Summer 8-1-2022

Essays in Applied Microeconomics

Béla Figge
Georgia State University

ABSTRACT

ESSAYS IN APPLIED MICROECONOMICS

BY

BÉLA FIGGE

August, 2022

Committee Chair: Dr. Daniel Kreisman

Major Department: Economics

This dissertation has two chapters in the field of applied microeconomics. Chapter one studies Crisis Pregnancy Centers and fertility outcomes. The second chapter, co-authored with Stefano Carattini, Alexander Gordan and Andreas Löschel, investigates municipal building codes and solar photovoltaic adoption.

Chapter 1: 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 4 to 6 percent among teenagers and young women. CPCs also cause an increase in birth rates among older women.

Chapter 2: National policies promoting the adoption of solar photovoltaics may be counteracted by local policies defining the aesthetics of the built environment. As solar photovoltaic energy reaches or approaches grid parity globally, non-pecuniary barriers to the adoption of this important renewable energy source will become increasingly salient. Using unique data from Germany, a leader in solar adoption, we document that the expansion of solar photovoltaics has been accompanied by a rise in municipalities amending their building codes to restrict solar installations, often with an eye toward preserving the historical nature of the town. We find that municipalities that implement solar policies have less solar photovoltaic capacity than municipalities in the control group.

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A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY

2022

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

Dissertation Chair:	Dr. Daniel Kreisman
Committee:	Dr. Thomas A. Mroz
	Dr. Stefano Carattini
	Dr. Lauren Hoehn-Valesco
	Dr. Sebastian Findeisen

Electronic Version Approved:

Dr. Sally Wallace, Dean
Andrew Young School of Policy Studies
Georgia State University
August, 2022

Acknowledgments

This dissertation was made possible and infinitely better because of the support of my mentors, colleagues, friends, and family. Thank you all very much. I would like to especially thank Dan Kreisman, my dissertation chair, for his unwavering support and focus on what is important. I thank Tom Mroz for his generosity and for challenging me to think carefully. Many thanks to my committee members Stefano Carattini, Lauren Hoehn-Valesco and Sebastian Findeisen for their thoughtful mentoring. Thanks also to my classmates, Tien Hoàng and Marc Sleiman, in particular, who made sure I made it to the finish line.

For chapter 1, I would like to thank Jim Marton for his encouragement and supervision during the early stages of the project. I would like to thank Charles Epstein at the North Carolina Department of Health and Human Services and Dr. Daniela Nitcheva at the South Carolina Department of Health & Environmental Control for their data support. Special thanks to the staff at the Wilson Library at the University of North Carolina for providing yellow pages records. I would also like to thank Caitlin Knowles Myers for helpful comments and abortion provider data. Finally, I would like to thank participants at the American Economic Association annual conference for helpful comments.

For chapter 2, I would like to thank my co-authors Stefano Carattini, Alexander Gordan, and Andreas Löschel, as well as our outstanding research assistants Leo Boehringer, Noelia Asucena Caceres Ortega, Maryam Huseynova, and Binia Sonnen. I thank the staff at thousands of German municipalities who took the time to respond to our survey. Lastly, I would like to thank participants and discussants at the annual conferences of the Association of Environmental and Resource Economists, the International Association for Energy Economics, and the Western Economics Association International.

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Chapter 1

The Role of Crisis Pregnancy Centers in Fertility Decisions

1.1 Introduction

The federal legalization of induced abortion in the United States in 1973 fundamentally changed women's ability to make reproductive choices. Since then, activists in the "pro-life" movement, rooted in Christian religious beliefs, have opened Crisis Pregnancy Centers (CPCs) to prevent abortions in communities across the country (Care Net, 2022). CPCs provide counseling services, pregnancy tests, ultrasounds, abstinence education, and material support, among other services. CPCs compete with abortion providers and focus on serving young women who experience an unplanned or unwanted pregnancy.[1] CPCs have increasingly been the focus of lawmakers, most recently because of concerns that online searches for abortion services sometimes direct users to CPCs (Bellware, 2022). Several studies show that CPCs misrepresent their services, mimic medical providers, and provide misleading and false medical information (Lin and Dailard 2002; Waxman 2006; Rosen 2012; Swartzendruber et al. 2018). Thus far, we have not known if CPC are effectively reaching women that consider terminating their pregnancy.

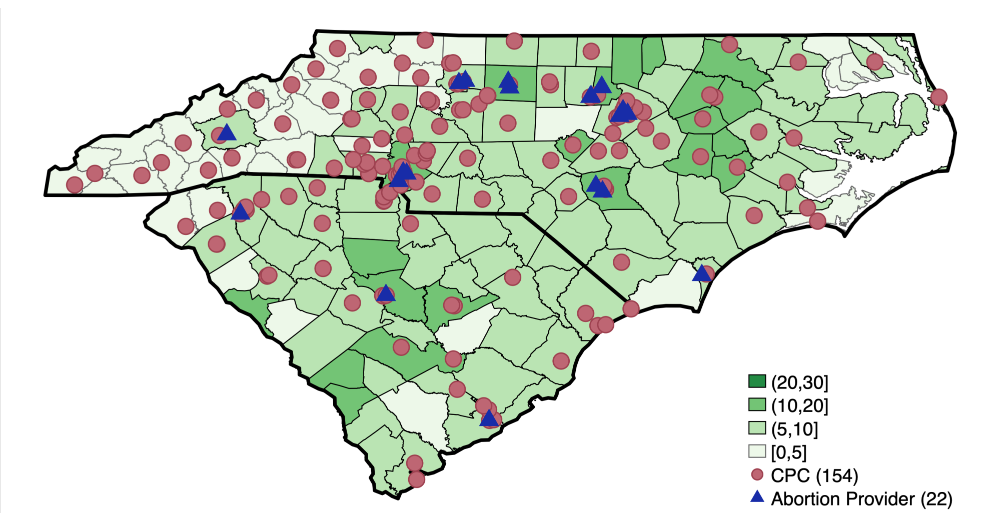
There are between 2,500 and 4,500 CPCs across the United States and more than half of women of reproductive age live closer to a CPC than an abortion provider (Jones and Jerman, 2017; McVeigh, Crubaugh, and Estep, 2017; Swartzendruber and Lambert, 2020; Thomsen, Baker, and Levitt, 2022). CPCs are present in all U.S. states and, in the 2021/22 Fiscal Year, $89 million of federal and state funding has been allocated to CPCs across a dozen states (Kruesi, 2022). Most CPCs are independently run and affiliated with one of four national organizations: Care Net, Heartbeat International, Birthright International and the National Institute of Family and Life Advocates. Care Net has more than 1,100 CPC affiliates and was launched as the Christian Action Council in 1975, with the goal of overturning *Roe v. Wade* (Care Net, 2022).

Abortion has been part of broader shifts in social norms with respect to sex, which have been of

[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.

interest to economists for some time (see, for example, Goldin and Katz, 2002; Myers, 2017). Akerlof, Yellen, and Katz (1996) argue that the legalization of abortion, empowered (and pressured) women to engage in sex outside of marriage, leading to an increase in pregnancies among young unmarried women. Women who are fundamentally opposed to abortion may have experienced a decline in dating and marriage prospects as a result of legal abortion and changing social norms (see Akerlof, Yellen, and Katz 1996). In this context, CPCs can be understood to have a dual purpose. First and foremost, CPCs exist to end the practice of abortion, in accordance with the beliefs of CPC founders and supporters. Hence, CPCs counsel pregnant women against terminating their pregnancy. More broadly, CPCs seek to reverse the liberalization of social norms. To this end, CPCs provide sexual abstinence programs, which discourage sexual activity outside of marriage and teach that having children out of wedlock is harmful to children and parents.

Figure 1.1: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2019



First, I study the location choice of CPCs. Second, I study how CPCs affect the abortion rate. The analyses build on a unique, 30-year panel of CPCs and abortion providers and vital statistics records.[2] I focus on North Carolina and South Carolina for several reasons. These states provide fertility counts by age and ethnicity by county of residence starting in the year 1990, allowing me

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

to study the majority of CPC openings and the fertility outcomes of young women. Moreover, there have not been any state-level policy changes that would have led to significant changes in abortion access during the study period. Lastly, North Carolina and South Carolina counties are of relatively small and homogenous size, which allows me to study travel distances to CPCs.

I use a logit model to study the strategic location choice of CPCs and find that CPCs locate near abortion providers, and in counties with higher population and urban areas. Moreover, CPCs are less likely to open in a community that already has a CPC, suggesting that expanding to new areas is prioritized. I then study the effect of CPC exposure at the county level on the abortion rate. The main identification challenge stems from the CPC location choice, which may be informed by unobserved community characteristics that also shape fertility outcomes. The location choice model helps identify the community characteristics that need to be incorporated into the fertility model. I use a generalized difference-in-differences approach to show that CPCs lower the county-level (log) abortion rate among teenagers and young women. Among women between 20 and 24 years of age, CPCs decrease the local abortion rate by 4 percent. The reduction in the abortion rate among teenagers and young women demonstrates that CPCs are effectively counseling women not to have abortions. To validate the main results, I present event study results and results from a two-stage least least squares estimation. I use a data-driven approach to construct instrumental variables for the endogenous variables, the number of CPCs in a county and the driving distance from county centroids to the nearest CPC. In section 1.2 I describe the mission of CPCs, funding sources, and regulatory issues. Section 1.3 describes data sources. In section 1.4 I explain the CPC location choice. In section 1.5 I describe the empirical strategy to identify the effect of CPCs on fertility outcomes. Section 1.6 explains the results and section 1.7 concludes.

1.2 Crisis Pregnancy Centers

CPCs are relatively small non-profits. On average, the organizations in the analysis sample had annual revenues of $230,275 in 2018. 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. Almost all CPCs offer 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. The ultrasounds are typically performed by Registered Diagnostic Medical Sonographers. A small share of CPCs employees registered nurses, OBGYNs and other medical professionals. Further, some CPCs have partnerships with off-site physicians. Beyond health services, centers provide ongoing classes on pregnancy, relationships, and parenting. 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.

The founder of the first CPC, Robert Pearson, published a 93-page manual on how to start a CPC (Pearson, 1984). The author recommends that activists locate CPCs near abortion facilities, choose neutral-sounding names and show women a slide show about the health risks of abortion. Existing research on CPC service provision suggest that many CPCs follow a model as outlined in the Pearson guide. 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). Cartwright, Tumlinson, and Upadhyay (2021) found that 13.1 percent of women searching for abortion services online visited a CPC during their pregnancy. Living closer to a CPC was also associated with greater odds of visiting a CPC and women who had visited a CPC were 21 percentage points less likely to have had an abortion. Jacobson and Royer (2011) show that acts of extreme violence by "pro-life" activists against abortion providers reduces abortion services in targeted areas.

In the 2021/22 Fiscal Year, $89 million of federal and state funding has been allocated to CPCs across a dozen states. 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.

1.2.0.1 Abstinence Education Programs. Sex education in public schools is, typically, either abstinence-based or comprehensive. Comprehensive education includes teaching on the use and benefits of contraceptives. Abstinence education teaches teenagers that abstaining from sexual activity is beneficial and sexual abstinence outside marriage is standard. Traditionally, local school boards and state legislatures decide on the provision and nature of sex education programs to students. Over the past three decades, abstinence sex education curricular have become more widely taught, with some states mandating them (Carr and Packham, 2017). The federal government has became increasingly important to funding these programs. Congress has recognized the long-term and social consequences of teenage pregnancy and authorized the U.S. Department of Health and Human Services (HHS) to administer programs with a focus on teen pregnancy prevention. In total, seven federal programs addressing teenage pregnancy have been implemented, four of which are currently in place (Fernandes-Alcantara, 2018).[3] Historically, the greater share of sex education funding is allocated to comprehensive sex education. However, abstinence education has received increasing amounts of funding, starting during the Presidency of George W. Bush. Spending on abstinence education rose from $80 million in Fiscal Year 2001 to $137 million in FY 2004 and $204 million in 2007 (Sabia, 2006). Alongside abstinence education, CPCs became a focus of federal policies. In 2000, Congress created the Special Projects of Regional and National Significance Community-Based Abstinence Education Program, which became later known as the Community-Based Abstinence Education (CBAE).[4] The CBAE program was supported from 2001 to 2010, with funding ranging from $20 million to $108.9 million per year. Under CBAE funding for abstinence education has been directed at CPCs and other public and private organizations. Organization that offers comprehensive sex education programs that promote

[3]The discontinued programs are the Adolescent Family Life (AFL) program, the Community-Based Abstinence Education (CBAE) program, and the Competitive Abstinence-Only program. Congress appropriated annually between $1.4 million and $30.4 million to the the AFL program, which was established in 1981 and funded through the Fiscal Year 2001. The AFL program focus was initially on pregnancy and parenting. Abstinence education was added in 1998 (Fernandes-Alcantara, 2018).

