, living closer to a CPC lowers the probability of obtaining abortion services, regardless of whether a CPC is present in the same county or elsewhere.

6C. Robustness Checks

Do the Effects on Abortions Show up in Birth Rates? Mechanically, fewer abortions would be expected to lead to more births. However, exposure to CPCs, particularly via abstinence education, could lead to changes in sexual behavior and contraceptive use, which could reduce or increase birth rates on its own. Moreover, reductions in abortions at healthcare facilities could be offset by increases in self-induced abortions or by travel to healthcare providers outside of North Carolina and South Carolina. Therefore, the effect of CPCs on birth rates is a priori ambiguous. In Appendix Table 10 and Figure 12 I show the results of the main TWFE specification and the robust DID_l specification. CPCs increase the birth rate by an estimated 1.1 percent. To compare the effect size to the abortion rate estimates, the base rate of abortions and birth needs to be considered. The average abortion rate in the sample is approximately 11 per 1,000 women and the average of birth rate is approximately 46 per 1,000 women. Thus, a 1.1 percent change in the birth rate corresponds to one additional birth for every 2,000 women. In absolute terms, the increase in the birth rate is approximately half as big as the reduction in the abortion rate.

In Appendix Table 11, I present the results of additional robustness checks. Estimating Equation (2) using the untransformed abortion rate and using Poisson regression support the main results, though the effect sizes are smaller. Finally, in Appendix 8G., I describe the instrumental variable strategy in detail and present the results from the two-stage least squares (2SLS) estimation. The 2SLS estimates in Appendix Table 12 are larger than the OLS estimates but clearly underline that the main results that CPCs lower the abortion rate.

7 Conclusion

The pro-life movement has spearheaded policies behind restricting abortion access (Weissert, 2013). The results in this paper demonstrate that this movement has also successfully created a large network of CPCs that reaches young women in their communities and reduces local abortion rates (Care Net, 2018). CPCs choose to locate in communities that are hitherto underserved by CPCs and in counties with a larger share of teenagers, the prime demographic of the organizations. I also show that CPCs shape fertility outcomes in important ways. First, CPCs reduce local abortion rates, particularly among teenagers and young women. This is best explained if CPCs are effectively counseling girls and young women not to have abortions. Second, CPCs increase local birth rates, a result that is mechanically plausible. An important unexplored question is the role of CPCs since the reversal of legalized abortion at a national level, particularly in states that have banned abortions.

