THE ROLE OF CRISIS PREGNANCY CENTERS IN FERTILITY DECISIONS*

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Abstract

For the past 50 years, the "pro-life" movement has sought to end the practice of abortion in the United States. 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 their impact on fertility outcomes. CPCs lower the local abortion rate by 10.0 percent, with larger effects observed among teenagers and young women. I also show that the presence of CPCs leads to an increase in birth rates.

JEL Classification: J11, J12, J13, and K23

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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). Activists in the "pro-life" movement, rooted in Christian religious beliefs, have since opened CPCs to lower the incidence of abortions in communities across the country. CPCs focus on reaching young women facing an unplanned or unwanted pregnancy, and in pursuing their mission, the centers 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 abstinence education to teenagers.

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 to 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 fiscal year (FY) 2021–22, $89 million in federal and state funding was allocated to CPCs across a dozen states (Kruesi, 2022). Thus far, there is little evidence that CPCs achieve their goal of reducing the incidence of abortion. 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 the first evidence that CPCs effectively lower local abortion rates.

[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 such pregnancies resulted 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, approximately 1 in 10 abortions (Care Net, 2018). Care Net (2018) 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".

I use a generalized difference-in-differences approach to show that CPCs lower the county-level (log) abortion rate by 10.0 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 and South Carolina.[3] I validate the robustness of the main result using alternative specifications that consider CPC revenues, the driving distance to a CPC, and age-specific heterogeneity, as well as techniques from the latest difference-in-differences literature (see De Chaisemartin & d'Haultfoeuille, 2022b). An important identification challenge stems from CPCs' location choice, which may be endogenous to the extent that it is informed by unobserved community characteristics that also shape fertility outcomes. To better understand and assuage this potential endogeneity concern, I construct a logit model of CPC location choice and devise a data-driven instrumental variables (IV) approach, which uses predictions from the 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 CPCs decrease the local abortion rate. Prior work has provided descriptive analyses of the location choice of CPCs, service provision of CPCs, and the competition between CPCs and abortion providers (Cartwright, Tumlinson, & Upadhyay, 2021; Swartzendruber, Solsman, & Lambert, 2021; Yuengert & Fetzer, 2010). In a separate strand of the literature, several authors have demonstrated 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 significantly reduce

[3] Maps in Section 10A. show the spatial distribution of CPCs and abortion providers. "Abortion providers" include clinics, for example, Planned Parenthood clinic locations, that do not offer abortion services themselves but refer patients to other clinics.

abortion rates, a result that is distinct from the reduction in abortion rates due to restrictions on abortion providers. This result is plausibly explained by CPCs reaching young women seeking pregnancy counseling and support near their homes without having to travel long distances to a healthcare provider.

The remainder of this paper proceeds as follows. In Section 2, I describe the mission of CPCs, their funding sources, and the policy landscape. Section 3 describes the data sources. In Section 4, I explain the model of CPC location choice. Section 5 presents 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 intended to inform about the gestational age, heartbeat, and viability of the pregnancy.[4] CPCs also offer material aid, such as baby clothes, cribs, diapers, and direct financial assistance. Some CPCs provide abstinence education or "sexual integrity" classes. Abstinence education targets teenagers and is held either at the CPC or in schools.

CPCs are relatively small nonprofit organizations. On average, the organizations in

[4]The provision of ultrasound services does not necessarily imply that the CPC offers comprehensive medical examinations. A review of CPC websites indicates that only some CPCs have staff who are certified as registered diagnostic medical sonographers and that a small share of CPCs employ registered nurses, obstetrician-gynecologists and other medical professionals. Further, some CPCs have partnerships with offsite physicians.

the analysis sample had annual revenues of $230,275 in 2018. Some of this funding comes from the federal and state governments. In FY2021–22, $89 million in federal and state funding was allocated to CPCs across a dozen states (Kruesi, 2022). Historically, CPCs primarily received public funding in their role as providers of abstinence education programs. Over the past decade, CPCs have received increasing amounts of Temporary Assistance for Needy Families (TANF) funding and, for a few years, Title X funding for the provision of reproductive healthcare. North and South Carolina, the two states in my 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, similarly to most state motor vehicle departments, sells "Choose Life" license plates, with the proceeds allocated to CPCs.

There is some research on who visits CPCs. Rice, Chakraborty, Keder, Turner, and Gallo (2021) find that 13.5 percent of surveyed women in Ohio reported having ever visited a CPC. CPC attendance was higher among Black women, women with lower incomes and women without college degrees. Cartwright et al. (2021) find that 13.1 percent of women searching for abortion services online visited a CPC during their pregnancy. This study also finds that living closer to a CPC is associated with greater odds of visiting a CPC and that women who report having visited a CPC are 21 percentage points less likely to have had an abortion.

Systematic evidence on the information content of CPC counseling is lacking, but

[5]Federal funds were first used in FY2014 and have been supplemented by state funding since 2018 (see Table IV). The North Carolina General Assembly began 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.

public health researchers have analyzed the information that CPCs provide online, which is indicative of their counseling content. Swartzendruber et al. (2018) find that CPC websites contain false and misleading health information, that the advertised services do not align with prevailing medical guidelines, and that 58 percent of CPC websites fail to disclose that they do not provide abortion services or refer clients to an abortion provider. Some of these findings have been corroborated by Rosen (2012), who identify that CPC websites commonly provide inaccurate information on the medical risks of abortion. It is thus unsurprising that Cartwright et al. (2021) report that 58% of CPC clients are unaware of CPCs' "pro-life" mission and or are even seeking abortion services. Similarly, (Swartzendruber et al., 2021) finds that many CPC clients hold misconceptions about CPC policies and practices.

CPCs are almost universally unregulated. Most CPCs are not licensed medical facilities, meaning that medical ethics rules and patient privacy laws are not applicable. In instances when women have felt misled by CPCs, state attorneys have mostly declined to open investigations because CPCs do not charge fees 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), passed in 2015. This legislation intended to limit CPC practices deemed deceptive, particularly regarding 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.

[6]Under the law, unlicensed CPCs would have had to disclose to their clients in writing, or post on 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. However, some CPCs in California are licensed medical providers. The FACT Act required licensed CPCs not providing 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.