[4]The CBAE program was a competitive grant authorized under Title XI, 1110, of the Social Security Act. Funding recipients had to conform to the eight-point definition outlined in 510 of Title V of the Social Security Act. Initially, CBAE was administered by the Maternal and Child Health Bureau. In 2005, control over CBAE shifted to the Administration for Children, Youth, and Families (ACF).

the use of contraceptives are excluded from CBAE funding. CBAE ended in 2010. From Fiscal Years 2012 to 2015, the Competitive Abstinence-Only program appropriated funding with an exclusive focus on abstinence education, providing between \$4.7 million and \$10 million annually Fernandes-Alcantara, 2018. Overall, it is clear that CPCs have received substantial amounts of federal funding to provide abstinence education but the precise number is unknown. The evidence, with some exceptions, suggests that abstinence education is ineffective at preventing teenage sexual intercourse or pregnancy. Kohler, Manhart, and Lafferty (2008) find abstinence-only education did not reduce the likelihood of engaging in vaginal intercourse. Cannonier (2012) finds that Title V abstinence-based funding only significantly decreases birth rates for white 15-17-year olds but not other groups. Trenholm et al. (2008) find that abstinence education caused no difference in teen sexual activity and no differences in rates of unprotected sex. Similarly, Carr and Packham (2017) find that state-level abstinence education mandates have no effect on teen birth or abortion rates. Aside from this study, abortion is a largely overlooked outcome in the abstinence education literature. Preventing abortion is not an explicit goal of sexual abstinence eduction but some abstinence education providers, for instance CPCs, are anti-abortion.[5] This study contributes to our understanding of abstinence education with respect to fertility outcomes, and in particular, abortion.

1.2.0.2 TANF & Title X Funding. Today, in at least a dozen states, CPCs are funded by federal programs, totaling \$89 million in the Fiscal Year 2021/22 (AP, 2022) (see Table A.1 for funding figures by state). Much of the funding stems from block grants the federal government issues to states under the TANF program. TANF is well known for its monthly assistance payments to low-income families with children.[6] The sporadic use of TANF block grants to fund CPCs began

[5]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.

[6]TANF also funds a wide range of services that serve one of four purposes (see Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA)):

1. Provide assistance to needy families so that children can be cared for in their own homes or in the homes of relatives
2. End the dependence of needy parents on government benefits by promoting job preparation, work, and marriage
3. Prevent and reduce the incidence of out-of-wedlock pregnancies

in the 2000s, though an early attempt at legislating federal CPC funding under TANF failed in the senate in 2005. The State of Texas allocates the most TANF funds to CPCs under a program called "Alternatives to Abortion." In the Fiscal Year ending in 2021, Texas allocated $46,156,327 to four contracted organizations that distribute funds to individual CPCs. These funds have in some instances been allocated without a competitive bidding process. "Alternatives to Abortion" served 126,533 unduplicated clients at 177 CPC locations in the Fiscal Year 2021.[7] This implies an average cost of $365 per client, a cost similar to providing a first trimester abortion to a patient.

In the years 2019 and 2020, some CPCs received funding under Title X, which is the only federal grant program aimed at providing comprehensive family planning and related preventive health services. The largest recipient of Title X funding was Obria, an organization based in southern California that has 48 affiliated CPCs across seven states (New York Times, 2022).[8] To summarize, until the 2010s, most federal funding was broadly under the umbrella of abstinence education but more recently TANF funding has eclipsed other public funding for CPCs.

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 the funds to over 70 affiliated CPCs. Federal funds were first used in the Fiscal Year 2014 and have been supplemented by state funding since 2018. North Carolina has also redirected $650,000 to CPCs from federal Maternal and Child Health Services grants, which are supposed to improve the health of low-income women. South Carolina's Department of Motorvehicles, like most in the United States, sells "Choose Life" license plates. The proceeds are allocated to CPCs.

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4. Encourage the formation and maintenance of two-parent families

[7] Only partial self-reported data on the number of clients served is available in the analysis sample.

[8] Notably, with the passing of the Hyde Amendment in 1980, certain federal funds cannot be used to pay for pregnancy termination. Title X funds cannot be used to pay for abortion services.

1.2.1 Regulation of Crisis Pregnancy Centers

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 for their services.

Some states have made attempts to oversee and regulate CPCs. In the early 2000s, the Office of the Attorney General of the State of New York investigated CPCs in the state in regard to misleading advertising and inappropriate medical counseling. A preliminary investigation raised concerns that CPCs advertising and practices could lead women to believe that they provide medical services, in particular, that they provide abortion services. Several CPCs were issued subpoenas. In 2002, an agreement was reached with one CPC. The consent decree imposed a number of requirement on the CPC. Among other items, the CPC is required to inform persons who inquire about abortion or birth control that it does not provide (or refer) those service. Further, the CPC has to inform that it is not a medical facility and that only medical providers can confirm a pregnancy and provide medical advice (Office of the Attorney General, New York, 2002). The remaining subpoenas were dropped but the final outcome of is not documented. [9]

In 2015, The State of California passed the California Reproductive Freedom, Accountability, Comprehensive Care, and Transparency Act (FACT Act) (CA AB 775). This legislation intended to limit CPC practices that were deemed deceptive, particularly in regard to anti-abortion counseling. Under the law, unlicensed CPCs must 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

[9] It is important to note that although CPCs provide some services that appear to be medical in nature, such as pregnancy tests and ultrasounds, that does not imply that CPCs provide medical services. Some of the existing literature has referred to these types of services as "medical services." The consent decree in the State of New York required the CPC to clarify that over-the-counter pregnancy tests are not a medical service (Office of the Attorney General, New York, 2002). Therefore, in this text, I add the prefix "non-medical" or "health" to services performed by CPCs that might otherwise appear to be medical in nature but are not necessarily provided by a licensed medical provider.

care, to post a sign that says that the state provides free or low-cost access to reproductive care, including abortions. In the 2018 decision *National Institute of Family & Life Advocates v. Becerra*, the Supreme Court of the United States reversed and remanded the Ninth Circuit and deemed the FACT Act unconstitutional on the grounds that it violates the First Amendment, which protects free speech. Justice Thomas delivered the opinion, criticizing that "one of the state sponsored services the licensed notice requires petitioners to advertise is abortion–the very practice that petitioners are devoted to opposing."

In 2021, The State of Connecticut enacted PA 21-17 that prohibits deceptive advertising crisis pregnancy centers that "do not directly provide, or provide referrals for, abortions or emergency contraception." The law is challenged by Care Net Pregnancy Resource Center of Southeastern Connecticut. Specifically, PA 21-17 prohibits the dissemination of deceptive statements about the provision of pregnancy-related services. Further, PA 21-17 defines limited services pregnancy centers as a facility that does not provide abortions, abortion referrals or emergency contraception. To summarize, CPCs are almost universally unregulated. This is in stark contrast to the licensing and regulatory requirements that abortion providers face in many states.

1.3 Data

I study the location choice of CPCs and the effect of CPCs on fertility outcomes. This analysis requires detailed longitudinal data on CPCs, specifically the geographic location and timing of opening. Second, outcome measures of births and abortions are needed. Third, data on county characteristics (including unemployment, election vote shares, religiosity) is required. I construct a dataset with these three elements for two states, North Carolina and South Carolina, for the time period 1990 to 2019. I report summary statistics at the county level for the first and last year in the sample in Table 1.1 and Table A.3.

Table 1.1: County Characteristics: NC & SC 2019

	All		No CPC		CPC only	
	Mean	SD	Mean	SD	Mean	SD
Female Population Age 10-44	24,744	(39,978)	8,640	(9,475)	39,849	(54,239)
Share age 10-19	0.29	(0.02)	0.30	(0.01)	0.29	(0.02)
Non-white share	0.33	(0.19)	0.41	(0.20)	0.26	(0.16)
Unemployment rate	3.97	(0.94)	4.26	(1.09)	3.64	(0.77)
House Price Index (County)	211	(31)	211	(22)	214	(38)
No. of CPCs	1.00	(1.38)	0.00	(0.00)	1.95	(1.60)
Dist. Nearest CPC in miles	14.78	(13.53)	27.67	(10.66)	5.50	(4.43)
Non-profit Avg. Pay (1000s)	3.64	(0.38)	3.66	(0.34)	3.64	(0.41)
Abortion provider (or referrer)	0.39	(0.49)	0.49	(0.50)	0.00	(0.00)
Pregnancy count	1,260	(2,282)	441	(447)	1,958	(3,168)
Pregnancy rate	52.15	(12.64)	52.85	(10.57)	49.66	(13.63)
Abortion count	214	(475)	65	(78)	337	(665)
Abortion rate	7.13	(2.77)	7.10	(2.64)	6.81	(2.81)
Abortion rate girls age 10-19	2.51	(1.35)	2.61	(1.55)	2.27	(0.96)
Birth count	1,040	(1,806)	373	(376)	1,611	(2,498)
Birth rate	44.70	(11.67)	45.42	(9.94)	42.56	(12.57)
Birth rate girls age 10-19	12.05	(4.73)	13.69	(5.33)	10.64	(3.87)
Mainline protestant share	0.19	(0.08)	0.17	(0.07)	0.20	(0.09)
Evangelical protestant share	0.30	(0.12)	0.28	(0.12)	0.32	(0.11)
Catholic share	0.02	(0.02)	0.02	(0.02)	0.03	(0.03)
Black protestant share	0.04	(0.04)	0.06	(0.05)	0.03	(0.03)
U.S. House GOP vote share	0.60	(0.19)	0.58	(0.20)	0.58	(0.15)
N	142		61		56	

1.3.1 CPC and Clinic Data

The new database of CPCs is an important contribution of this paper. I construct a data set of addresses of crisis pregnancy centers 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). The number of locations exceeds the number of CPC organizations because some organizations operate at multiple facilities. See Figures A.1 to A.4 for CPC and clinic locations over time. Further, I observe when a CPC is relocated.[10] There are CPCs are typically 501(c)(3)) nonprofit organizations. For almost every organization addresses and foundation dates ("ruling dates") were obtained from financial disclosure forms. I validate this data against information from a database maintained by the umbrella organization Birthright that contains the majority of CPCs, both its affiliates and independent CPCs. I further cross-check this information using internet research for websites of each facility and phonebook entries. In the case of CPCs, I also can observe some address changes and closures in financial fillings from news articles too. Between 1990 and 2019, the period for which fertility data is available, I observe the opening of approximately two-thirds of the CPCs in North and South Carolina. Figures A.1 to A.4 show CPCs and abortion providers over time, overlayed on a map of county-level abortion rates in N.C. and S.C.

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. This data allows me to observe address changes and closures for the years 2013 - 2018. 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

[10]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.

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.

1.3.2 Outcome Data

The primary outcomes considered here are the abortion rate and the birth rate in a county, defined as the abortion (birth) count per 1,000 women age 10 to 44, in years 1990 to 2019. I also consider the pregnancy rate. The number of pregnancies is defined as the sum of births, abortions and fetal deaths. The fertility counts were obtained from administrative and vital records provided by vital statistics offices in North Carolina and South Carolina. Note that all males, and females below the age of 10 or above the age of 44, are excluded from the analysis.[11] Rates are constructed using Census data that contains demographic information on age groups, ethnicity, and county of residence. The data on abortions, births, and fetal deaths was provided by county of residence of the women, aggregated by age groups and ethnicity (white/non-white).[12] In most states, including North Carolina and South Carolina, abortion providers are required to submit regular and confidential reports to the state. The patient's address are self-reported to the abortion service provider, who provides this information to the state as well. Birth count data is sourced from birth certificates. The year 1995 saw 29,938 abortions to North Carolina residents and 11,075 abortions to South Carolina residents. This number had dropped to 23,018 in North Carolina in 2018 (a 28 percent change), and 10,716 in South Carolina in 2016 (a 3 percent change).