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8 Appendix

8A. Maps

Figure 4: CPCs, Abortion Providers and Abortion Rate (NC & SC): 1990

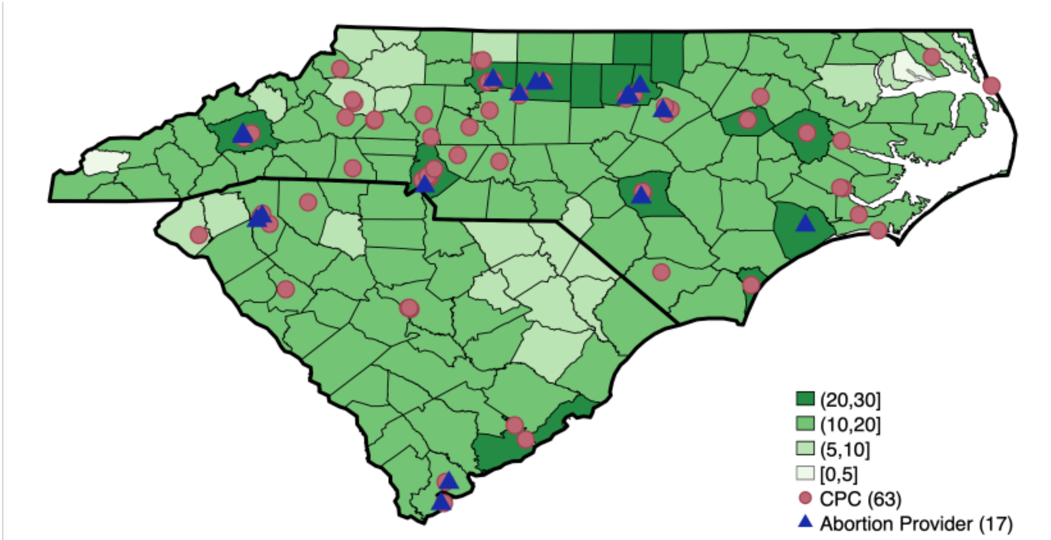


Figure 5: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2000

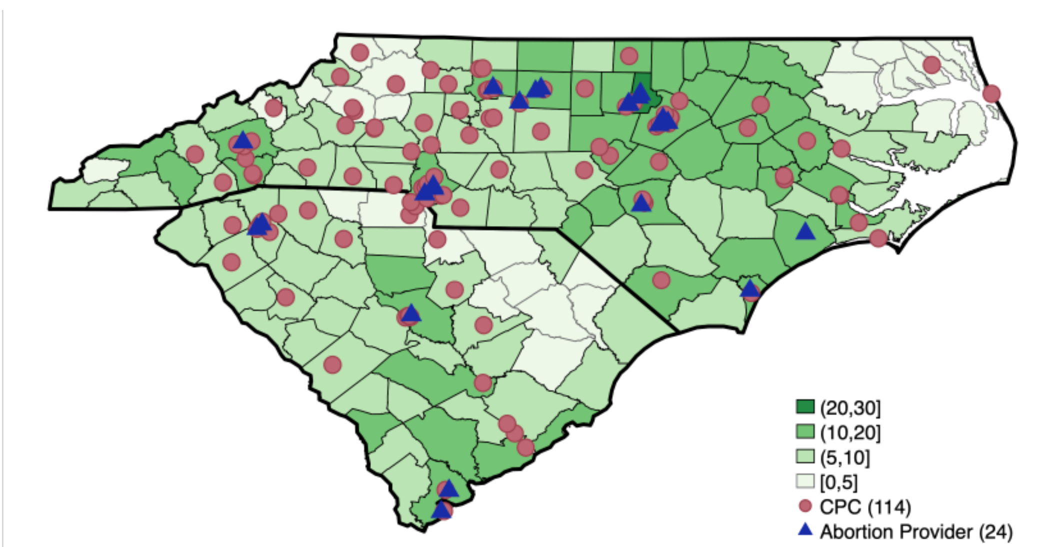


Figure 6: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2010

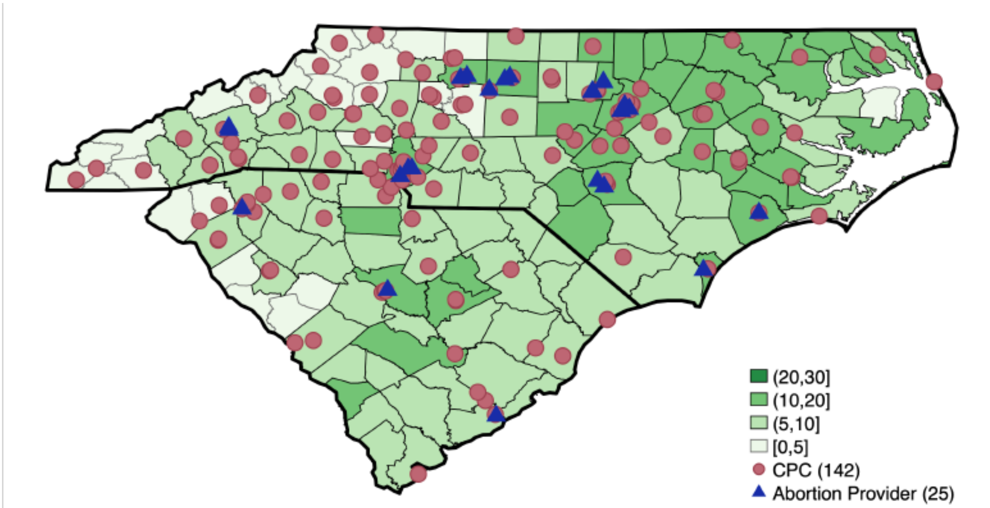
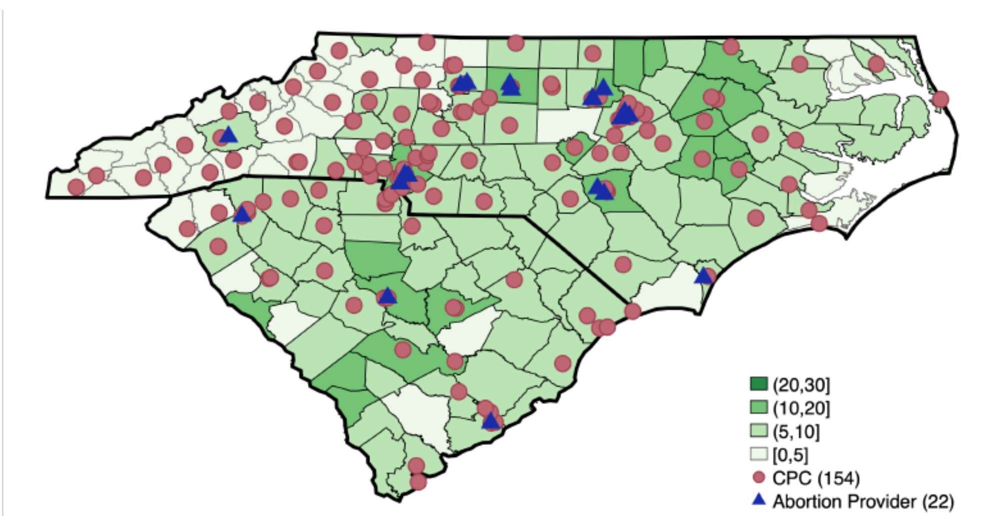


Figure 7: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2019



8B. Background Tables

Table 6: CPC Funding (2010-2021)

Texas	$204,076,058
Pennsylvania	$86,989,000
Missouri	$44,930,673
Florida	$43,000,000
Minnesota	$37,641,000
Indiana	$18,250,000
Louisiana	$15,968,738
Ohio	$13,000,000
North Carolina	$10,303,437
Georgia	$9,000,000
Oklahoma	$5,000,000
North Dakota	$3,500,000
Michigan	$3,300,000

Source: State budgets and health departments via Associated Press report, "Millions in tax dollars flow to anti-abortion centers in US." Kimberlee Kruesi. 02/05/2022.