2B. Abortion Access

In North and South Carolina, abortion was legal during the entire period under consideration in this paper. Over time, state laws placed restrictions on abortion providers, required waiting periods, and prohibited health insurance reimbursement for abortion services.[7] In North Carolina, a 1973 law legalized abortion up to 20 weeks of gestation (NC G.S. 14-45.1). Since 2011, abortion providers in North Carolina have been required to consult with a patient at least 72 hours before an abortion procedure. The state also requires the physical presence of the physician for both surgical and medical abortions (NC G.S. Ch. 90, Art. 1I.). In 2023, outside the study period, legal abortion was limited to 12 weeks' gestation, except under specified circumstances (NC G.S. 90-21.81B). In South Carolina, a 1974 law broadly legalizes abortion up to 24 weeks of gestation and under specified circumstances beyond 24 weeks of gestation (SC Code Ann. §§ 44-41-20). In 1995, state law was revised such 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 (SC Code Ann. §§ 44-41-75). In 2010, Sec. 44-41-330 was 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 has been observed in Texas and elsewhere. Several recent studies have shown that increased travel distances to abortion clinics because of closures reduce the abortion rate (Fischer, Royer, & White, 2018; Lindo

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

et al., 2020; Quast, Gonzalez, & Ziemba, 2017). Furthermore, increases in travel distances to abortion providers increase the birth rate (Lu & Slusky, 2019). As barriers to abortion access are mounting, with several U.S. states having banned the practice entirely, the role of CPCs may continue to evolve. CPCs do not face any of these restrictions when providing their services, possibly meaning that more women are seeking abortion counseling outside the healthcare system.

3 Data

I study the location choice of CPCs and the effect of CPCs on the abortion rate. These analyses require 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 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 women by age group over a long time horizon. In addition, North 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 time period 1990 to 2019, and the first and last year of the sample are reported in Table II.

3A. CPC and Clinic Data

Obtaining a longitudinal registry of CPCs is an important contribution of this paper. I construct a dataset of CPC and abortion clinic addresses, 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). These data are the basis 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 are available. Figures I to IV show CPCs and abortion providers over time, overlaid on a map of county-level abortion rates in NC and SC. To extend the analysis to the financial strength of CPCs, I add information from tax filings for years 1996-2019.[8]

Data on abortion clinics (and referrers) are sourced from records of Title X grant recipients, which include many abortion providers, which are 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.

Furthermore, I obtain state licensing information on abortion clinics in NC and SC. I cross-check this information with the provider lists of the National Abortion Federation and Planned Parenthood and through a generic online search of newspaper reports. The resulting dataset provides the precise geographic location of each facility and allows me to

[8]The number of locations exceeds the number of CPC organizations because some organizations operate 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; and (4) Yellow Pages entries. In the case of CPCs, I can also observe some address changes and closures in financial fillings from news articles.

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 women, for the period from 1990 to 2019.[9] Abortion and birth counts were obtained from administrative and vital records provided by vital statistics offices in North and South Carolina. Pregnancy outcome data were provided by a woman's county of residence, aggregated by age group and ethnicity (white/nonwhite). In most states, including North 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, and 35-44. All males are excluded from the analysis.[10] Rates are constructed by combining fertility rates with Census data on demographic information on age group, 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 have a balanced panel structure.[11] Analyses are conducted at both at the county level and the age–ethnicity–group level.

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

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

4 Location Choice of CPCs

The nonprofit sector is primarily community-based and locally operated, where needs and resources in a particular region determine the number of nonprofit 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 CPCs locate near population centers and in counties with a high share of Catholics, whereas McVeigh et al. (2017) found that CPC location is associated with the share of evangelicals and Catholics in a county. However, we lack evidence from longitudinal data on the location choice of CPCs.

The location choice problem is motivated by community support for the opening of a CPC and demand for CPC services. Should CPCs open in areas with high demand and low community support or in areas with low 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 for the 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, protestants, 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 reduce the local abortion rate and provide social services. Intuitively, we can regard their 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 nonprofits in the area in which a CPC is located. Finally, CPCs compete with existing abortion providers, so the distance from a CPC location to the 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 across counties, depending on the benefits and costs of opening a CPC. For example, the individuals that

[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} denotes 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 chooses a CPC location and the resulting organization ("CPC") are treated as the same entity.

[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 differed from the calculated route.

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 nonprofits. 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 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 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 dissuade her from seeking 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, as 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 seeking any available support or mistake a CPC for 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 education, but some abstinence education providers, for instance CPCs, are anti-abortion.[15] If CPCs providing abstinence education reduce the 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) found that abstinence-only education did not reduce the likelihood of engaging in intercourse. Similarly, Trenholm et al. (2008) reported that abstinence education caused no difference in teen sexual activity and no differences in rates of unprotected sex, and Carr and Packham (2017) noted that state-level education mandates have no effect on teen birth or abortion rates. In contrast, Cannonier (2012) showed 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.

[15] See 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.

5A. Identification Strategy

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. Most important, a woman's place of residence and whether she visits a CPC are unobserved. Given this constraint, proxies for women's exposure to CPCs are used in the analysis. The goal is to identify the causal effect of CPC openings on the local (log) abortion rate. The main treatment variable is defined as the number of CPCs per 10,000 women aged 10-44 in a county.[16] 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).

CPCs are opened in counties at various points in time, and some counties receive more than one CPC. Hence, the treatment is conceived to be repeated and nonabsorbing. To identify the effect of 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.

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

5B. Two-way Fixed Effect Estimation

Estimating the effect of CPCs on the abortion rate using two-way fixed effect (TWFE) estimation exploits within-county variation over time while controlling for aggregate time-varying shocks. Under a set of assumptions described below, the quasiexperimental 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 obtain 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. 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 (De Chaisemartin and d'Haultfoeuille 2022b). Equation (2) thus assumes that the treatment effects are identical across counties within a similar group (control or treated).

However, heterogeneity in treatment effects can arise across time periods and counties. For example, the control group in Equation (3) includes both the never- and always-treated counties. The recent literature on difference-in-differences has demonstrated that in a more complex setting, such as the present application, the TWFE estimand does not have always have a straightforward interpretation. In a survey paper, De Chaisemartin and d'Haultfoeuille (2022b) showed that, as TWFE estimates are weighted sums of treatment effects in each county–year unit, negative weights can be attributed to some changes in outcome variables among always-treated counties. In the case of heterogeneous treatment effects, such negative weights lead to biased TWFE estimates. Some authors have proposed tests to assess the extent of the resulting bias (De Chaisemartin and d'Haultfoeuille 2022b; Goodman-Bacon 2021).[17]

To investigate the validity of the parallel trends assumption, I conduct event studies and develop a data-driven IV strategy that exploits the CPC location choice, thus explicitly accounting for potentially endogenous CPC location (see Appendix 8A.). 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 to alternative specifications, I also study the effect of CPCs on the untransformed abortion rate using both OLS and Poisson regression.