1.3.3 Variable Construction

Two key variables are needed to study CPCs. The first variable of interest is CPC, which is defined as the number of CPCs per 10,000 women of age 10-44 in a county in a given year. CPC is a continuous variable constructed using the information on the number of CPCs in a county

[11] 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 et al., 2000).

[12] 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.

and Census population data. A typical county in the sample has approximately 10,000 women of childbearing age. 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)). The second variable is the driving distance from a population-weighted county centroid to the nearest CPC, which is represented by $Dist$. This variable is a proxy for how far women have to travel to reach the closest CPC. It is well-established that driving distance is relevant to the decision of an individual to utilize a provider, in this case, a CPC. Because distance matters to the client, it is plausible that a CPC location is chosen in such a way as to minimize the distance to the population that is being served. The driving distance was obtained from the HERE geolocation and routing service using an API.[13]

1.4 The Location Choice of Crisis Pregnancy Centers

The non-profit sector is primarily community-based and locally operated (Wolpert, 1993; Bielefeld and Murdoch, 2004). Therefore, needs and resources in a particular region (i.e. county or city) determine the number of non-profit organizations. In the sociology and economics literatures, some attention has been paid to the location choice of CPCs. 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, Crubaugh, and Estep (2017) found that CPC location is associated with the share of evangelical and catholics in a county. Both studies are cross-sectional, providing a snapshot of CPC locations and operations at one point in time. What we lack to date is evidence from longitudinal data on the location choice of CPCs.

I conceive of CPCs as independent, utility maximizing entities that choose locations under a cost constraint. CPCs want to prevent abortions and provide social services. Intuitively, we can think of utility increasing with the number of clients served (up to a point). I use a logit model to

[13]Since routing is only available for the 2021 road network, the shortest route in previous years may have been different from the calculated route.

explain the location choice of a CPC (McFadden, 1973).[14] The opening decision is made across all counties and every year between 1990 and 2019.[15] The utility of the CPC consists of observable and unobservable components. Observable attributes of the choice alternatives include existing CPCs and the abortion rate. 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 – $\epsilon_{c,t}$ – 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.

The location choice problem can be 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 population density/log of county population and the abortion rate proxy local demand for a CPC. The he 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 in federal elections. Non-profits, like any other organization, operate under cost constraints. The two largest cost items for CPCs are mortgages or rents (proxied by real estate prices), and wages (proxied by the wage cost of other social service non-profits in the area).

[14]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 $U_{ij} = \eta_{ij} + \epsilon_{ij}$.

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

Finally, CPCs compete with existing abortion providers, so the distance of a CPC location to the nearest abortion clinic enters the model.

Since a county may experience more than one CPC opening, the number of CPCs in a county follows a renewal process (a repeated hazard). Following Mroz (2012), I estimate the count of CPCs with a hazard model decomposition. 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 evaluating the following logistic regression equation using maximum likelihood:

$$Logit(p) = ln\left(\frac{p}{1-p}\right) = \tag{1.1}$$

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

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 of 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 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 (the county is dropped from the estimation sample).

1.5 The Impact of CPCs on Fertility Outcomes

CPCs seek to affect fertility outcomes by providing pregnancy counseling and abstinence education. Pregnancy counseling is aimed at reducing the probability that a woman terminates her pregnancy. CPCs that counsel and lend support to a woman who is fully aware of the CPC mission can be seen as providing a valuable community service. As part of their counseling, some CPC provide referrals to adoption services, which may be a meaningful alternative to abortion for some women. Any observed changes in fertility are plausibly the result of CPCs affecting the fertility decision of a woman who is on the margin, that is, uncertain whether to have a child or terminate the pregnancy. There is some probability that this woman visits a CPC and that this visit changes the pregnancy outcome.[16]

Existing research suggests that some CPC clients are seeking abortions services and are not aware of the "pro-life" mission (Cartwright, Tumlinson, and Upadhyay, 2021). According to Swartzendruber et al. (2018), 58% of CPC websites do not indicate that they are neither abortion providers nor referrers. Further, a survey conducted in the State of Georgia, indicates that most adults who had visited a CPC held misconceptions about CPC policies and practices (Swartzendruber, Solsman, and Lambert, 2021). Thus, CPCs are potentially delaying or preventing access to medical care, in particular, as barriers to abortion access are mounting. Lu and Slusky, 2019 show that increases in travel distances to abortion providers increases the birth rate and Fischer, Royer, and White, 2018 find that reduced access to abortion and family planning services lowered the abortion rate. Studies by Lindo et al., 2020 and Quast, Gonzalez, and Ziemba, 2017 also show that greater distances to abortion clinics reduce the abortion rate. Abortions are only provided up to a certain number of weeks of gestation, which varies by state. Moreover, a number of states impose waiting periods between the first abortion consultation with a physician and the pregnancy termination.[17] CPC-provided counseling, typically involving an ultrasound and information about

[16] Consider the decision to be somewhere between certain birth and certain abortion. Women who are at either end of the spectrum are neither targeted by CPCs nor likely to revert their decision.

[17] Women that are being denied an abortion due to gestational age limits suffer negative long-term economic consequences Miller, Wherry, and Foster (2020).

abortion risks, is intended to change women's decision with respect to the pregnancy outcome. Systematic evidence on the information content of CPC counseling is lacking but public health research has 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.

The second channel, abstinence education, is about the role of CPCs before a pregnancy occurs. CPCs may plausibly increase or decrease the rate of unintended or unwanted pregnancies. Given the mixed evidence of the efficacy of abstinence education, a CPC may, inadvertently, increase the chance of pregnancy among teenagers and young adults. The relative importance of this channel will be studied in two ways. Any observed difference in the magnitude of the effect of CPCs on the abortion and birth rates for different age groups provides a clue as to the role of sexual abstinence education. For example, if CPCs cause both the abortion and birth rates to decline among teenage girls, effective abstinence education would be a plausible explanation. Hence, I compare fertility outcomes in counties where CPCs offer abstinence education to counties without abstinence education.

1.5.1 Model

The goal is to identify the causal effect of CPCs on the (log) abortion rate.[18] Using a binary indicator for the presence of a CPC (the treatment) in a given county would be an imperfect measure because counties vary in population size and some counties have several CPCs. Hence, I construct a treatment measure that captures the treatment intensity that women in a county experience: The number of CPCs per 10,000 women age 10-44 in a county. The goal is to identify a parameter which captures a weighted average of causal responses to a unit change in treatment. Intuitively,

[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, birth and pregnancy rates. The inverse hyperbolic sine function is defined at zero. This function closely approximates the natural log transform (though less closely near zero), which is why "log" is used throughout to describe the outcome variables.

this can be thought of as a treatment dose. To identify the causal effect of CPCs on the abortion rate, I estimate Equation (2) with a standard fixed effect estimator and using an instrumental variable approach:

$$Y_{ict} = \theta_0 + \theta_1 CPC_{ct} + \theta_2 Age_{ict} + \theta_3 CPC_{ct} \times Age_{ict} +$$
$$+\theta_8 DistClinic_{ct} + \theta_9 X_{ict} + \gamma_s + \gamma_c + \alpha_t + \epsilon_{ict} \tag{1.2}$$

Y_{ict} represents the fertility outcome of interest. The unit of observation is a demographic age-ethnicity group i in county c in year t. The effect of CPCs on a fertility outcome 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. This permits heterogenous treatment effects by age. This is important because CPCs are focused on providing services to young, unmarried women, which suggests possible differential treatment effects by age. 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.

1.5.2 Fixed Effects Estimation

Estimating the effect of CPCs on fertility outcomes using a generalized difference-in-differences design makes use of within-county variation over time while controlling for aggregate time-varying shocks. This approach provides causal evidence if key assumptions are met. A number of authors have shown that, in the case of a binary treatment, fixed effects estimation only identifies the average treatment effect on the treated (ATT) if the parallel trends assumption holds and the treatment effect is homogenous (see, for example, Goodman-Bacon 2021; Baker, Larcker, and Wang 2021). Callaway and Sant'Anna, 2021 discuss the challenges of identifying average causal response parameters. For continuous treatments, both the level and slopes of the dose-response relationship are required to gain a complete understanding of the treatment effects of a group-varying continuous treatment. They show that a stronger parallel trends assumption needs to hold in a scenario with multiple time periods and staggered adoption of continuous treatments. This stronger assumption restricts paths of treated potential outcomes by treatment dose group: All dose groups treated at a particular time need to follow the same path of potential outcomes at every dose. An example of a violation of this assumption is a CPC choosing to locate in one county over another because it can more effectively change fertility outcomes. Callaway and Sant'Anna, 2021 show that if this assumption is violated, selection bias is introduced to the estimated effect. This bias of unknown sign stems from heterogeneity in the response to a particular treatment dosage. Some of this heterogeneity in the response can be modeled explicitly. CPCs focus on serving young women, which suggests that age-specific heterogeneity in the treatment effect is present. To address this, I allow the effect of CPC_{ct} to vary by age group. Lastly, I have assumed that CPCs only serve women in the county where the CPC is located. This is a fair assumption because CPCs focus on serving a local population. However, spillover effects–women visiting a CPC in a neighboring county–are possible. The "no spillovers" assumption is relaxed by estimating Equation (2) using a treatment variable that measures the distance from the county centroid to the nearest CPC, $Dist_{ct}$, instead of the CPC_{ct} variable. The identification requirements for this specification are similar, because the distance variable is also continuous.

1.5.3 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. Bharagava (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, and Klaauw (2010). I construct instrumental variables to estimate this dynamic model using two-stage least squares. Instrumental variable estimators were developed by a number of authors (see, for example, Sargan 1959; Amemiya 1974; Hansen 1982; Newey 1990). In essence, 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:

$$AR_{ct} = x_{ct}^{'}\beta + \epsilon_{ct}, \quad \mathbf{E}\left[\epsilon_{ct}|z_{ct}\right] = 0 \tag{1.3}$$

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 Newey 1993; Heckman and Robb Jr 1985). 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 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."[19] The optimal instruments are defined as:

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

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

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).

[19] 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 time series of exogenous factors, $z_{c1990,...,ct}$, and simulated values for the endogenous variables in x_{ct}, are used to generate $\mathbf{E}\left[\widehat{CPC}_{ct}\middle| z_{c1990,...,ct}\right]$ and $\mathbf{E}\left[\widehat{Dist}_{ct}\middle| z_{c1990,...,ct}\right]$. 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 1.4, 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.[20] Using the logit prediction, a "coin flip" determines if a new CPC opens in a particular county and year.[21] The "coin flip", determining the opening of a CPC, 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" 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 $\mathbf{E}\left[\widehat{CPC}_{ct}|z_{c1990,...,ct}\right]$ and $\mathbf{E}\left[\widehat{Dist}_{ct}|z_{c1990,...,ct}\right]$. 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 $\mathbf{E}\left[\widehat{Dist}_{ct}|z_{c1990,...,ct}\right]$. See Appendix A for a detailed description of the process used to construct the instrumental variables.

[20]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 1.2.

[21]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.