Table 7: North Carolina Funding: Carolina Pregnancy Care Fellowship

FY14	$250,000 federal funding, no state funding
FY15	$300,000 federal funding, no state funding
FY16	$300,000 federal funding, no state funding
FY17	$300,000 federal funding, no state funding
FY18	$400,000 federal funding, $1,300,000 state non-recurring funding
FY19	$400,000 federal funding, $1,000,000 state non-recurring funding
FY20	$400,000 federal funding, $400,000 state non-recurring (carry forward)
FY21	$400,000 federal funding, no state funding

Source: North Carolina Department of Health and Human Services.

Table 8: CPC Services

	No. of CPCs	% Share
Over-the-Counter Pregnancy tests	93	0.80
After abortion support	76	0.66
Ultrasound services	65	0.56
Adoption agency or adoption support	52	0.45
Abstinence education in schools	42	0.36
Abortion reversal pill consult/provison.	29	0.25
Off-site partnership with physician	25	0.22
STI testing	20	0.17
N	116	

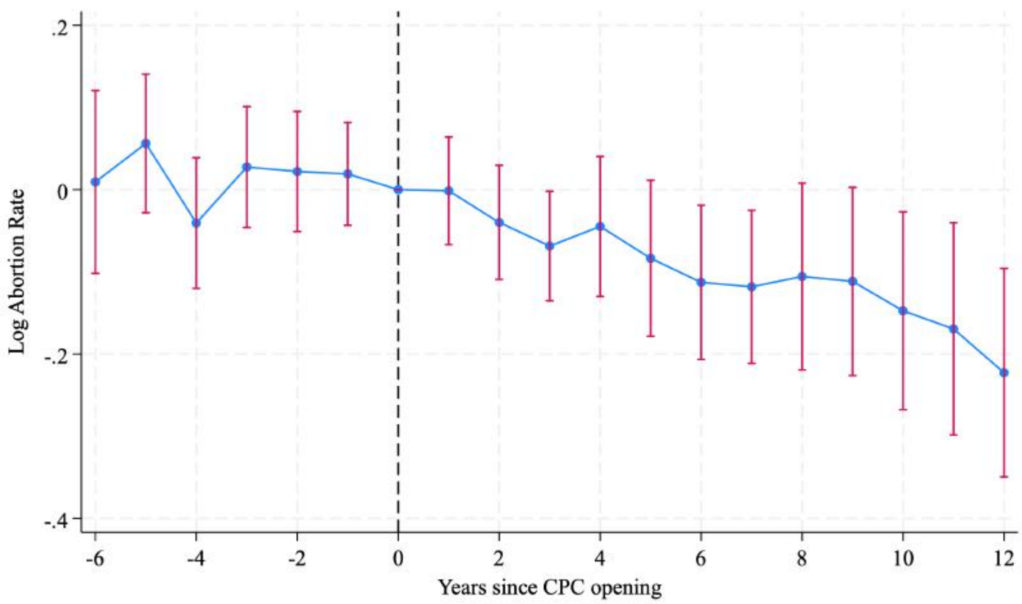
Source: Birthright database (2019). Author review of CPC websites.

Table 9: Subsample Analysis: CPC Abortion Rate by Age

	(1) Age 10-19	(2) Age 10-24	(3) Age 30-44
No. of CPCs (per 1,000)	-0.0701	-0.113	-0.0565
	(0.0405)	(0.0417)	(0.0272)
N	17520	26280	8760
R^2	0.314	0.315	0.305
Dep. Var. Mean	2.910	2.981	1.654
Control Vars.	Yes	Yes	Yes
Pop. weighted	No	No	No
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