5C. Robust Difference-in-Differences

Given the limits of TWFE to recover treatment effects in complex settings, I turn to 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 heterogeneous effects in a multiperiod setting (Callaway, Goodman-Bacon, and Sant'Anna 2021; De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). However, most of these estimators are valid only in the context of staggered designs, where the units of observation, i.e., counties, are treated once and remain treated. De Chaisemartin and d'Haultfoeuille (2022a)'s DID_l estimator is robust to heterogeneous treatment effects when the treatment is nonabsorbing, which means in the context of this

[17]Following De Chaisemartin and d'Haultfoeuille (2020), I also compute the regression weights, which provide insight into the extent of the bias associated with the TWFE specification. This reveals that 1226 LATEs receive a positive weight and 734 receive a negative weight. The sum of positive weights is 1.022, and the sum of negative weights is comparatively small (-0.027).

paper that CPCs are permitted to sequentially open in the same county and remain open.

The DID_l estimator compares the evolution of outcomes between counties where a CPC opens in a given period and counties with the same treatment level whose treatment, in the relevant period, has not yet changed. The idea behind the DID_l estimator is to separately estimate 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 subsequently aggregate them. The DID_l estimates capture the effect of being exposed to a (weakly) larger treatment for l period compared to the baseline treatment. I thus estimate a dynamic version of Equation (2) using DID_l. The estimator relies on a weaker parallel trends assumption that can be tested using placebo estimators that compare the outcome trends of switchers and nonswitchers with the same period-one treatment, before switchers switch. This assumption rules out time-varying treatment effects and the effects of lagged treatments on the outcome. If the parallel trends assumption holds, this estimator is an unbiased measure of the effect of CPC openings (counties switching into treatment) on the (log) abortion rate. In addition to estimating dynamic treatment effects, De Chaisemartin and d'Haultfoeuille (2022a) proposed 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.

5D. Instrumental Variables

In the fertility model, the main identification challenge stems from the potential endogeneity of CPC openings 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 effects 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 the fact 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 period. In the context of an IV approach, this means that every lag of each instrument can have a separate effect on the contemporaneous value of the endogenous explanatory variables Bhargava (1991). A similar identification strategy, in the context of a nonlinear dynamic model, has been used by (Liu, Mroz, & Van der Klaauw, 2010). In Appendix 8A., I explain how I construct IVs to estimate this dynamic model using two-stage least squares estimation.

5E. Further Analyses

5E..1 Heterogeneity by Age

A central proposition of this paper is that CPCs attempt to reach girls and young women. To investigate heterogeneous treatment effects by age, 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 aged 10-44 in a county, 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.

$$Y_{ict} = \theta_0 + \theta_1 D_{ct} + \theta_2 Age_{ict} + \theta_3 D_{ct} \times Age_{ict} + \\ + \theta_4 DistClinic_{ct} + \theta_5 X_{ict} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ict} \quad (3)$$

Y_{ict} represents the (IHS) abortion rate.[18] The unit of observation is a demographic age 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 aged 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 aged 10-19, 24-29, 30-34, and 35-44 for white and nonwhites. 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 dataset.

5E..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 the service capacity of these facilities. To study the impact of CPC service capacity, I construct a second treatment variable using revenue data. 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 assess whether CPC revenues are an important mechanism

[18] 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 rates. The inverse hyperbolic sine function is defined at zero. This function closely approximates the natural log transform (except near zero).

that drives the effect of CPCs on the local abortion rate.[19]

5E..3 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 localized 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 (4), which replaces the CPC per capita measure with a treatment variable that measures the driving distance from the population-weighted county 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.[20]

6 Results

6A. CPC Location Decision

The results from the logit model of CPC location choice appear in Table VI. I focus on the results in Column (1), which are used to construct the IVs discussed in Appendix 8A. The main result is that an existing CPC reduces the probability of additional CPC openings

[19] CPC tax filing data are available only from 1997 onward, resulting in a shorter time series.
[20] The driving distance was obtained from the HERE geolocation and routing service.

in the same county by 5.0 percent. This is also indicated by the CPC distance coefficient, which 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 surprising is that there is no clear pattern of CPC location choice in response to religious affiliations in a community.

Considering the above findings, 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 or that have a larger 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 VII, with the preferred specification in Column (2) being discussed here. 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 of the number of CPCs per 10,000 women.

6B..2 Robust Difference-in-Differences

Column (4) of VII 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 examine whether key assumptions (parallel trends, no anticipation) are met. To this end, I present Figure V, 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 the preperiod reflects a significant difference between the treated and nontreated 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 hold. This is confirmed by the result of the joint significance test that all the six pretreatment estimates are null (p=0.11).

The event-study effects in Figure V are the average effects of having been exposed to a weakly higher treatment dose for l period. Only counties whose treatments have not changed from period 1 to t are used as controls, resulting in a smaller analysis sample. In Figure V, the effect at t=1 is the instantaneous effect of a CPC opening. The effect at t=2 is the treatment change that happened 1 period ago, representing the effect of a CPC opening t=1 periods ago on the (log) abortion rate. The event study estimates in Figure V 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 VI, I also show the normalized event-study estimators $\mathrm{DID}_{\mathrm{nl}}$ that normalize $\mathrm{DID}_{\mathrm{l}}$ 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.

6B..3 Age-specific Heterogeneity

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

6B..4 CPC Revenues

Table X shows the effect of the CPC revenue per 1,000 women in a county on the log abortion rate. The coefficient of -0.0071 in Column (1), 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 reduction in the local abortion rate of 0.71 percent. This effect is small compared to the main effects in Table VIII. CPCs largely rely on volunteer labor and face no regulatory burden, which helps explain why 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. Figure IX 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 V, none of the estimates from the preperiod shows a significant difference between the treated and nontreated counties. This is confirmed by the result of the joint significance test that all the six pretreatment estimates are null (p=0.93).

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). Furthermore, I show that the driving distance to the nearest CPC is of minor importance relative to the effect of being exposed to local CPCs.