1.5.4 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:

$$CPC_{ct} = \theta_0 + \theta_1 \widehat{CPC}_{ct} + \theta_2 Age_{ict} + \theta_3 \widehat{CPC}_{ct} \times Age_{ict} + \theta_4 NonWhite_{ict} +$$

$$+ \theta_5 Age_{ict} \times NonWhite_{ict} \ + \theta_6 DistClinic_{ct} + \theta_7 X_{ct} + \gamma_c + \alpha_t + \epsilon_{ct} \tag{1.4}$$

There is one first first-stage for every interaction of $\widehat{CPC}_{ct}$ and Age_{ict}. In the first stage, CPC_{ct}, the number of CPCs in county c and year t, is a function of the instruments $\widehat{CPC}_{ct}$, and the interactions of $\widehat{CPC}_{ct}$ with each age-group, as well as Age_{ict}, $NonWhite_{ict}$, $DistClinic_{ct}$, and X_{ct}. County fixed effects are denoted by γ_c and time fixed effects are denoted by α_t. The second stage is:

$$Y_{ict} = \theta_0 + \theta_1 \widehat{CPC}_{ct} + \theta_2 Age_{ict} + \theta_3 CPC \times Age_{ict} + \theta_4 NonWhite_{ict} +$$

$$+ \theta_5 Age_{ict} \times NonWhite_{ict} + \theta_6 DistClinic_{ct} + \theta_7 X_{ct} + \gamma_c + \alpha_t + \epsilon_{ict} \tag{1.5}$$

In this specification, Y_{ict} is the log of the abortion rate (the birth rate or pregnancy rate). The unit of observation is a demographic age-ethnicity group i in county c in year t. The age groups are women age 10-19, 24-29, 30-34, and 35-44. The variable 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. The effect of CPCs on a fertility outcome Y_{ict} is given by θ_1, the number of CPCs per 10,000 women age 10-44 in a county, and θ_3, the interaction of the number of CPCs and one of the five age groups. This allows for the effect of CPCs to vary by age.

1.5.5 Event Study

To strengthen the argument that I am measuring a causal effect of CPCs on the local abortion rate I estimate the following event study specification:

$$Y_{ct} = \sum_{j=-20}^{20} \beta_j C_{ct}^j + \beta_1 Clinic_{ct-1} + \beta_2 \mathbf{X}_{ct-1} + \mu_c + \theta_t + \gamma_s + \delta_{HHS} \times t + \epsilon_{ct} \qquad (1.6)$$

Here C_{ct}^j are binned treatment variables that indicate the opening of the first (second, third) CPC in a county, an approach to estimating staggered treatment as discussed by (Schmidheiny and Siegloch, 2019). Counties that experience a CPC opening prior to 1990, the first year in the analysis sample, are excluded from the event study. A key assumption is that the first opening has the same effect as a second or third opening in the same county, and that the fourth and subsequent CPC openings have no additional effect.[22] This specification contains the same lagged covariates, $Clinic_{ct-1}$ and $\mathbf{X}_{ct-1}$, as Equation (2). The county fixed effect is denoted by μ_c, the year fixed effect is represented by θ_t, and $\delta_{HHS} \times t$ are health region-specific time trends. Health regions are defined by the state and comprise several counties. The event study framework has an advantage over the standard fixed effect estimator, insofar as it is unaffected by the variance-weight issues raised by (Goodman-Bacon (2019). However, assumptions on the homogeneity of the the treatment effects across units and time do need to be met for the event study estimates to be unbiased (Baker, Larcker, and Wang, 2021).

1.5.6 Further Analysis: CPC Services

To study which CPC services are driving changes in the abortion rate, I categorized all reported CPC services into four groups. The service groups are standard services that most CPCs provide (including counseling, pregnancy tests and ultrasounds), health services (onsite medical staff or

[22] A fourth CPC and subsequent CPC openings occur relatively late in the observed period and the inclusion of these CPC openings would shorten the event study analysis window substantially. Only four counties experience a fourth or fifth CPC opening during the analysis period. Note that this estimation equation using the treatment variable C_{ct}^j is misspecified, because it does not take into account the population size of the county served by the CPCs. The event study framework of course does not allow for a continuous treatment variable.

offsite partnership with physician, and STI testing), maternal services (adoption services, maternity home) and abstinence education & sexual integrity classes. To study the role of services I estimate the following equation:

$$Y_{ict} = \theta_0 + \theta_1 CPC_{ct} + \theta_2 H_{ct} + \theta_3 M_{ct} + \theta_4 A_{ct} + \theta_5 Age_{ict} + \theta_6 NonWhite_{ict} +$$
$$+\theta_7 Age_{ict} \times NonWhite_{ict} + \theta_8 DistClinic_{ct} + \theta_9 X_{ct} + \gamma_c + \alpha_t + \epsilon_{ict} \qquad (1.7)$$

This equation closely resembles equation (1). Importantly, the continuous variables H, M, and A are added. Each of these variable counts the number of services in that category in county c and year t across all CPCs in a county, and is adjusted for the population of the county. The variables are zero if no CPCs exist. This analysis shows which type of services are associated with lower abortion rate. A causal interpretation is not possible because CPCs may choose to provide certain types of services in certain communities for reasons related to the local abortion rate.

1.6 Results

1.6.1 CPC Location Decision

The results from the logit model of CPC location choice are in Table 1.2. Most parameter estimates are similar across all three specifications but in some cases the inclusion of county fixed effects flips the estimated sign on factors that are relatively constant over time, for example, the share of non-white women in a county. I focus on the results in column (2), excluding the county fixed effects because they tell a more complete story of CPC location choice. The models without county fixed effects, in column 1 and 2, include time-invariant indicators for the status of a county as metropolitan urban area (reference category), urban area adjacent to metro, urban area not adjacent to a metro, and rural areas. The average marginal effect of the number of CPCs on the probability of a new CPC is - 1.02 percent. Similarly, the greater the distance of a population-weighted county centroid to a CPC, the higher the probability of a CPC opening. For every 10 miles of distance, the the probability of a CPC opening increases by 0.36 percent. This suggests that CPCs do not compete with other CPCs in a Hotelling-style competition. Rather, individual CPCs choose locations where no CPCs services are available, a pattern more consistent with central planning to maximize the number of clients served. The focus on serving many people is also indicated by CPCs choosing to locate in counties with greater populations and urban areas. If a given county has a population that is 10 percent higher than the average county, the probability of a new CPC increases by 1.5 percent.

Table 1.2: Predicting the Opening of Crisis Pregnancy Centers

	(1)	(2)
No. of CPCs (lagged)	-0.000718	-0.0567
	(0.00157)	(0.0147)
Dist. Nearest CPC (lagged)	0.000528	0.000603
	(0.000158)	(0.000960)
Dist. Nearest Clinic (Lagged)	-0.0000122	-0.0000773
	(0.0000839)	(0.000421)
Abortion rate 1000 women 10-44 (lagged)	0.0000723	0.00223
	(0.000926)	(0.00363)
Log. Population (lagged)	0.0205	0.262
	(0.00441)	(0.114)
Pop. share age 10-19 (lagged)	-0.0419	-0.129
	(0.157)	(0.718)
Non-white share (lagged)	-0.0924	0.306
	(0.0256)	(0.499)
U.S. GOP vote share (lagged)	-0.0192	-0.0548
	(0.0150)	(0.0379)
Urban Area adj. Metro	-0.00419	
	(0.00602)	
Urban Area not adj. Metro	-0.00789	
	(0.00853)	
Rural Area	-0.0110	
	(0.0130)	
Share of Protestants (lagged)	0.0379	0.163
	(0.0237)	(0.170)
N	4333	2109
State-County FE	No	Yes
Time Trend	Yes	Yes

Standard errors in parentheses

The focus appears to be on serving white population groups, indicated by a 9.6 percent lower probability of opening in areas with higher shares of non-white population groups. The coefficient of the variable measuring the distance from a CPC to the nearest abortion provider is estimated to be zero, indicating that CPCs do not open in a location to reduce the distance between existing abortion providers and CPCs. However, this is 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. The labor cost in county does not appear to inform the location choice. A higher vote share of the GOP in elections to the House of Representatives is associated with a lower probability of a CPC opening. This is perhaps also surprising because GOP policies align with CPC values and goals. There is also no clear sign that the share of adherents to a particular faith increases the probability of a CPC opening (the reference category is the population share that is not a member of a church). Overall, CPCs are focused on locating in counties with higher population and urban areas. The potential support for a CPC, proxied by shares of evangelical and catholic faith adherents and Republican Party vote shares appears less important.

1.6.2 Fertility Outcomes

The primary goal of this paper is to estimate the causal effect of CPCs on local abortion and birth rates. The main results are in Table 1.3. Increasing the number of CPCs per 10,000 women age 10-44 by one, decreases the abortion rate by 24.7 percent among teenage girls and by 12.7 percent among 20 to 24-year-old women. Women between the ages of 20 and 24 have the highest fertility rates. For women 25 and older the effect of CPCs on the abortion rate remains negative, with point estimates between 5.5 and 11.5 percent. A one unit change in this specification is large, because 1 CPC per 10,000 women corresponds to the 90th percentile of CPC exposure. A more representative change is given by using one third of the standard deviation (0.636) in the number of CPCs per capita. This effect of increased CPC presence can be gauged by dividing the coefficients in Table 1.3 by five. In addition to the presence of a CPC in a woman's county of residence, the distance to the nearest CPC matters. The distance variable is particularly important because it allows for the plausible case that women travel to the nearest CPC regardless of which county it is in.

The first CPC to open in a county drastically reduces the driving distance to the nearest CPC, whereas subsequent CPCs do not substantially reduce the travel distance for women.

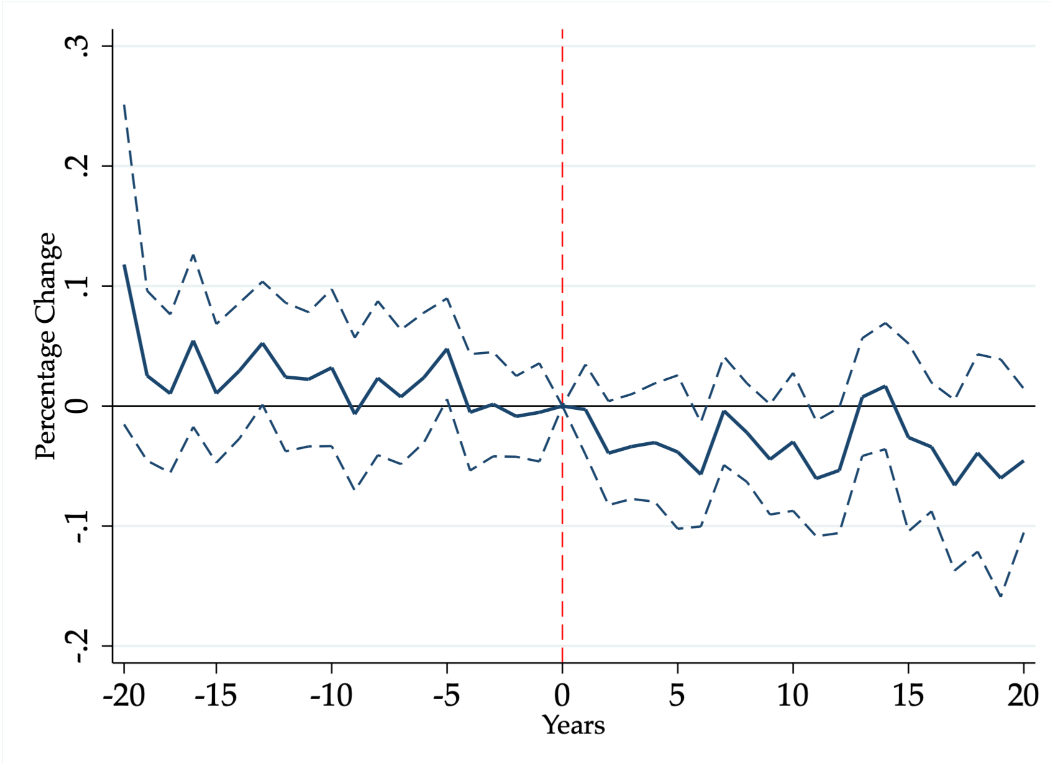
Table 1.3: The Effect of CPCs on the Abortion Rate

	(1)	(2)	(3)
No. of CPCs per capita X Age 10-19	-0.192	-0.198	-0.181
	(0.0324)	(0.0325)	(0.0322)
No. of CPCs per capita X Age 20-24	-0.0929	-0.0985	-0.0812
	(0.0313)	(0.0308)	(0.0288)
No. of CPCs per capita X Age 25-29	-0.0291	-0.0348	-0.0177
	(0.0379)	(0.0375)	(0.0350)
No. of CPCs per capita X Age 30-34	0.00172	-0.00406	0.0131
	(0.0306)	(0.0302)	(0.0283)
No. of CPCs per capita X Age 35-44	0.0192	0.0134	0.0310
	(0.0287)	(0.0291)	(0.0272)
N	43718	43718	43718
R^2	0.664	0.667	0.669
Dep. Var. Mean	2.672	2.672	2.672
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Urban-Rural X Year	No	Yes	No
Health Region X Year	No	No	Yes

Standard errors in parentheses

The event study estimates shown in Figure B.5 also demonstrate that the opening of CPCs in a county leads to an overall reduction in the abortion rate in the short and long term. To illustrate the magnitude of the results, let us translate the estimated percentage changes into absolute numbers. A typical county has approximately 3,000 girls between 10 and 19 years of age. The average abortion rate for this age group is 7.7 and the average birth rate is 26.9. This means 23 abortions and 81 births occur in a given year. A decrease in the abortion rate of 9.2 percent is equivalent to 2.1 fewer abortions to age group in a typical county per year. We also see that the greater the distance that women travel to abortion providers, the lower the abortion rate in the county. Though this distance coefficient is not precisely estimated, the negative sign matches findings in the recent literature on abortion access (Fischer, Royer, and White 2018; Lindo et al. 2020; Lu and Slusky 2019).