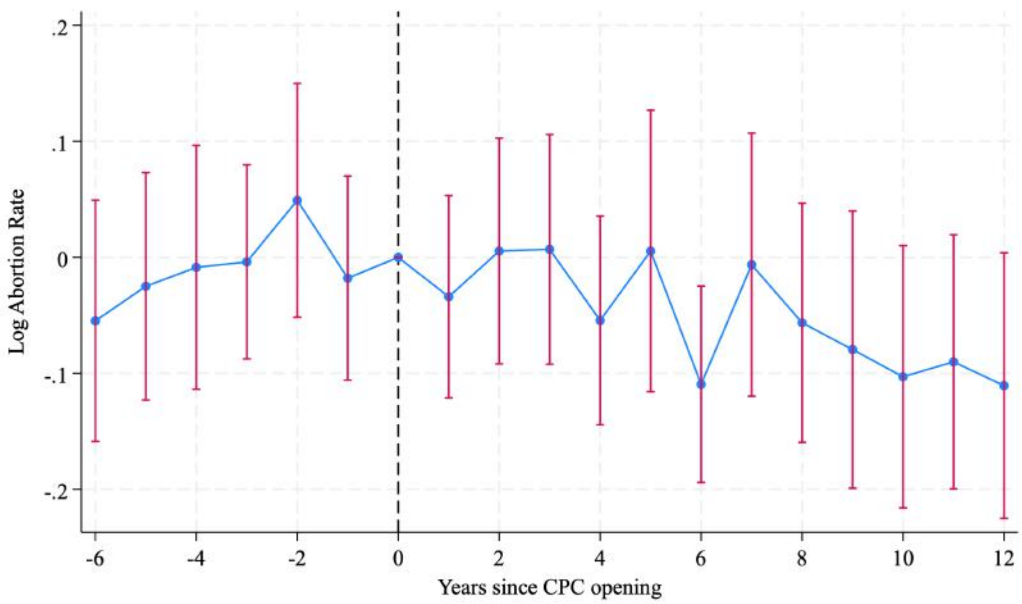
Standard errors in parentheses

Figure 8: Event Study of CPC Openings: Younger Women



Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line on the figure shows the $\mathrm{DID}_{\mathrm{nl}}$ estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. The estimator $\mathrm{DID}_{\mathrm{l}}$ is normalized by the average total incremental treatment dose received by switchers with respect to their baseline treatment. This normalization ensures that $\mathrm{DID}_{\mathrm{nl}}$ estimates a weighted average of effects of the current treatment and of its l-1 first lags on the (log) abortion rate.

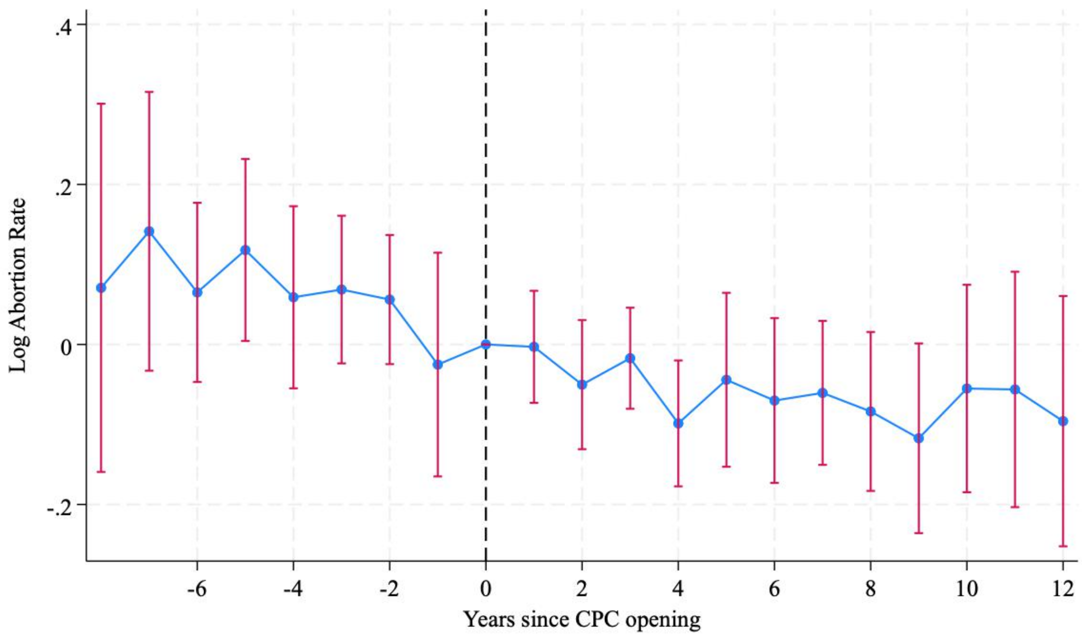
Figure 9: Event Study of CPC Openings: Older Women



Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line on the figure shows the DID_{nl} estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. The estimator DID_{l} is normalized by the average total incremental treatment dose received by switchers with respect to their baseline treatment. This normalization ensures that DID_{nl} estimates a weighted average of effects of the current treatment and of its l-1 first lags on the (log) abortion rate.