In the analysis sample, 50 percent of the population-weighted driving distances to the nearest CPC are under 18 miles, and 90 percent are under 45 miles. As noted earlier, the community roots of CPCs suggest that they serve very local populations. Figure X shows 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 XI, 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 meaningfully change the coefficient representing the county-wide exposure to CPCs. The distance variable coefficient 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 XI shows that up to a distance of 12 miles between the population center and the nearest CPC, the (log) abortion rate increases in the distance that women travel to abortion providers. 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

Does the effect on abortions appear 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 and 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 and South Carolina. Therefore, the effect of CPCs on birth rates is *a priori* ambiguous. In Table XII and Figure XI, 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 rates of abortions and births need 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 large as the reduction in the abortion rate.

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

7 Conclusion

The pro-life movement has spearheaded policies intended to restrict 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 on which these organizations focus. I also show that CPCs shape fertility outcomes in important ways. First, CPCs reduce local abortion rates, particularly among teenagers and young women. The most intuitive explanation for this result is that CPCs effectively counsel girls and young women not to have abortions. Second, CPCs increase local birth rates, a result that is mechanically plausible. An important unexplored issue is how the role of CPCs has developed since the overturning of *Roe v. Wade*'s protection of abortion at the national level, particularly in states that have banned abortion.

8 Appendix

8A. Instrumental Variable Approach

In the fertility model, the main identification challenge stems from the 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 IVs to estimate a dynamic model using two-stage least squares. In this context, the IVs are a reweighting 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 whether a CPC opened in year (t) and county (c), and $Dist_{ct}$, characterizing 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."[21] The optimal instruments are defined as follows:

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

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

If the functional form used to estimate $\mathbf{E}\left[CPC_{ct}\right]$ (and $\mathbf{E}\left[Dist_{ct}\right]$) is correctly specified, the IVs will have the smallest asymptotic variance in this class of estimators. The IV approach yields consistent estimates even if the functional form is misspecified (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 (4), as introduced in Section 4, as the initial condition. By evaluating Equation 4, I obtain the probability of a CPC opening in each county in 1990, the first year in the analysis sample.[22] Using the logit prediction, a "coin flip" determines whether a new CPC opens in a particular county and year.[23] 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

[21]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.

[22]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 VI.

[23]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.

over time. I impose the exogeneity assumption that the unobserved determination 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 future CPC openings. The process is repeated a large number of times, generating many estimates of the endogenous variables "Number of CPCs" 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, 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 $\mathbf{E}\left[\widehat{Dist_{ct}}|z_{c1990,\ldots,ct}\right]$.

8B. Instrumental Variable 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.[24] 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

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

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. As an example, consider Alamance County in NC, which as of 1990 had 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 whether the logit prediction leads to new CPC opening in Alamance County in 1991. 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 whether 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.

8B..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:

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

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

The results in Columns (1) and (2) of Table I 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, however. This provides reassurance that CPCs do lower the abortion rate, although the effect could be even larger than discussed earlier.

Table I: 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

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9 Tables

Table II: Summary Statistics

	1990-2019		1990		2019	
	Mean	SD	Mean	SD	Mean	SD
Abortion rate (per 1,000 women)						
Total	11.07	(4.90)	16.81	(5.95)	8.63	(3.14)
Age 10-19	7.86	(5.35)	19.02	(6.56)	2.91	(0.99)
Birth rate (per 1,000 women)						
Total	45.87	(15.03)	49.45	(13.39)	42.02	(13.44)
Age 10-19	22.06	(10.28)	34.09	(8.86)	9.73	(3.63)
Crisis Pregnancy Centers						
No. of CPCs	2.15	(2.46)	1.11	(1.40)	2.81	(2.80)
No. of CPCs (per 1,000 women)	0.35	(0.39)	0.20	(0.30)	0.41	(0.42)
Nearest CPC (in miles)	11.65	(14.30)	20.44	(20.80)	7.68	(9.35)
Annual CPC revenue (in $1,000s)	463.30	(1,013.04)	.	(.)	799.33	(1,312.19)
County Characteristics						
Female population age 10-44	67,406	(69,966)	48,246	(42,286)	88,599	(92,885)
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)	27.90	(26.12)	32.66	(29.63)	29.32	(23.92)
Unemployment rate	5.95	(2.66)	4.36	(1.54)	3.56	(0.79)
U.S. House GOP vote share	1	(0)	0	(0)	1	(0)
Protestant share	0.54	(0.12)	0.60	(0.12)	0.51	(0.11)
Catholic share	0.04	(0.03)	0.02	(0.02)	0.04	(0.03)
No. of county-level obs.	4,380		146		146	

Sources: The CPC operation data were compiled by the author, annual county-level population estimates come 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.

Notes: Population-weighted summary statistics calculated for the years 1990, 2019, and 1990-2019. Fertility rates are calculated using the population of females in the age bracket 10-44 (and 10-19) as the denominator. "Annual CPC revenue ($1,000)" is shown for the time period 1996 to 2019 (instead of 1990-2019).

Table III: 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 IV: 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 nonrecurring funding
FY19	$400,000 federal funding, $1,000,000 state nonrecurring funding
FY20	$400,000 federal funding, $400,000 state nonrecurring (carry forward)
FY21	$400,000 federal funding, no state funding

Source: North Carolina Department of Health and Human Services.

Table V: 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 VI: 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)
Nonwhite 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 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.

Table VII: 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	4,376	4,376	4,376	2,734
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 aged 10-44. Columns (1)-(3) report two-way fixed effect estimates. Column (4) shows the estimates from the heterogeneity-robust DID_l estimator. Robust standard errors are in parentheses.

Table VIII: 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	43,800
Control Vars.	Yes
Year FE	Yes
County FE	Yes
State FE	Yes

Notes: This table shows the results from estimating Eq. (3) using OLS: $Y_{ict} = \theta_0 + \theta_1 CPC_{ct} + \theta_2 Age_{ict} + \theta_3 CPC_{ct} \times Age_{ict} + +\theta_8 DistClinic_{ct} + \theta_9 X_{ict} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ict}$. The level of analysis is age-group - county - year. Robust standard errors in parentheses.

Table IX: 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	17,520	26,280	8,760
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

Notes: This table shows the results from estimating the main model (Eq. 2) using OLS for three subsamples. The level of analysis is age-group - county - year. Robust standard errors are in parentheses.

Table X: CPC Revenue and Abortion Rate

	(1)	(2)	(3)
CPC Revenue (per 1,000)	-0.00713	-0.00529	-0.00915
	(0.00138)	(0.00119)	(0.00137)
N	3,354	3,354	3,354
R^2	0.703	0.782	0.684
Dep. Var. Mean	2.020	2.114	2.020
Control Vars.	Yes	Yes	No
Pop. weighted	No	Yes	No
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Notes: This table shows the results from re-estimating the main model (Eq. 2) using the total annual CPC revenue (per $1,000s) per 1,000 women in a county. Revenue data is available for years 1996 to 2019. Robust standard errors are in parentheses.