Figure 1.2: Event Study: CPC Opening in County (1st, 2nd, 3rd CPC)



The alternative specification that investigates the effect of the distance from the population weighted county centroids to the nearest CPC on fertility outcomes validate the results reported above. The distance variable coefficient indicates that a one mile increase in driving distance from a CPC increases the abortion rate by 0.9 percent among women age 20-24 and by 1.2 percent among teenagers. This effect decreases with greater distance but at a very small rate (see squared distance term). As with the main specification, the effect size approaches zero for older women. The two-stage least square results are smaller, in the range of 0.2 to 0.8 percent, but more precisely estimated. Note that the nearest CPC may be in a county different from the resident county of an individual that experiences a fertility outcome. Counties range in area from 172 to 1133 square miles, with most in the 300 to 700 square mile range. The geometric distance from one border of a county to the opposite border is typically in the range of 15 to 30 miles. The distance coefficients are estimated with less precision than the estimates of the effect of CPCs per 10,000 women age 10-44, which is likely the result of measurement error in the driving distance between women's place of residence (proxied by the population weighted county centroid) and the nearest CPC.

The 2SLS effects of CPCs on the birth rate are approximately zero for teenage girls and women age 20 to 24. For women 25 to 45, CPCs increase the birth rate by 6 to 7 percent. The distance specification shows estimates not different from zero for teenagers and young women and small decreases in the birth rate, in the range of 0.1 to 0.2 percent for every mile of additional driving distance. The event study estimates shown in Figure B.6 also show that the opening of CPCs in a county leads to an increase in the overall birth rate in the long term. Overall, the 2SLS estimation results show that CPCs lower the abortion rate. CPCs also increase the birth rate among all age groups except teenagers.

Equation (10) tells us which services explain the changes in fertility outcomes. Standard services do not cause any additional change in fertility outcomes beyond the presence of CPCs. Only small changes are observed as a result of CPCs providing health services or services to mothers. Counties in which abstinence education is provided see a 6.3 percent reduction in the abortion rate (see column (1)). The birth rate, see column (3), increases by 5.8 percent reduction in the abortion rate, which is a slightly larger change in absolute terms than the reduction in abortions. This suggests that CPC-provided abstinence education increases risk of pregnancy occurrence, while also discouraging women from terminating their pregnancy. Abstinence education is thus an important mechanism by which CPCs change fertility outcomes and prevent teenage abortions.

1.7 Discussion

The observed changes in the abortion and birth rates lead to three joint conclusions. First, CPCs reduce abortion rates, particularly among teenagers and young women. Second, in counties where CPCs offer abstinence education, teenage girls have fewer abortions and more births. Third, CPCs increase birth rates among women 25 and older. The reduction in the abortion rate among teenagers and young women suggests that CPCs are effectively counseling women not to have abortions. Mechanically, if there are fewer abortions, there should be more births. The fact that this is not observed among teenagers is plausibly explained by abstinence and sexual integrity programs increasing pregnancies overall. Existing research shows that abstinence education is largely ineffective at preventing sexual activity among teenagers and pregnancies (see, for example, Trenholm et al. 2008; Carr and Packham 2017). The results presented here suggest that CPC-provided abstinence education increases overall pregnancies, while lowering the abortion rate. The marked increase in the birth rate for women age 25 to 44 suggests that CPC support services may encourage women to have more children later in life.

Chapter 2

Municipal Building Codes and the Adoption of Solar Photovoltaics

2.1 Introduction

Competing societal goals give rise to policy trade-offs. For instance, policy goals defined at the national, or even global level, may conflict with policy goals at the very local level. Local policies that challenge national policy are sometimes referred to as NIMBYism, from 'not in my backyard.' In this paper, we show that municipal policies reduce the pace of solar capacity expansion.

Many governments recognize the necessity of expanding renewable energy to tackle climate change, as well as to ensure energy security in an age of renewed geopolitical uncertainty. Renewable energy targets are often determined by carbon emission reductions goals, 'Nationally Determined Contributions,' under the Paris Agreement. The share of renewable electricity has been increasing substantially across the globe, yet most countries are relatively far from reaching their goals. On a positive note, the widespread use of subsidies to renewable energy has contributed to a decrease in the price of solar installations, exceeding expectations (Creutzig et al., 2017; REN21, 2018). As solar energy reaches grid parity in many countries, governments are phasing out the subsidy schemes used to promote the installation of solar photovoltaics (PV), which are often expensive and regressive (Marcantonini and Ellerman, 2015; Borenstein, 2017). This new era comes with new challenges for academics and policymakers. Assessing the role of non-price obstacles to the adoption of solar PV represents, arguably, the new frontier in research and policymaking. Here, we focus on the role of local policies, whose aims conflict with the national goal of spurring the adoption of solar PV.

Our paper identifies trade-offs between municipal building code requirements and polices aimed at defining the aesthetics of German towns, and the adoption of solar PV. To do so, we combine geolocalized data on the universe of solar installations in Germany with a unique survey on municipalities current and past building codes affecting the adoption of solar PV. While technological advances in the market for solar PV have been consistently improving the aesthetics of solar installations, we observe that German municipalities have become increasingly restrictive in regulating the installation of solar PV. Hence, while from a technological perspective such trade-offs may be in the process of becoming obsolete, from an economic policy perspective analyzing the role of building codes on the adoption of solar PV, an aspect largely neglected so far, seems to be more relevant than ever.

Germany, the country in the world with the highest penetration of solar energy and the most mature market for solar PV, is an ideal place to assess the role of building codes in either preventing the adoption of solar PV. Additionally, Germany is particularly well suited to this inquiry because the country has a decentralized administrative structure, which gives municipalities substantial leeway beyond the federal- and state building codes. A significant share of German municipalities have implemented building codes that explicitly or implicitly regulate the installation of solar panels on buildings, with this share increasing over time.

To date, no comprehensive registry of municipal solar policies exists. A major contribution of our study is to create such a registry based on survey responses from municipal officials. In this survey, delivered to all municipalities in Germany, we ask for information about how the local building code treats the installation of solar panels. Regulations of solar installations in some cases include explicit bans in certain areas or the entirety of the municipality. Some other municipalities have more subtle provisions, for example, such that solar installations cannot be visible from the street. We obtained information on when municipal policies became effective, as well as on past policies no longer in effect. We match this information to federal data resulting from the mandatory reporting of the location and technical specification of solar panels connected to the electric grid and municipal-level demographic and electoral statistics.

Municipalities do not randomly implement solar policies. First, our study explores the motivation for, and nature of, municipal solar policies. Second, we want to understand the causal effects of municipal policies on the adoption of solar photovoltaics. To this end, we devise an empirical strategy that addresses the challenge of estimating the causal effects of policies that are endogenously adopted. Our matched difference-in-difference approach also takes into account lessons from the recent advances in the microeconometric literature (see Baker, Larcker, and Wang, 2022; Roth et al., 2022; Abadie and Spiess, 2021).

We find that a significant portion (15.1%) of the municipalities in our sample have one or more of the local solar policies we study. Overall, we find that municipalities that implement any type of policy have 8.9 percent fewer solar photovoltaic installations and a 10.4 percent smaller solar capacity, effects driven mostly by small to medium-sized installations of 5-10 kW, consistent with the policy goals of shaping the urban built environment. The larger effect on capacity suggests that municipal policies are effective on both the extensive and intensive margins, leading to less adoption as well as smaller installations conditional on adoption.

This paper contributes to several strands of literature. First, an established literature on NIMBYism, including in relation to energy and environmental issues (e.g. Smith and Desvousges, 1986; Frey and Oberholzer-Gee, 1997; Levinson, 1999; Fischel, 2001; Feinerman, Finkelshtain, and Kan, 2004; Krekel and Zerrahn, 2017). Second, a growing literature on the economics and policy of solar adoption (e.g. Borenstein, 2017; Crago and Chernyakhovskiy, 2017; De Groote and Verboven, 2019; Gerarden, 2018; Gillingham and Tsvetanov, 2019). Third, a broader literature on the role of building codes in the transition towards a greener economy (e.g. Aroonruengsawat, Auffhammer, and Sanstad, 2012; Jacobsen and Kotchen, 2013; Levinson, 2016; Kotchen, 2017). Fourth, a complementary strand of literature analyzing the role of building codes in shaping urban environments and preserving the cultural and historical heritage of towns (e.g. Been et al., 2016; Zhou, 2021).

In terms of policy implications, our paper confirms and quantifies the trade-off between national and global climate mitigation goals and local historical preservation. While our analysis is positive and thus agnostic on whether historical preservation should prime over cost-effectiveness considerations related to the transition to a cleaner economy, we do note that the rapid technological evolution in solar photovoltaic technology has not only led to lower prices for solar panels but also to more options in terms of quality, in particular with respect to how ‘invasive’ solar panels may be. Going forward, such solutions may relax the trade-off that this paper analyzes, making some of the regulations that we cover obsolete or amendable. 'Invisible' solar installations could indeed often be compatible with the aesthetics of historical towns, increasing the potential for solar energy wherever a conflict arises between renewable energy goals and local preservation. Making solar 'invisible', either through regulations prescribing where solar panels can be located in historical districts or by prescribing the use of photovoltaic roof tiles, may still limit adoption indirectly through peer effects, which the literature finds to depend on an installation's visibility (see Carattini, Levin, and Tavoni, 2019 for a review). Yet, the direct effect of allowing for photovoltaic roof tiles, even if more expensive than conventional solar installations, could already substantially expand solar capacity in historical towns and other areas where similar aesthetic considerations apply.

The remainder of the paper is organized as follows. Section 2.2 presents the economic and policy background. Section 2.3 describes our data and methodology. Section 2.4 discusses the identification strategy and estimation. Section 2.5 presents our empirical results. Section 2.6 concludes.

2.2 Background

As part of the European Union's commitment to the Paris Agreement, Germany strives to become carbon neutral by 2050 (BMWi, 2016). Achieving carbon neutrality implies boosting considerably the uptake of renewable energy in the country, as does increasing energy security and reducing reliance on energy imports from third countries, issues that are back at the forefront of policymaking in recent times amid renewed geopolitical uncertainty. The primary policy instrument that has been used over the last three decades to promote renewable electricity is a feed-in tariff scheme (FIT) that guarantees a fixed price for green power. Germany first implemented this type of subsidy for electricity production from all renewable energy sources in 1991, as part of the Electricity Feed-in Law, or Stromeinspeisungsgesetz (SEG) (Stromeinspeisungsgesetz, 1990). The SEG required grid operators to purchase electricity produced by solar photovoltaics at a price equalling 90 percent of the average consumer price per kilowatt hour. In 1995, this corresponded to 8 cent/kWh, which did not cover the cost of electricity production from solar photovoltaics (Beste and Kälke, 2013). Hence, in 2000, the Renewable Energy Sources Act ("Erneuerbare-Energien-Gesetz" or EEG) replaced the SEG (Erneuerbare-Energien-Gesetz, 2000). Under the EEG, FITs are differentiated by energy source to offset technology-specific cost disadvantages compared to conventional power generation (Böhringer et al., 2017).