8C. CPC Revenues and the Abortion Rate

Figure 10: Event Study of CPC Openings

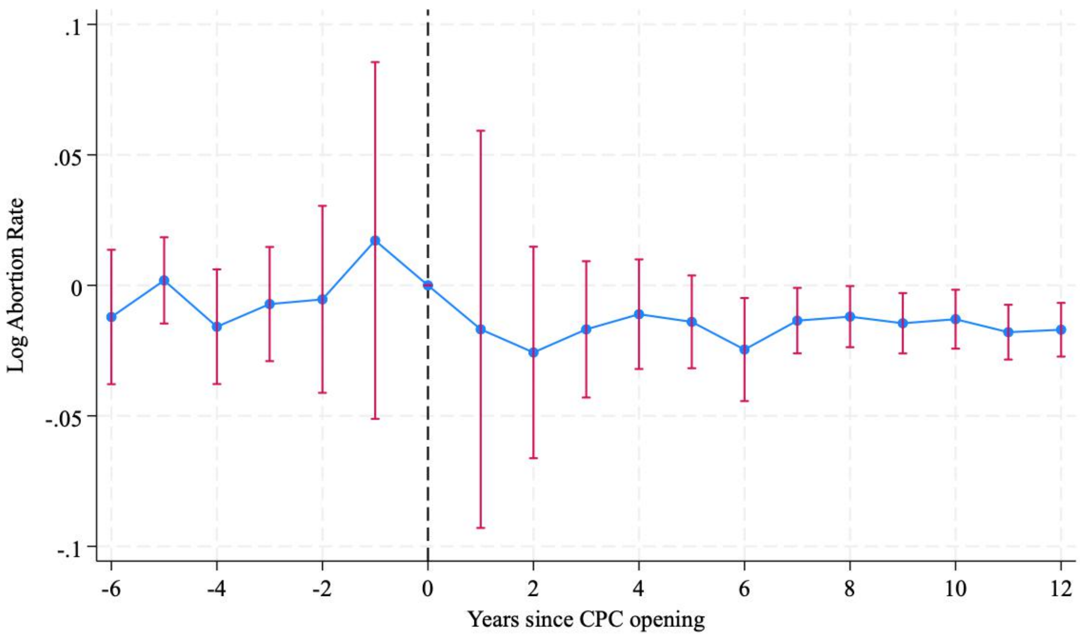


Notes: Treatment variable: $1,000 in CPC revenues per 1,000 women on the (log) abortion rate. To the right of zero, the blue line on the figure shows the DID_l estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. To the left of zero, the blue line shows the DID_l placebo estimates. At t=0, the placebo is normalized to 0.

Figure 3 shows the dynamic effects of $\$1,000$ in CPC revenues per 1,000 women on the (log) abortion rate. Just as in the case of Figure 2, of the estimates from pre-period shows a statistically significant difference between the treated and non-treated counties. This is confirmed by the result of the joint significance test that all the six pre-treatment estimates are null (p=0.93).

8D. Heterogeneity Robust Difference-in-Differences: Normalized Estimator

Figure 11: Event Study of CPC Openings



Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line on the figure shows the $\mathrm{DID}_{\mathrm{nl}}$ estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. The estimator $\mathrm{DID}_{\mathrm{l}}$ is normalized by the average total incremental treatment dose received by switchers with respect to their baseline treatment. This normalization ensures that $\mathrm{DID}_{\mathrm{nl}}$ estimates a weighted average of effects of the current treatment and of its l-1 first lags on the (log) abortion rate.

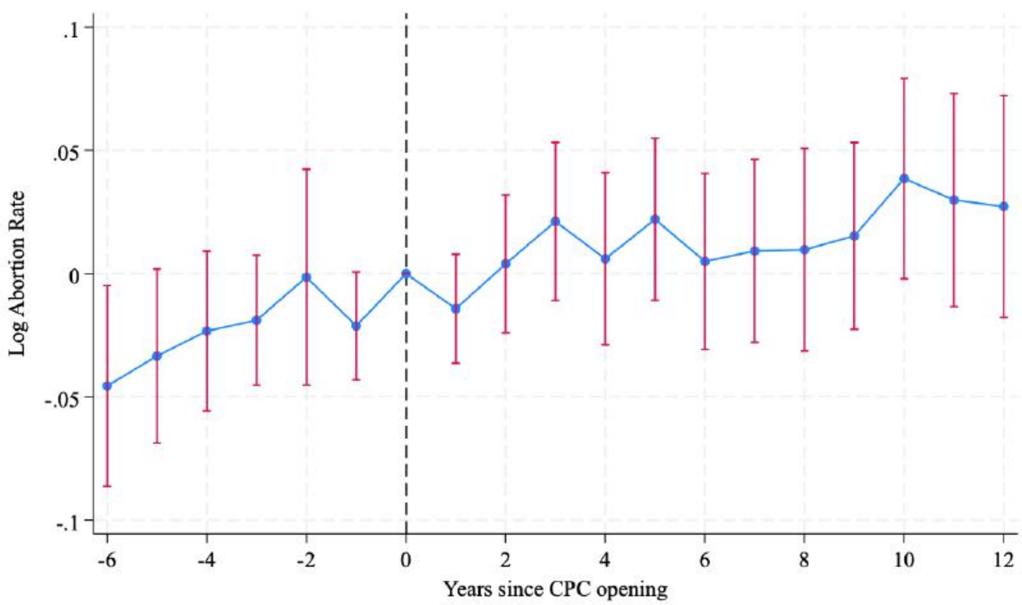
8E. Additional Robustness Checks

Table 10: Effect of CPCs on (Log) Birth Rate

	(1) TWFE	(1) DID_l
No. of CPCs (per 1,000)	0.0112	0.0137
	(0.00823)	(0.01427)
N	4380	2734
Control Vars.	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
State FE	Yes	Yes