Table XI: 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)

Notes: This table shows the results from estimating (Eq. 4) using OLS for three subsamples. The bottom panel shows the marginal effect of CPC presence and distance estimated at represented mile markers. Robust standard errors are in parentheses.

Table XII: 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	4,380	2,734
Control Vars.	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
State FE	Yes	Yes

Notes: This table shows the results from estimating the main model (Eq. 2) using (log) birth rate as outcome variable. Robust standard errors are in parentheses.

Table XIII: Alternative Specifications

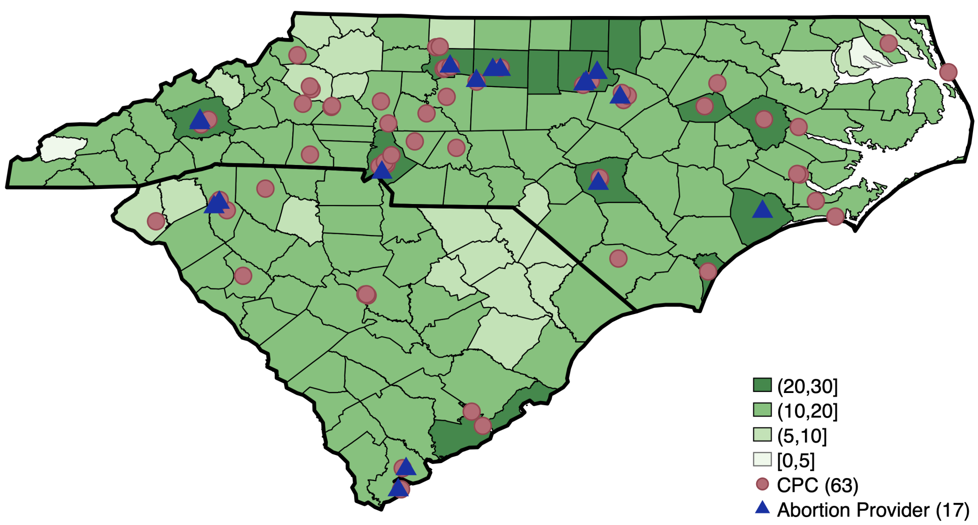
	Abortion Rate		(Log) Abortion Rate
	(1)	(2)	(3)
	OLS	Poisson	Poisson
No. of CPCs (per 1,000)	-0.208	-0.0736	-0.0685
	(0.146)	(0.0229)	(0.0209)
N	4,380	4,380	4,376
Control Vars.	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Notes: This table shows the results from estimating the main model (Eq. 2) using OLS for three subsamples. Robust standard errors are in parentheses.

10 Figures

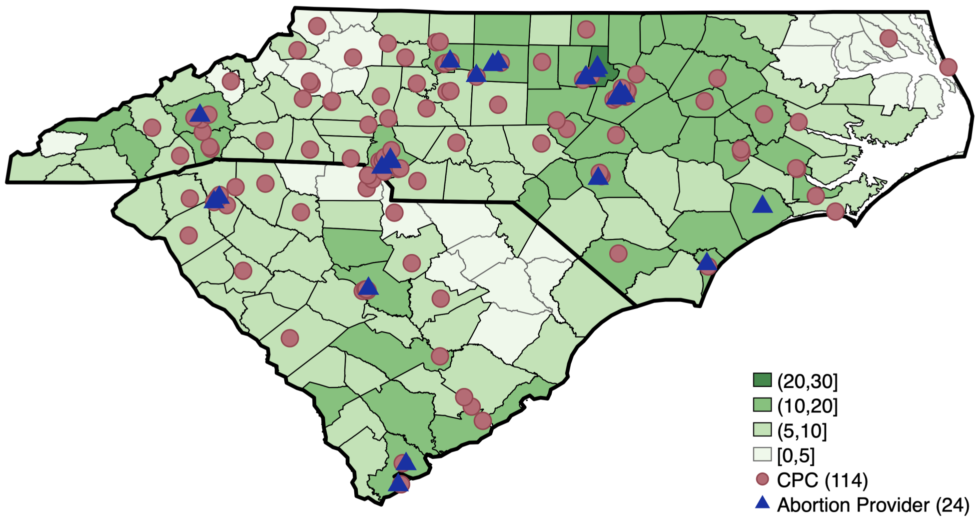
10A. Maps

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



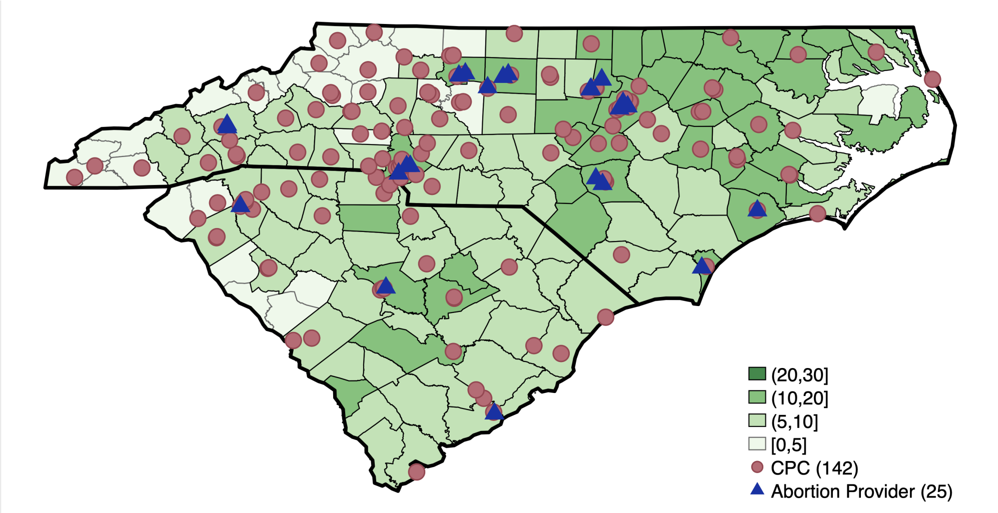
Notes: The green shading indicates the abortion rate per 1,000 women age 10-44.
Sources: The CPC data were compiled by the author, annual county-level population estimates were obtained from the U.S. Census Bureau (2019), and abortion counts were obtained from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control (2020).