Particularly for solar photovoltaics, the EEG dramatically increased feed-in-tariffs compared to the preceding scheme under the SEG. The EEG guarantees producers a fixed above-market price for renewable energy for 20 years from the date of installation. The guaranteed rate for electricity from solar photovoltaics was 50.6 cent/kWh in 2000, and has since dropped to 9.4 cent/kWh in 2020.[1] The EEG prescribed a steady decline in the FIT in anticipation of falling renewable energy generation cost. Any difference between feed-in tariffs paid by the grid operators and the market price is passed on to electricity consumers as a surcharge on the electricity bill. This framework and the structure of the FIT has been retained in a series of revisions of the EEG in 2004, 2009, 2012, 2014, and 2017. The subsidies fueled the growth in renewable energy production in Germany. The share of renewable energy in gross electricity consumption increased from 3.4% in 1990 to 6.2% in 2000 and to 31.7% in 2016, with solar energy accounting for approximately 20% of all renewable electricity in 2016 (AGEE-Stat, 2017).

The SEG and EEG are federal policies, but lower administrative units -- states, districts, and municipalities -- can alter their impact. Germany has a federal system of government that is shaped by the principle of subsidiarity, which holds that political issues should be addressed, wherever possible, at the most immediate level. The lowest administrative units are the municipality ("Gemeinde") and collective municipality ("Gemeindeverband"), superseded by districts, governmental districts, and the 16 states ("Länder"). Each state has their own building code that provides a framework for policies at the municipal level. With respect to solar photovoltaics, there are only very minor differences in policy across states. Most importantly, no state requires an application or permit to install solar panels, though municipalities are free to implement regulations beyond

[1]This fixed rate has been offered to owners of solar installations with a capacity under 30 kW, with slightly lower rates for higher capacity solar installations.

the state building code.[2] As of June 2019, there were, for the purpose of this study, 4,691 independent municipalities and 758 collective municipalities.[3] Collective municipalities are a union of at least two municipalities with the purpose of shared governance, administration and policy, with the constituting municipalities retaining some degree of autonomy. Commonly, collective municipalities are governed by one council and a first mayor. Municipal development, taxes and fees, statutes, ordinances, building codes, and municipal services are typically under the purview of the collective administration, though the degree of integration varies.[4] In sum, both independent and collective municipalities have far-reaching authority to enact building regulations that may affect solar adoption.

In this study, including in the survey to municipalities that we describe in the next section, We distinguish between four types of municipal solar policies: Bans, permit requirements, regulations, as well as policies promoting solar adoption. Bans, permit requirements, and other types of regulation are often implemented to preserve the appearance of historical buildings and districts. In our sample, which we describe in the following section, 34% percent of municipalities that implement solar policies are historical towns (see Table 2.1). Of the 4 policy types we study, bans are straightforward and prohibit homeowners from installing solar panels. Permit requirements are municipal policies that mandate homeowners to either apply for permission to install solar panels or submit building plans to obtain planning permission. Solar regulations cover all other types of policies that municipalities may implement to regulate solar installations. In our study, we request that municipalities explain what their regulation entails. There are three prevalent types of solar regulation that we ask about. These common regulations mandate (1) that solar panels are not visible from the street, (2) do not reflect light on other buildings or the street, and/or (3) that solar panels are integrated in the walls or roof of a building. Finally, we also gather information on

[2] One exception to this structure are independent cities, which are districts in their own right. Three cities (Berlin, Bremen, and Hamburg) are states in their own right. Hence, they are excluded from our study.

[3] Unless the distinction is critical we refer to both independent and collective municipalities simply as "municipalities."

[4] In particular, there are four states where the individual municipalities may maintain a greater than usual degree of autonomy: Saxony, Baden-Wurttemberg, Bavaria, and Thuringia. This heterogeneity across states had implications for the distribution of our survey, as discussed in Appendix 2.6.

the promotion of solar photovoltaics, which refers to municipal-level financial incentives, i.e. tax rebates, for homeowners to install solar panels on existing homes or include solar panels in the construction of a new building. As determined by our study, this latter type of municipal policy is relatively rare with respect to the overall penetration of policies limiting the adoption of solar photovoltaics, and is thus not the main focus our study, while we account for it when necessary. In sum, bans are the most restrictive solar policy that municipalities can impose, followed by permits and regulations. Across all policies, we distinguish between policies that apply to the entire municipality and policies that only regulate an area, for example, a historical district.

2.3 Data

We use three sets of data in our analysis. The first dataset is a registry of municipal building policies relating to the adoption of solar photovoltaics, which we created by conducting a survey sent to the building code offices of all municipalities in Germany.[5] To our knowledge, this is the first such registry, worldwide. The second dataset is the Marktstammdatenregister (MaStR), which contains data on the generating capacity of all solar power plants in Germany for the years 1991 to 2019, and is provided by the Federal Energy Agency (Bundesnetzagentur). The third dataset contains socioeconomic characteristics of municipalities and is sourced from the Federal Statistical Office of Germany (Destatis, Statistisches Bundesamt) and the Federal Employment Agency (Bundesagentur für Arbeit).

2.3.1 Building codes

Municipal regulations of solar installations are typically found either in zoning documents (Bauleitpläne) or in statutes (Satzungen). Many municipalities with substantial historical building stocks have dedicated building statutes (Gestaltungssatzungen) intended to regulate and protect historical buildings and the overall appearance of a municipal district. Our registry of municipal solar policies is primarily based on survey responses from municipal officials. In the survey, sent to all

[5] The survey was complemented with a manual search for all municipalities that did not provide the requested information through the survey, as detailed in Section 2.3.1.

municipalities in Germany, we asked about policies that explicitly concern the installation of solar panels, following the classification described in Section 2.2. We sequentially asked for information on both current and past municipal policies. Municipalities and collective municipalities (as described in Section 2.2) received identical surveys, with one exception: collective municipalities could indicate to which constituting municipalities the reported policies apply. To this end, we included an interactive checklist of (sub-)municipalities in the survey sent to collective municipalities. The survey starts with an overview of policies and asks the municipality to indicate which ones are present, based on the options described in Table B.2.

As mentioned, the survey asks whether a policy applies to the entire municipality or one or more geographic areas within the municipality. If the policy applies to an area within the municipality we asked to be provided a map, a shapefile with geocoded areas, or a precise description (i.e. cross streets). We also ask that the municipality report the zoning designation (e.g. mixed residential) of the area and whether it is considered an area of historical significance.

The survey was available to municipalities between September 2019 and December 2020. In order to contact all municipalities in Germany, we obtained contact lists from each German state, excluding the abovementioned three city-states. We conducted a small trial in early September 2019, where we sent the survey to 43 independent municipalities, and 23 collective municipalities, allowing us to inspect responses and obtain feedback to make adjustments before scaling up. In October 2019, we started administering the survey to all remaining municipalities. We randomly assigned all municipalities to 1 of 6 waves, and staggered the survey rollout by wave to allow us to provide municipalities with a timely response to questions or to follow up rapidly via email or phone calls in case some fields had been left incomplete. Each municipality received an initial invitation to participate via email (see Appendix Figures B.3 and B.4). The email provided a brief introduction to the research project and a link to the online survey. By the end of November 2019, all municipalities had been invited to participate in the survey.

During the remaining months through December 2020, continuing work on the survey primarily consisted of 3 tasks: (1) corresponding with municipal officials who submitted incomplete survey responses, or who reached out with questions about how to complete the survey; (2) obtaining updated contact information to re-send the survey when it was discovered that the State-provided contact lists gave deprecated or inappropriate email addresses; and (3) sending periodic reminders to municipalities which had not yet completed the survey.

In the case of municipalities that opted out of survey participation or never completed the survey, we supplement the dataset with information from publicly available municipal documents. We searched municipalities' websites to collect the same set of information that we required the municipalities to fill in the survey. In order to standardize the data collection as much as possible, we limited the search to certain types of official documents and searched the documents using a pre-defined set of keywords (see Table B.3).

In total, we contacted 4,678 independent municipalities and 756 collective municipalities, representing all municipalities in Germany save for a small handful for which we were unable to obtain contact information and the abovementioned three city states. by state). The survey response rate is 49.3% among municipalities (2,305 responses) and 32.3% among collective municipalities (244 responses), for an average response rate of 46.9%. Some of the responses are for various reasons not usable, for instance if the respondent failed to provide the start date of a policy, or otherwise left the survey incomplete. As a result, we have 1,102 complete responses for the municipalities, and 103 complete responses for the collective municipalities, implying completion rates of 48% and 42% respectively, and effective response rates of 24% and 14%. To these complete survey responses we add the entries from our manual search process, yielding 172 entries for the municipalities and 26 for the collective municipalities, bringing the total sample to 1,274 and 129, respectively. Notably, the 129 collective municipality responses translate to a higher number of observations in our main dataset, because our unit of observation is the individual constituent municipalities within the collective. Thus, the 129 responses from collective municipalities imply 600 total responses at the municipality level, bringing the total number of municipalities for which we have solar building code data to 1,874.

In Table B.1 we present the balance of covariates across survey respondents and municipalities overall. These summary statistics are shown separately for independent and collective municipalities. Collective municipalities are typically smaller than independent municipalities because their constituting municipalities are very small. Overall, municipalities with greater population were more likely to respond to our survey. However, differences between respondents and non-respondents across other observable municipality characteristics are not of meaningful size. Most notably, per capita measures of the number of solar installations added per year and the added annual capacity are not different across survey respondents and non-respondents.

2.3.2 Solar photovoltaics

Our outcomes of interest are the number of solar installations and solar capacity in each municipality and year. In 2019, the federal government made these data on energy market participants available to the public via the MaStR database. The German electricity market has many small producers, including more than 2 million solar installations, implying an overall gross production capacity of 59 GW at the end of 2021. Solar photovoltaics provided 9.1 percent of gross electricity consumption in 2021 (Fraunhofer, Umweltbundesamt, 2022). MaStR was created to provide reliable data on market actors in the energy sector, at a time when the German energy sector was liberalized and the transition to renewable energy was well under way (Bundesnetzagentur, 2018).[6] The MaStR registry contains installation and plant names, name of the owner if not an individual, addresses, type of energy source, and production capacity. Plant owners report the in-service date when the plant installation is completed.[7] All energy market participants are required by law to report any new or existing plant to the Federal Energy Agency and keep this information up to date, regardless of whether they are receiving energy generation subsidies. This rule applies to both conventional and renewable energy generation. The information is verified by the grid operator serving the electricity producer entering the information. Registration of a plant is required

[6]The Federal Energy Agency (Bundesnetzagentur) provides these data to the public in accordance with the federal code that regulates the energy sector (§ 111e and § 111f of the Energiewirtschaftsgesetz).

[7]MaStR also records a reporting date, which refers to the date that the plant information was entered in the database. New plants need to be registered within one month of the in-service date. Late registration can result in fines and the loss of subsidies. Existing plants that were registered with the Federal Energy Agency prior to the introduction of the MaStR database in 2019 are required to be re-registered with MaStR by the end of January 2021.

in order to receive federal subsidies or tax benefits. Failure to register can result in fines. While information about the postal code where the installation or plant is based is public, the street address is not public information for solar plants generating less than 30 kW. Further details about the assignment of solar installations to municipalities are detailed in Appendix 2.6.

2.3.3 Control variables

Our control variables, including demographic and socioeconomic characteristics, are provided by the Federal statistical office. These data are provided annually back to 2008, and are tabulated at the level of individual municipalities. In particular, even for municipalities which belong to a collective for administrative purposes and thus receive the collective version of the survey, the control data is still tabulated at the level of the individual municipalities. The specific variables that we include in the analyses are: population, share of males in the population, share of children in the population, the green party vote share, and, at the district level, average household income and unemployment rate.