Standard errors in parentheses

Figure 12: Event Study of CPC Openings: (Log) Birth Rate



Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line on the figure shows the DID_{nl} estimates of the effect of a CPC opening on the logarithm of abortion rate, the year of that first opening, and in later years. The estimator DID_l is normalized by the average total incremental treatment dose received by switchers with respect to their baseline treatment. This normalization ensures that DID_{nl} estimates a weighted average of effects of the current treatment and of its l-1 first lags on the (log) abortion rate.

Table 11: Alternative Specifications

	Abortion Rate		(Log) Abortion Rate
	(1)	(2)	(3)
	OLS	Poisson	Poisson
No. of CPCs (per 1,000)	-0.208	-0.0736	-0.0685
	(0.146)	(0.0229)	(0.0209)
N	4380	4380	4376
Control Vars.	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Standard errors in parentheses

8F. Instrumental Variable Approach

In the fertility model, the main identification challenge stems from the joint endogeneity of CPCs and the abortion rate. This implies that the strict exogeneity assumption, necessary for consistent fixed effects estimation, may not hold. To address this concern, I construct instrumental variables to estimate a dynamic model using two-stage least squares. In this context, the instrumental variables are a re-weighting scheme that corrects the endogeneity resulting from the strategic location choice of CPCs. Consider a simplified structural equation in terms of endogenous, x_{ct}, and exogenous, z_{ct}, variables:

$$AR_{ct} = x_{ct}^{'}\beta + \epsilon_{ct}, \quad \mathbf{E}\left[\epsilon_{ct}|z_{ct}\right] = 0 \tag{5}$$

The outcome AR_{ct} is the abortion rate. The main variables of interest, CPC_{ct} and $Dist_{ct}$, are endogenous components of x_{ct}. The exogenous component of x_{ct} is denoted by $z_{ct}^{'}$. Correlation between CPC_{ct} (and $Dist_{ct}$) and ϵ_{ct} is allowed, because $\mathbf{E}\left[\epsilon_{ct}|z_{ct}\right] = 0$ does not restrict the joint distribution of ϵ_{ct} and CPC_{ct} (and $Dist_{ct}$) (see Heckman and Robb Jr 1985; Newey 1993). Instruments are needed for the two endogenous variables of interest, CPC_{ct}, indicating if a CPC opened in year (t) and county (c), and $Dist_{ct}$, characterizing

[20] The population weighted county centroid is used to calculate the driving distance. A large number of instruments are generated using these two generated variables by interacting them with age groups and generated squared distance terms. Therefore, the "Expected number of CPCs" and the "Expected distance from a county centroid to the nearest CPC" are used in separate specifications.

the distance from the county centroid to the nearest CPC in year (t). The instruments are the "Expected number of CPCs" and the "Expected distance from a county centroid to the nearest CPC."[20] The optimal instruments are defined as:

$$\mathbf{E}\left[CPC_{ct}|z_{c1990,\ldots,ct}\right],$$

$$\mathbf{E}\left[Dist_{ct}|z_{c1990,\ldots,ct}\right].$$

If the functional form used to estimate $\mathbf{E}\left[CPC_{ct}\right]$ (and $\mathbf{E}\left[Dist_{ct}\right]$) was correctly specified, the instrumental variables have the smallest asymptotic variance in this class of estimators. If the functional form is misspecified, the instruments are nonetheless consistent (Newey, 1993).

In a data-driven approach, the time series of exogenous factors, $z_{c1990,\ldots,ct}$, and simulated values for the endogenous variables in x_{ct}, are used to generate $\mathbf{E}\left[\widehat{CPC}_{ct}\middle| z_{c1990,\ldots,ct}\right]$ and $\mathbf{E}\left[\widehat{Dist}_{ct}\middle| z_{c1990,\ldots,ct}\right]$. Intuitively, the identification stems from the time series variation in the exogenous variables, reflecting how the exogenous variables affect $\mathbf{E}\left[CPC_{ct}\right]$. I do not perfectly capture the true process that determines the opening of CPCs but conditioning on exogenous variables ensures that $\mathbf{E}\left[\widehat{CPC}_{ct}\right]$ is an exogenous prediction. The simulation procedure uses the prediction from the logit model of CPC location choice, as introduced in section 4, as initial condition. By evaluating equation (1), I obtain the probability of a CPC opening in each county in 1990, the first year in the analysis sample.[21] Using the logit prediction, a "coin flip" determines if a new CPC opens in a particular county and year.[22] The "coin flip" orthogonalizes the variable that counts the number of CPCs in each county and year. I simulate the values of the endogenous variables across all counties over time. I impose the exogeneity assumption that the unobserved determinance of the propensity of a CPC opening is not related to the unobserved factors affecting the current abortion rate. In other words, it assumed that the abortion rate is endogenous to the event of a CPC opening but orthogonal to CPC openings in the future. The process is repeated a large number of times, generating many estimates of the endogenous variables "Number of CPCs"