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



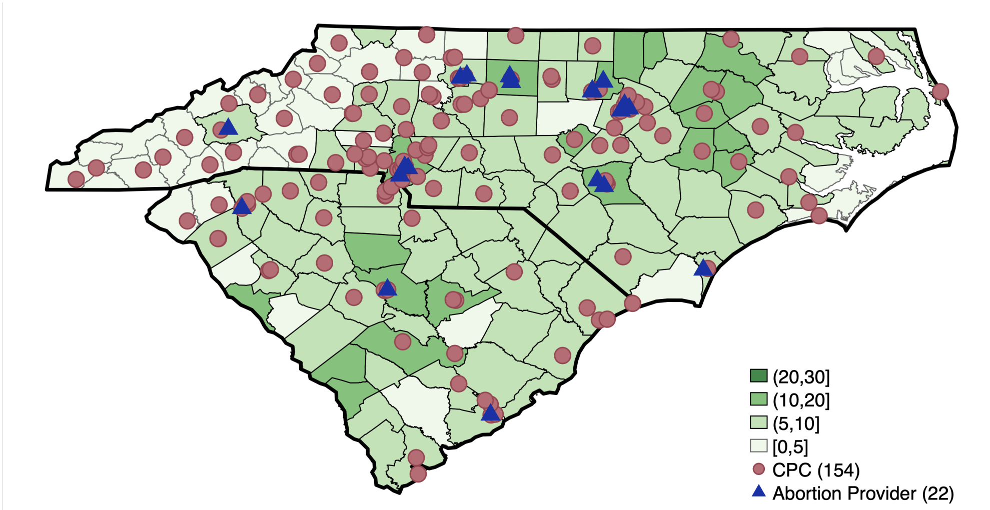
Notes: The green shading indicates the abortion rate per 1,000 women age 10-44.
Sources: The CPC data were compiled by the author, annual county-level population estimates were obtained from the U.S. Census Bureau (2019), and abortion counts were obtained from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control (2020).

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



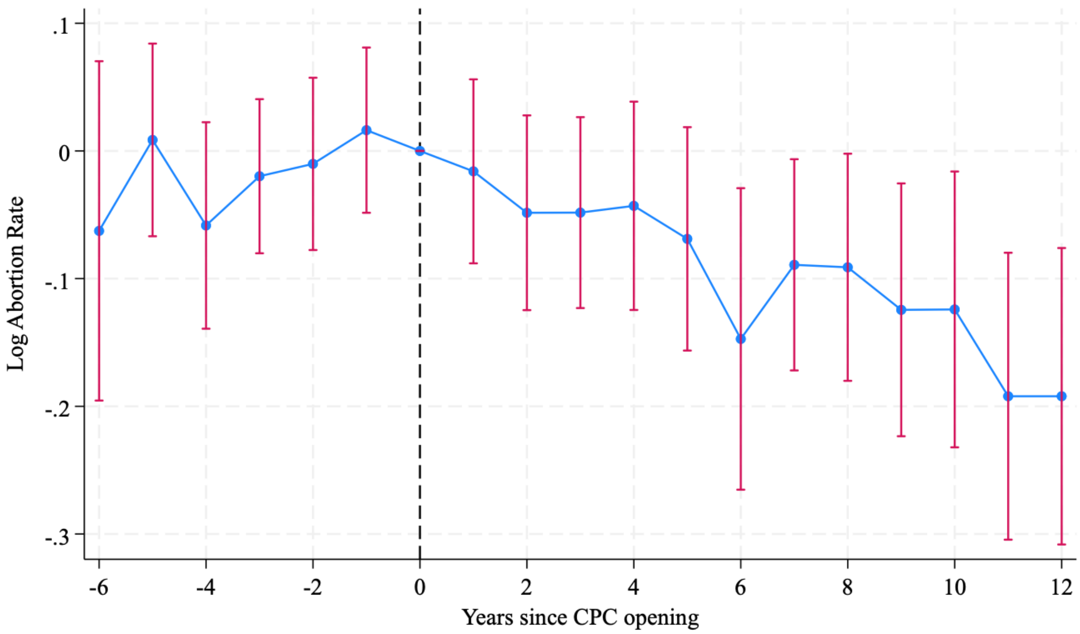
Notes: The green shading indicates the abortion rate per 1,000 women age 10-44.
Sources: The CPC data were compiled by the author, annual county-level population estimates were obtained from the U.S. Census Bureau (2019), and abortion counts were obtained from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control (2020).

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



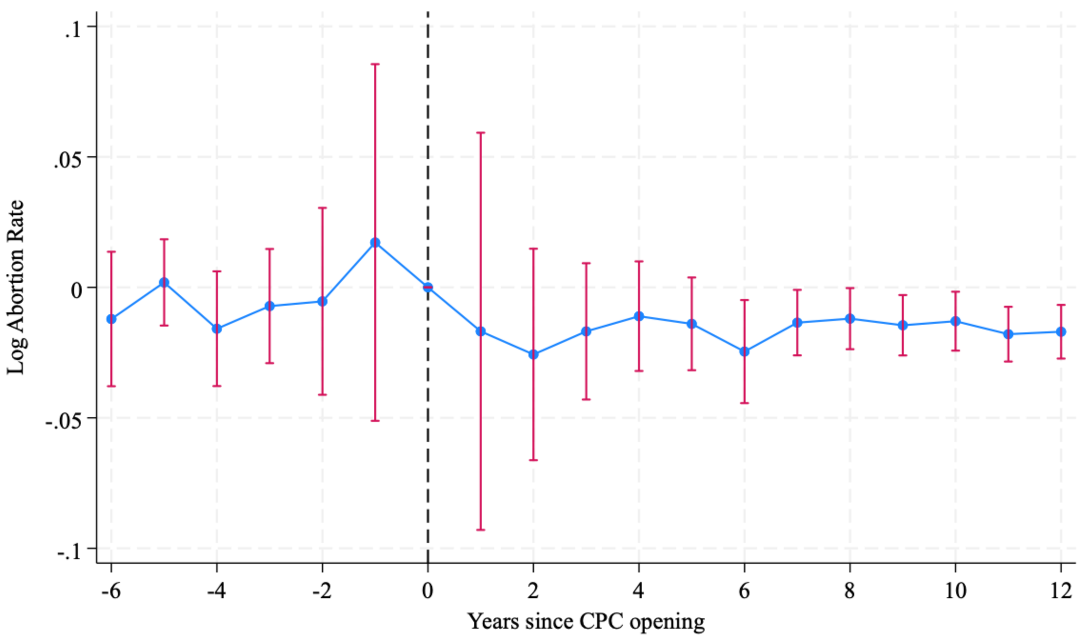
Notes: The green shading indicates the abortion rate per 1,000 women age 10-44.
Sources: The CPC data were compiled by the author, annual county-level population estimates were obtained from the U.S. Census Bureau (2019), and abortion counts were obtained from the North Carolina Department of Health and Human Services and the South Carolina Department of Health and Environmental Control (2020).