2.3.4 Descriptive Statistics

Our final dataset is a yearly panel of 1,874 municipalities[8] from 1991 through 2019. This panel includes data on municipal solar building policies, adoption of solar PV, and time-varying socioeconomic characteristics of the municipalities. Recall that we distinguish between four types of policies: Bans, permits, regulations, and policies that promote solar expansion. In our sample, 294 municipalities have one or more of these policies in place. 153 municipalities regulate the installation of solar panels, 44 require a permit, 22 impose a ban on solar panels, and 33 promote the installation of solar photovoltaics (in addition to existing federal subsidies). Within our dataset, it is necessary to define treatment and control groups based on the solar building policy data we collected. The treatment group is defined as the 252 municipalities whose treatment status may turn positive sometime between 1991 and 2019. The control group consists of all 1,579 municipalities

[8]The dataset is defined using the municipality definitions which were current as of 2019, when the survey we used to gather data on municipal solar policies began, as described in Appendix 2.6.

which never receive treatment.[9] We see that historical towns implemented solar policies at much higher rates than towns without historical districts. In the control group, 12 percent of municipalities are historical towns. In contrast, 34 percent of municipalities that implemented solar policies have historical districts. As described in the following section, the empirical approach takes care of these differences.

Figure B.1 presents the cumulative adoption of municipal solar building policies in Germany from 1991 through 2019. At each point in time it presents the proportion of municipalities which have implemented solar policies, as a fraction of all municipalities which at some point adopt a policy that we a priori expect to have a negative impact on solar adoption and which are the main focus of this study: bans, permits, and regulations. About 10% of these municipalities report that their policies were in place prior to 1991, and therefore for the purpose of our study do not provide any useful variation in policy. From 1991 through 2019, the adoption of solar policies then occurs at a moderately increasing rate, with only roughly 25% of municipalities treated by 2000, and then nearly 60% treated by 2010.

The boom in solar photovoltaics followed the major increase in the feed-in-tariff rate in the year 2000. We found that 94 municipalities in the sample introduced policies that directly (or indirectly) define rules concerning the installation of solar photovoltaics. Prior to 2000, the average number of solar installations that existed before the implementation of a relevant building code is only 0.17. The average installed capacity installed is 0.66 KW per year. Hence, these building codes were written at a time when only a handful of solar PVs existed in these municipalities. Typically, pre-2000 building codes excplicitly mention solar PVs in passing, for example, alongside antennas and satellite dish regulations.

Since our data on solar installations includes a wide range of installations, ranging from small

[9] Note that these figures do not sum to 1,874 because of sample restrictions that we had to impose. We exclude from the main estimation sample municipalities which indicate that they had multiple policies of different types in effect at a given time. There are 27 municipalities indicating that they have both regulations regarding how panels are to be installed as well as a requirement for permits to install panels. There are 7 municipalities reporting both regulations and a ban, 6 reporting a permit requirement and a ban, 2 reporting a permit requirement and promotion, and 1 reporting regulations and promotion. There are no municipalities reporting both promotion of solar panels and a ban on them. Thus, the total number of municipalities in the treatment and control groups is only 1,831, as shown in Table 2.1.

rooftop installations to massive solar fields, it is useful to construct measures of solar adoption that allow us to focus on different categories of installations. In particular, since the urban policies we study should be expected to have implications only for panels within the urban area, we should not expect effects for particularly large installations. To this end, we define outcome variables that separate solar installations into 5 categories, corresponding to the quintiles of the overall gross capacity distribution for all installations from all municipalities and years. Specifically, this results in separate outcomes for PV installations in the capacity ranges of 0-5 kW, 5-7.44 kW, 7.44-10.5 kW, 10.5-22.1 kW, and 22.1 kW and above. Figure B.2 shows the cumulative amount of solar capacity installed among each of these separate categories of PV installations from 1991 to 2019, for the 1,874 municipalities in our dataset. From this figure it is evident that while the majority of the 13 GW of capacity installed come from the largest category of installations, there is also a total of 3.7 GW of capacity installed from the 4 smaller categories of installations, and 2.3 GW of capacity from the 3 smallest categories, where we expect the impact of the building policies that we study to be concentrated.

Table 2.1 provides balances of covariates measuring possible selection across treatment status, using control data for the years 1991 to 1999, prior to any significant installation of solar capacity in the country. From Table 2.1, we can see that treated municipalities tend to have greater land area and higher population. For this reason, as described in detail in Section 2.4, we implement a matching approach that significantly reduces the observable differences between treated and control municipalities.

2.4 Empirical Strategy

2.4.1 Nearest Neighbor Matching

Our goal is the estimation of the causal effects of municipal policies on the adoption of solar photovoltaics. Municipalities do not randomly implement solar policies. The main challenge in the estimation of causal effects stems from the fact that municipalities choose to implement solar policies.

The descriptive statistics in Table 2.1 tell us that treatment status may in part be correlated with observable municipality characteristics. Hence, to reduce observable differences between municipalities, we use matching as a pre-processing step, followed by regression analysis. More precisely, we implement one-to-many nearest-neighbor matching without replacement. Abadie and Spiess, 2021 show that matching as a pre-processing step to estimation yields valid regression standard errors if matching is done without replacement and standard errors are clustered at the level of the match. We follow this approach. The set of matching variables is chosen to produce a comparison municipality that has similar characteristics to a treatment municipality, while maximizing the number of successful matches. For the main estimations, the matching variables are, at the municipality-level, population, share of women, share of children, land area, green party vote share, and at the district-level, the unemployment rate and household income. In our main specification, we match on the average value of these variables for the years 1991 to 1999. Municipalities in both treatment and control group have some existing solar capacity in the late 1990s. However, the timeframe is chosen such that the positive effect of the 2000 renewable energy legislation on solar adoption does not play a role. As we can see in Figure B.2, almost all the solar capacity installation occurred after the year 2000. Approximately one third of municipalities in the main estimation sample implemented solar policies prior to 2000, suggesting that in those cases the policy decision was not driven by existing solar capacity.

As we can see in Table 2.1, matching reduces observable differences between treated and control municipalities but does not completely eliminate them – though an exact match is not a necessary condition for identification.

To evaluate the robustness of the matching strategy, we implement a number of alternative specifications. First, we construct our analysis sample by matching on 1995 values of control variables, a year in which almost no solar capacity existed in Germany. Results based on this alternative matching strategy are discussed in Section 2.5.3.

We also restrict our sample to the years 2000 to 2019 to focus on a period of significant solar expansion. Here we match not only on the 2000 values of the covariates but on the level of installed

Table 2.1: Municipality Characteristics (Averages over 1991-1999): Unmatched vs. Matched set

	All			Matched		
	Control Mean (SD)	Treated Mean (SD)	Pre-Match Diff.	Control Mean (SD)	Treated Mean (SD)	Post-Match Diff.
Municipal population	12,416	23,493	-11076.89***	10,870	13,295	-2,425.00
	(36,845)	(88,967)	(-3.44)	(13,131)	(16,383)	(-1.71)
Share of males	0.50	0.49	0.00**	0.50	0.50	0.00
	(0.01)	(0.01)	(3.18)	(0.01)	(0.01)	(0.30)
Share of children	0.07	0.06	0.01***	0.06	0.06	0.00
	(0.03)	(0.02)	(3.51)	(0.02)	(0.02)	(0.16)
Unemployment rate	0.05	0.05	-0.00*	0.05	0.05	-0.00
	(0.02)	(0.02)	(-2.41)	(0.03)	(0.03)	(-0.08)
Household income	21,284.59	21,319.68	-35.09	21,240.96	21,217.67	23.30
	(3,820.34)	(4,504.94)	(-0.13)	(4,423.37)	(4,364.38)	(0.06)
Green Party vote share	0.06	0.07	-0.01***	0.06	0.06	-0.00
	(0.03)	(0.03)	(-3.84)	(0.03)	(0.03)	(-0.41)
Historical municipality	0.12	0.34	-0.22***	0.17	0.32	-0.16***
	(0.32)	(0.48)	(-9.48)	(0.38)	(0.47)	(-3.82)
PV capacity (KW)	234.05	292.62	-58.57*	249.93	267.21	-17.28
	(324.65)	(410.09)	(-2.56)	(298.83)	(357.74)	(-0.55)
PV installations	9.73	13.30	-3.57***	10.67	11.51	-0.84
	(11.52)	(18.51)	(-4.14)	(10.93)	(11.66)	(-0.78)
Installed KW per km^2	5.64	5.76	-0.12	5.87	6.01	-0.14
	(6.51)	(6.26)	(-0.26)	(6.25)	(6.50)	(-0.22)
Solar installations per km$\hat{2}$	0.26	0.28	-0.02	0.27	0.29	-0.01
	(0.21)	(0.23)	(-1.51)	(0.22)	(0.22)	(-0.60)
Installed KW per 1000 inhabitants	40.84	39.88	0.97	36.94	42.93	-5.99
	(63.52)	(120.64)	(0.19)	(59.90)	(128.89)	(-0.62)
Solar installations per 1000 inhabitants	1.58	1.34	0.24**	1.46	1.39	0.06
	(1.33)	(1.20)	(2.65)	(1.27)	(1.21)	(0.53)
N	1,579	252	1,831	219	219	438

solar capacity installed prior to treatment. As a last robustness check of the matching strategy, we create analysis samples using one-to-one nearest neighbor matching.

In the estimation of our main specification, we treat the introduction of a municipal solar policy as a canonical binary effect. Some municipalities have solar policies that apply only to a subset of the total land area of the municipality. As a robustness test, we include an additional set of estimations where we account for area-specific policies using a continuous variable (see Section 2.5.3).

2.4.2 Empirical Specification

Once we obtain the matched sample, we use a two-way fixed effects estimator to identify the average treatment effect on the treated (ATET) of municipal solar policies on installed solar capacity. Since municipalities implement solar policies in staggered fashion, our analysis departs from the canonical difference-in-difference design. Roth et al. (2022), in a review of the recent difference-in-difference literature, show that a standard two-way fixed effects approach yields the ATET of a staggered policy if the treatment effect is homogenous and not dynamic. To assuage concerns that our estimate is biased due to treatment effect heterogeneity, we separately analyze different types of policies, and quintiles of solar capacity. Hence, we estimate regression equations of the form:

$$Y_{it} = \beta * Treated_{it} + \gamma Z_{it} + \alpha_i + \alpha_t + \epsilon_{it} \tag{2.1}$$

Where $Treated_{it}$ is a binary variable indicating whether a given municipality i has adopted the policy under consideration. Y_{it} is one of twelve outcome variables measuring the yearly flow of new solar in a municipality, with one outcome variable for the total, and one variable for each of the 5 quintiles defined in Section 2.3.4, measured in either (natural) log of the number of installations or log of total gross capacity installed. Z_{it} is a vector of time-varying control variables that mirrors the covariates used in the matching procedure: (Log) population, the share of males in the population, the share of children in the population, the share of green party voters, household income, and the unemployment rate. The α's are municipality and year fixed effects, and ϵ is an error term.

Any generalized difference-in-difference approach requires careful discussion of the parallel trend assumption. In our case, we assume that the newly installed (log) solar capacity in treated municipalities would have followed the same trajectory (in the absence of solar policies) as newly installed (log) solar capacity in control municipalities.{We make an analogous assumption for the number of solar PV installations that are added. The parallel trend assumption tends to be sensitive to the functional form of the estimated model (Roth and Sant'Anna, 2022). We choose the (natural) log of capacity and log of installations as our outcome variables because in the absence of a solar policy because it is plausible that solar capacity in a treated municipality would have increased by a constant proportion.

In our main specifications, we assume that the parallel trend assumption holds conditional on matching and covariates. We conduct a series of event studies, following Borusyak, Jaravel, and

Spiess (2021). We estimate the event studies on the entire analysis sample (rather than the matched sample) and reject the presence of significant pre-trends. Further, in one event study analysis, we impose the parallel trend assumption without conditioning on covariates. Testing the parallel trend hypothesis allows us to also account for potential anticipatory effects, leading homeowners in regulated towns to adopt solar just prior to the regulation's entry into force.