[21] The specification including a polynomial time trend and county fixed effects is used to obtain the logit prediction. Estimation results are reported in column (2) of Table 2.

[22] In more detail, this probability is obtained by taking a random draw from a uniform distribution. If the draw is smaller than $e^{(X\beta)}/[1+e^{(X\beta)}]$, a CPC opens.

and “Distance from a county centroid to the nearest CPC.” The randomization procedure, or “coin flip,” implies that variable estimates converge to their expected values, that is, I obtain $\mathbf{E}\left[\widehat{CPC}_{ct}|z_{c1990,\ldots,ct}\right]$ and $\mathbf{E}\left[\widehat{Dist}_{ct}|z_{c1990,\ldots,ct}\right]$. Hence, the “Expected number of CPCs” in a county, conditional on observables, affects the abortion rate only through the timing of the exogenous determinants of the number of CPCs, but not through endogenous channels. By construction, the instruments are relevant because the “Expected number of CPCs” is related to the observed number of CPCs. The same applies to $\mathbf{E}\left[\widehat{Dist}_{ct}|z_{c1990,\ldots,ct}\right]$.

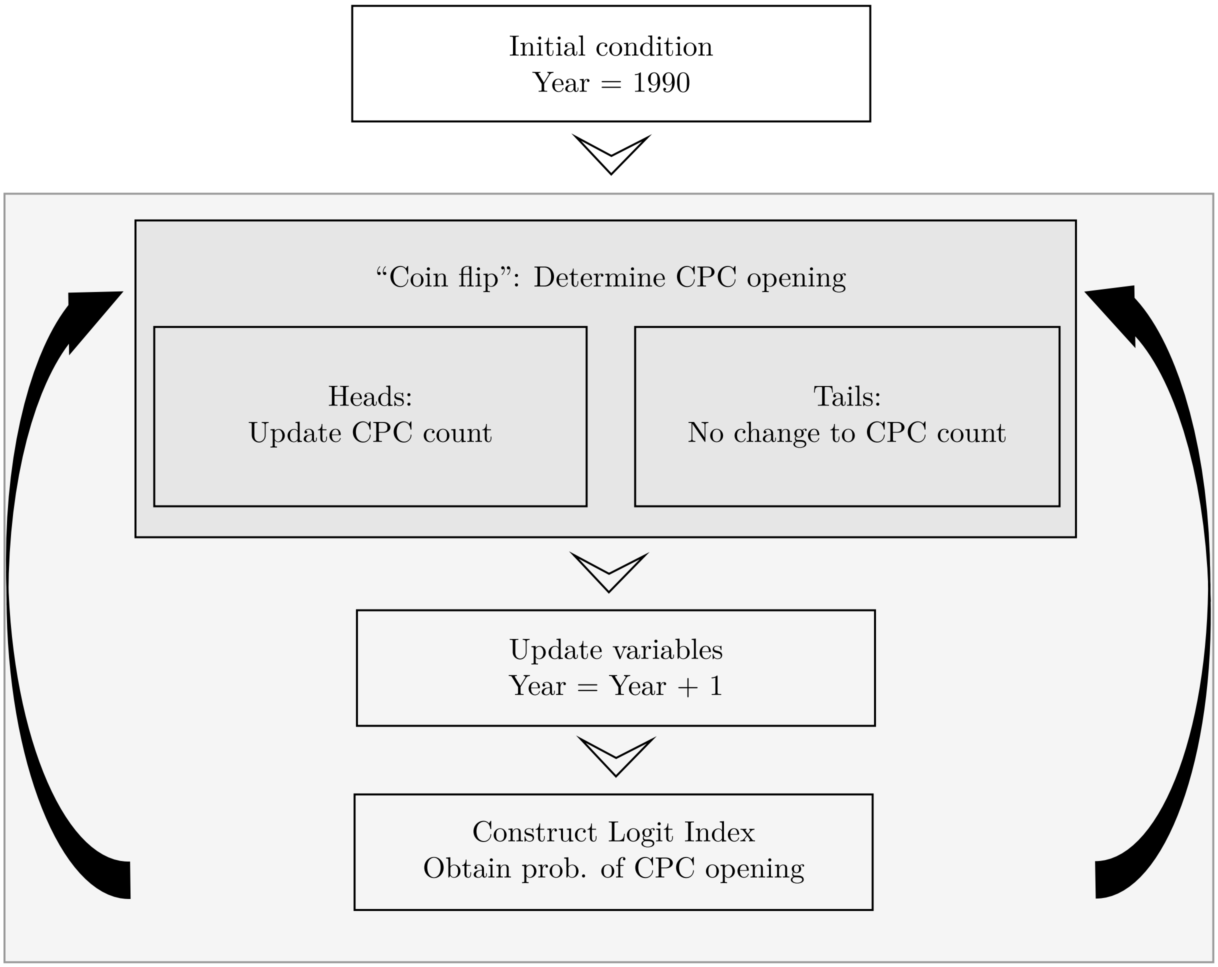
8G. Instrumental Variables Construction Example