Figure V: Event Study of CPC Openings



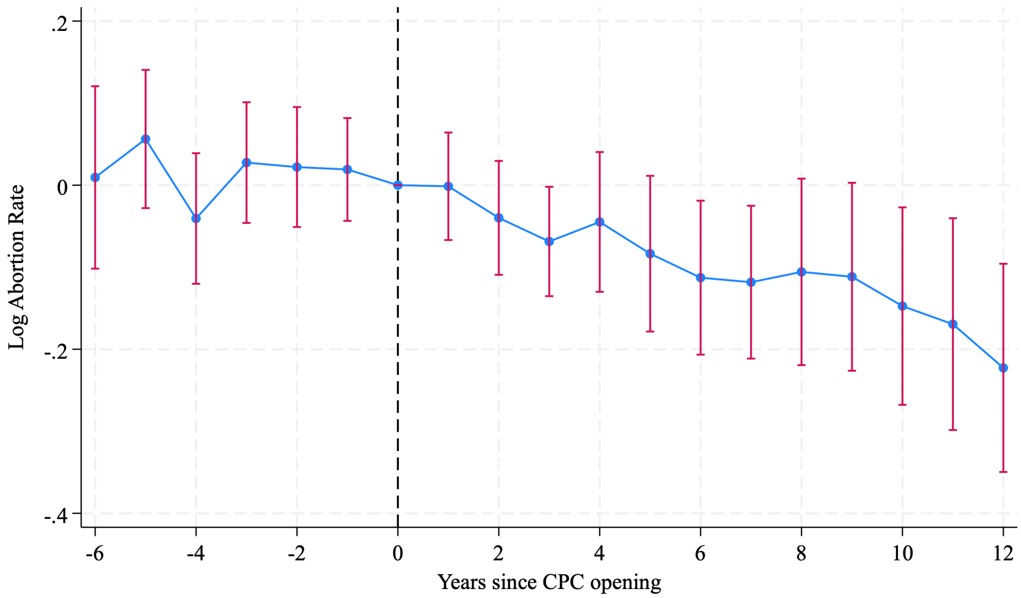
Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line in the figure shows the DID_l estimates of the effect of a CPC opening on the logarithm of the abortion rate in the year of that first opening and in later years. To the left of zero, the blue line shows the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

Figure VI: Event Study of CPC Openings: Normalized Estimator



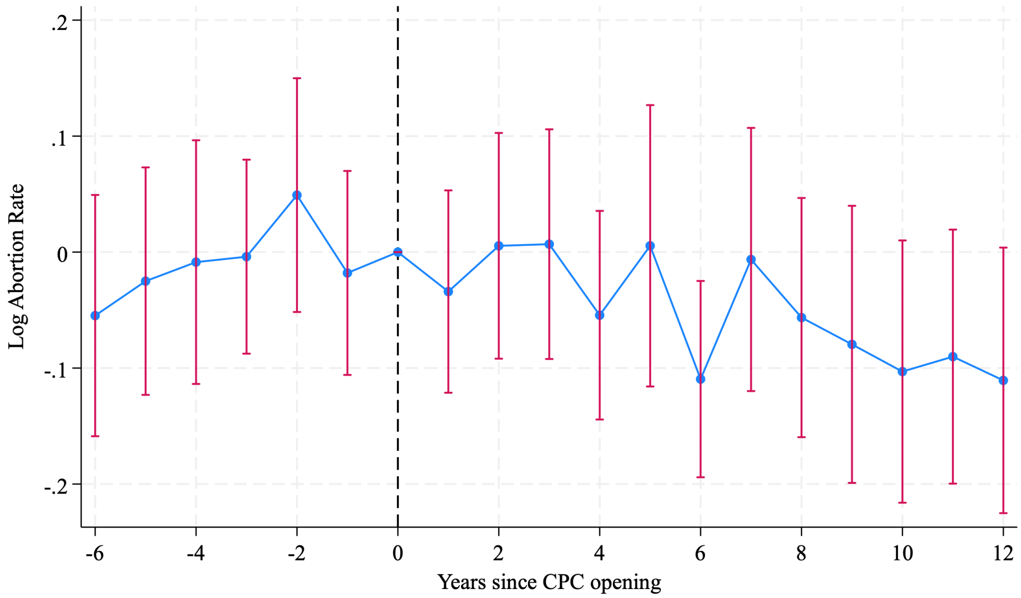
Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line in the figure shows the DID_{nl} estimates of the effect of a CPC opening on the logarithm of the abortion rate in the year of that first opening and in later years. The estimator DID_{l} is normalized by 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 its l-1 first lags on the (log) abortion rate.

Figure VII: Event Study of CPC Openings: Younger Women



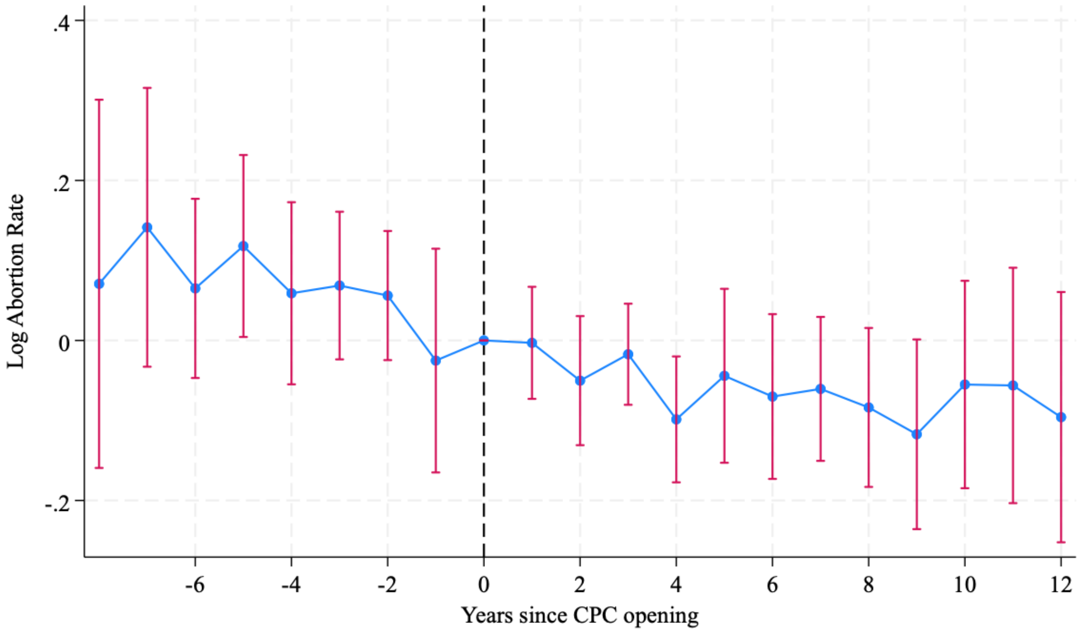
Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line in the figure shows the $\mathrm{DID}_{\mathrm{nl}}$ estimates of the effect of a CPC opening on the logarithm of the abortion rate in the year of that first opening and in later years. The estimator $\mathrm{DID}_{\mathrm{l}}$ 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 the effects of the current treatment and its l-1 first lags on the (log) abortion rate.