A new CPC changes the distance from a place of residence to the nearest CPC. Conveniently, additional CPCs reduce the driving distance, thus preserving monotonicity. The variable “Distance from a county centroid to the nearest CPC” is updated using an exogenous rule when a new CPC opens.[23] Every time a CPC opens, it causes a stochastic change in the abortion rate. Therefore, whenever the number of CPCs in a county changes, the abortion rate is updated. Once a CPC opened in 1991, the probability of a CPC opening in 1992 needs to reflect this changed county environment. Three key variables are updated to reflect the change resulting from a CPC opening. These variables are the “Number of CPCs”, (which is increased by 1 if a CPC opened at $t-1$), the “Distance from the County Centroid to the Nearest CPC” (a new CPC opening closer to the centroid reduces this distance), and the “Abortion Rate” (updated using an exogenous rule). The distance measure is updated using the median distance from a county centroid to the nearest CPC if there is one (two, three, ...) CPC in the county. The logit model is estimated once again, using the updated variables, to obtain the probability of a CPC opening in Alamance County in 1992. Another “coin flip” determines if a CPC opens in 1992. Finally, I generate the “Expected number of CPCs” for each county and year. This variable is called $Exp(\widehat{CPC}_{ct})$. The same approach applies to the $Dist_{ct}$ variable. The logit model is evaluated once again, using the updated variables, to obtain the probability of a CPC opening in the following year. As an example, consider Alamance County in N.C., which, by the year 1990, never had a CPC. What is the probability that a CPC opens in Alamance County in 1991? The probability of a CPC opening is given by $logit(X\beta)$, estimated using equation (1). A “coin flip” determines if the

[23]The exogenous rule is a function of the median driving distance in a county with n CPCs.

logit prediction leads to new CPC opening in Alamance County in 1991.

Figure 13: Instrumental Variables: Simulation Flow Chart



8G..1 Two-stage Least Squares Estimation

The variable $\widehat{CPC}_{ct}$ is used to instrument for CPC_{ct}. The first-stage equations are defined as follows:

$$CPC_{ct} = \theta_0 + \theta_1 \widehat{CPC}_{ct} + \theta_2 \widehat{Dist}_{ct} + \theta_3 X_{ct} + \gamma_c + \alpha_t + \epsilon_{ict}$$

In the first stage, CPC_{ct}, the number of CPCs in county c and year t, is a function of the instruments $\widehat{CPC}_{ct}$, $DistClinic_{ct}$, and X_{ct}. The same applies to $\widehat{Dist}_{ct}$. County fixed effects are denoted by γ_c and time fixed effects are denoted by α_t. The second stage is:

$$Y_c t = \theta_0 + \theta_1 \widehat{CPC}_{ct} + \theta_2 \widehat{Dist}_{ct} + \theta_3 X_{ct} + \gamma_c + \alpha_t + \epsilon_{ict}$$

In this specification, Y_{ict} is the log of the abortion rate (the birth rate or pregnancy rate). The unit of observation is a county c in year t.

Table 12: 2SLS Estimation Results

(Log) Abortion Rate	(1)	(2)	(3)	(4)
No. of CPCs (per 1,000)	-0.182	-0.186	-0.085	-0.088
	(0.040)	(0.076)	(0.078)	(0.061)
CPC Distance (in miles)		0.006	0.055	0.038
		(0.011)	(0.023)	(0.021)
Distance Sq.		0.006	-0.002	-0.001
		(0.011)	(0.001)	(0.001)
Distance Cube.			0.000	0.000
			(0.000)	(0.000)
N	4,376	4,376	4,376	4,376
State-County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	7.0	17.2	9.9	10.0
Kleibergen-Paap rk Wald F statistic	120.0	15.1	3.2	2.9

Standard errors in parentheses

The results in columns (1) and (2) of Table 12 are from specifications that closely resemble the OLS specifications in the main text. The point estimates of interest, namely of *No. of CPCs*, are significantly larger though. This provides reassurance that CPCs do lower the abortion rate, though the effect could be even larger than discussed earlier.