Figure VIII: Event Study of CPC Openings: Older Women



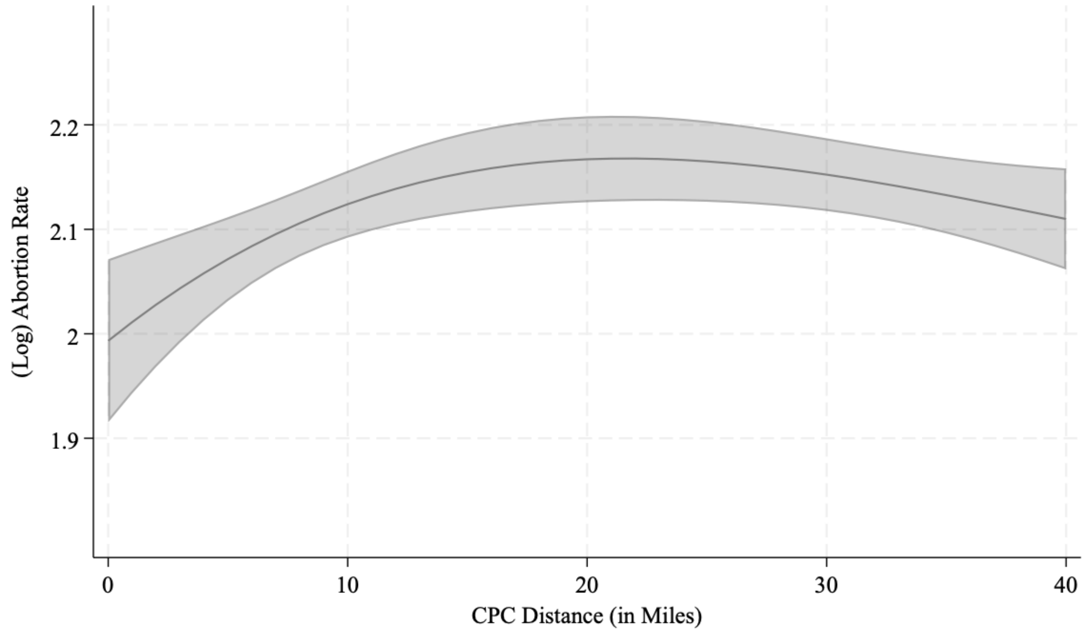
Notes: Treatment variable: Number of CPCs per 10,000 women. To the right of zero, the blue line in the figure shows the DID_{nl} estimates of the effect of a CPC opening on the logarithm of the abortion rate in the year of that first opening and in later years. The estimator DID_l is normalized by the 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 its l-1 first lags on the (log) abortion rate.

Figure IX: Event Study of CPC Openings: Revenues



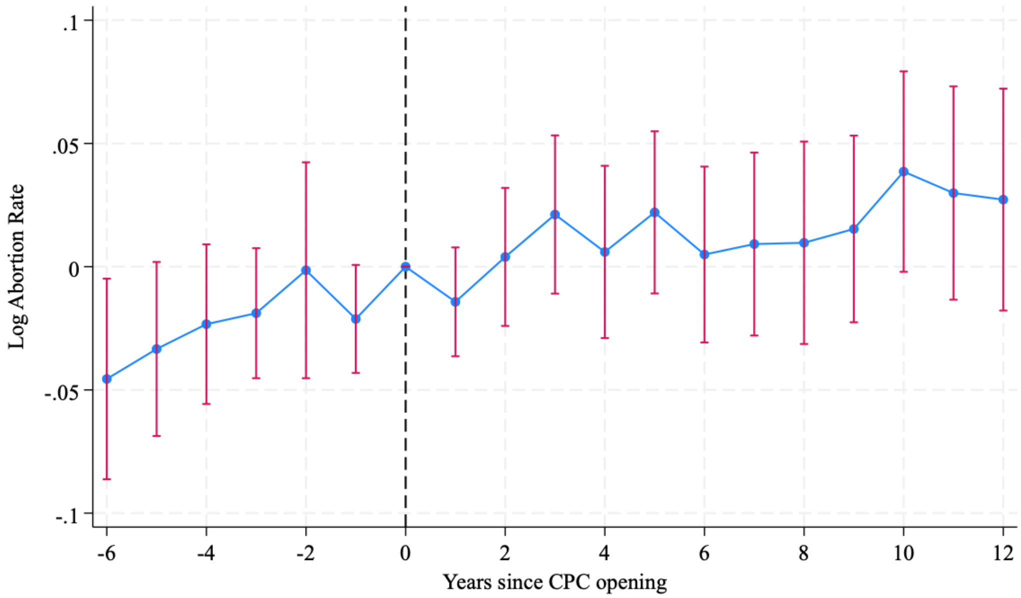
Notes: Treatment variable: $1,000 in CPC revenues per 1,000 women on the (log) abortion rate. To the right of zero, the blue line in the figure shows the DID_1 estimates of the effect of a CPC opening on the logarithm of the abortion rate in the year of that first opening and in later years. To the left of zero, the blue line shows the DID_1 placebo estimates. At t=0, the placebo is normalized to 0.

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



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

Figure XI: 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 in the figure shows the DID_{nl} estimates of the effect of a CPC opening on the logarithm of the abortion rate in 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 its l-1 first lags on the (log) abortion rate.

Figure XII: IVs: Simulation Flow Chart