We further strengthen our argument that the parallel trends assumption is plausible by re-running our main regression, leaving out one municipality at the time. We conclude that the results are not driven by any one municipality.

2.5 Empirical results

2.5.1 Main Regressions

Tables B.4 and B.5 present the main results of estimating a number of regression equations of the form specified in Section 2.4, equation 2.1; each cell of these tables provides a different estimate $\hat{\beta}$ from a different specification estimated on data from 1991 through 2019. Table B.4 shows the treatment effect estimates for all solar policies. Table B.5 shows the treatment effect estimates for permits and regulations. The rows of each table correspond to different outcome variables, so the first row presents results based on the total capacity installed per year, followed by the smallest solar installations (<5 kW) and the bottom row presents results on the largest installations (>22.1 kW). The first column shows the results for (log) capacity, the second column shows the results for the (log) number of installations.

The estimand $\hat{\beta}$ should be understood as the average difference between observed solar installations (or capacity) per year in a municipality which has adopted a given policy and a counterfactual estimate of the solar installations the municipality would have seen if it had not adopted the policy. The counterfactual is informed by the national time trend in solar adoption (year fixed effects), translated up or down to match the overall level of solar adoption in the municipality (municipality fixed effect), and allowed to accommodate differential trends across municipalities based on evolution in the municipality's demographic and economic characteristics (time-varying controls).

In Table B.4 we see that solar photovoltaic policies reduce the number of installations and solar photovoltaic capacity. Overall, municipal solar policies reduce the number of installations by 8.9 percent and reduce capacity by 10.4 percent. That is, we find a larger effect on capacity than on installations, pointing to the ability of municipal policies to influence both the extensive and intensive margins, leading to fewer installations as well as smaller installations conditional on adoption.

The policy effect on the number of installations is smaller for higher capacity solar photovoltaics. The reduction in capacity is most pronounced, and precisely estimated, for installations between the 20th and 60th percentile of capacity. This corresponds to installations between 5.0 kW and 10.5 kW of capacity, a typical size for single family rooftop solar photovoltaics. It makes also sense that the quintile with the smallest installations may be less affected, as small installations generally tend to be less invasive.

In Table B.5 we see that the overall effect of the most common types of policies, regulations and permit requirements, reduce capacity by 18.5 percent and the number of installations by 16.3 percent. For these two most common types of policy we also see the largest reduction for installations between the 20th and 60th percentile of capacity.

In order to interpret these results at the aggregate level, it is useful to begin by considering the aggregate impact among all municipalities in our sample. One simple way to estimate this impact is to calculate the total amount of solar capacity installed in treatment municipalities during treatment years, and then multiply it by the obtained regression coefficients. For simplicity, in the following calculations we consider only the effects for the 3 bottom quintiles of the capacity distribution, since this is where we find most action to take place. The yearly average amount of solar capacity within treated municipalities is 54 MW for the smallest installations, 91 MW for the next capacity class, and 154 MW for the middle quintile. Multiplying by the Table B.4 coefficients of 9.0%, 14.1%, and 16.6%, respectively, the estimated impact of solar policies on solar adoption in each size class is 5 MW, 13 MW and 26 MW, for a total of 44 MW. The total amount of solar capacity installed among the municipalities in our sample over the entire sample is 2,276 MW, so the aggregate impact is about a 2% effect. Interpolating to the national level, a 2% effect would represent a loss of 160 MW of solar, as there is a total of 7,500 MW of installed capacity among the 3 size categories throughout Germany.

2.5.2 Event Study

In this section, we present the results of our event study, which follows the methodology described in Section 2.4. Figures B.5 to B.22 display the main results from this exercise. First, we look at the ex-ante period and confirm that there is no evidence of significant pre-trends, which supports the analyses presented in this section.

Then, we discuss how the event study replicates our main results, as presented above, as well as the timing of treatment effects, which event studies allow us to measure. Generally speaking, the event analyses replicate our main results well, with larger effects for permits and regulations, which are, as mentioned, the most popular policies in our sample, and somewhat smaller effects when all municipal policies are taken together.

As expected, the results are particularly clear for installations at or below the 60$^{\text{th}}$ percentile of capacity. In terms of timing, the effects grow in magnitude over time, and after 5 years we see annual reductions in the range of 10 to 15 percent for the smaller installations, as shown in Figures B.6 and B.7 for installations and Figures B.12 and B.13 for capacity.

For robustness purposes, we also realize our event study with a specification that does not use include covariates, as shown in see Figures B.23 to B.40.

2.5.3 Additional Robustness Tests

In this section we present the results of a battery of robustness tests around our main results, as presented in Tables B.4 and B.5. Table B.8 presents results using a different strategy for the matching pre-processing step, as mentioned in Section 2.4.1 Here, instead of matching treatment to control municipalities on the basis of their average control variable values in 1990, we use only the values from the year 1995 (see Table B.8), at which time essentially no solar capacity still existed in Germany. The results obtained with this different matching strategy are smaller and noiser but have the same sign as the baseline results in Table B.5, once again providing robustness to our main findings. The coefficient estimates from the restricted sample that starts in the year 2000, when the feed-in-tariff subsidies were increased, closely match the main results as well (see Table B.7). The results are also robust to exact matching on the historical status of a municipality (see Table B.9).

Table 2.2: Effect of any Solar Policy on Solar Adoption

	(1) Log Capacity	(2) Log Installs
any percentile	-0.144	-0.0965
	(0.125)	(0.0819)
20 percentile	-0.101	-0.0546
	(0.0782)	(0.0522)
40 percentile	-0.172	-0.0833
	(0.111)	(0.0687)
60 percentile	-0.176	-0.0809
	(0.119)	(0.0691)
80 percentile	-0.119	-0.0531
	(0.121)	(0.0563)
80 over percentile	-0.113	-0.0448
	(0.167)	(0.0630)
Time-varying controls	Yes	Yes
N	12145	12145
Adj. R^2	0.624	0.646
Adj. within R^2	0.00639	0.00734

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

In Table B.10 we present the estimation results of a modified version of equation 2.1, with $Treated_{i,t}$ redefined as a treatment intensity measure. We see in Table B.10 that increasing the urban area covered by regulations and permit requirements by 10% reduces capacity by 3.6 percent and the number of installations by 2.5 percent.

In Table B.12, we conduct a robustness test with a slightly different sample restriction that allows for municipalities indicating that they had multiple different policies in place to be included in the estimation sample. Our main results are robust to this additional specification, which leads to a slightly larger sample.

In another robustness test, we remove the states of Baden-Württemberg and Bavaria from our sample. These 2 Southern states account for 43% of the 13 GW of total solar capacity in our sample. Similarly, they account for 50% of all municipalities in the treatment group. While feed-in tariffs are constant across the country, Southern states generally benefit from more sunlight. It is therefore reasonable to be concerned about our results being potentially driven by municipal policies in these 2 states. Table B.13 presents the results of these regressions. Despite the smaller sample, the effect of municipal policies is larger and more precisely estimated in the Northern parts of Germany, for instance in the case of installations pointing to a higher fraction of marginal adopters.

As a further extension of the above exercise, Figure B.59 displays the range of estimates obtained for the effect of solar policies on adoption of the smallest installations over 78 different permutations of the estimation sample. In each permutation, 2 states are removed from the estimation sample, so that we assess the robustness of our findings not only to the removal of 2 particular large states, but to all states in the data. With a total of 13 states, there are 78 possible combinations of 2 states to remove. The resulting point estimates of the effect are tightly clustered around an average of -0.17, with the smallest effect size being approximately -0.1, consistent with our baseline results.

We presented 12 separate regression estimates, which may lead to a false discovery rate, as described by Benjamini and Hochberg (1995). Hence, we also present the main regression results with q-values. Table B.14 contains these results, which show broadly similar patterns in terms of which results are more robust. Namely, the results for smaller installations have smaller q-values around 0.2, while the results for the largest solar installations are much noisier, with q-values closer to 0.5. This pattern matches with the significance patterns of the individual hypothesis tests, and more importantly is consistent with our hypothesis that the primary impact of the solar regulations we study will be on smaller, rooftop PV installations.

2.6 Conclusions

Since the 1990s, subsidies to renewable energy, and to solar PV energy in particular, have been effective in promoting the adoption of new energy sources and spurring innovation in the renewable sector. In Germany in particular, particularly large subsidies have been available, and in this paper we document that in response to the widespread adoption of solar PV energy, a substantial share of German municipalities have amended their building codes to place restrictions on the adoption of solar PV, often with the aim of preserving the historical aesthetic of the town. With the cumulative innovation and economies of scale that have been achieved in solar PV energy over the past three decades resulting in grid parity, large subsidy programs are being gradually discontinued, making remaining non-pecuniary barriers to solar PV adoption an important topic for empirical research.

We document the rise in municipal policies that restrict the adoption of solar PV by means of administering a survey regarding such policies to all German municipalities. Additionally, our survey distinguishes between several varieties of policies which are adopted by municipalities, and we find that while outright bans of solar PV are relatively rare, there are a larger share of municipalities which require residents to go through a permitting process before installing solar, and a still larger share that regulate the precise manner in which solar can be installed, for instance requiring that they be installed on a portion of the roof such that they not be visible from the street.

We also combine this data on policies with comprehensive data on all solar installations connected to the German power grid, to assess the degree to which municipalities that adopt these policies see a reduced rate of solar adoption. Using a municipality-year level fixed-effects regression model, we find that a representative municipality in our estimation sample, which would have adopted a policy regulating the way in which solar is installed in 2010, would see an average reduction of 0.2 medium-sized (5-10.5kW) solar installations per 1,000 people per year, resulting in a cumulative reduction of 1.6 installations per 1,000 people, or roughly 10% of the medium-sized solar installations by 2020.

We contribute to a broader literature on the future of solar energy policy as the cost of solar decreases worldwide and grid parity is achieved or close to being achieved for many localities. We shed particular light on roof- and wall-mounted, urban PV systems, which contribute a substantial minority of solar energy in Germany and elsewhere. Past work has stressed the importance of spillover effects and social contagion in the spread of such PV systems, and future work on the topic of municipal solar policies may consider how these effects are moderated by local policymaking, particularly given our finding of the prevalence of policies that restrict the visibility of solar PV installations.

Appendix A. Chapter 1

Appendix A.1 Tables

Table A.1: 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 fl- -ow to anti-abortion centers in US." Kimberlee Kruesi. 02/05/2022.

Table A.2: North Carolina Funding for 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 A.3: County Characteristics: NC & SC 1990

	All		No CPC		CPC only	
	Mean	SD	Mean	SD	Mean	SD
Female Population Age 10-44	18,493	(21,183)	12,676	(12,058)	43,832	(35,940)
Share age 10-19	0.27	(0.02)	0.28	(0.02)	0.25	(0.02)
Non-white share	0.31	(0.20)	0.34	(0.21)	0.22	(0.14)
Unemployment rate	5.23	(2.01)	5.57	(2.12)	3.93	(1.01)
House Price Index (County)	100	(0)	100	(0)	100	(0)
No. of CPCs	0.39	(0.80)	0.00	(0.00)	1.67	(0.97)
Dist. Nearest CPC in miles	30.49	(21.51)	38.57	(18.27)	4.08	(2.26)
Non-profit Avg. Pay (1000s)	1.90	(0.15)	1.89	(0.16)	1.94	(0.10)
Abortion provider (or referrer)	0.37	(0.49)	0.35	(0.48)	0.00	(0.00)
Pregnancy count	1,226	(1,523)	831	(968)	2,925	(2,620)
Pregnancy rate	64.99	(13.51)	64.15	(13.59)	64.36	(14.02)
Abortion count	305	(467)	177	(222)	904	(881)
Abortion rate	13.80	(4.85)	12.72	(3.94)	17.89	(7.13)
Abortion rate girls age 10-19	15.37	(5.60)	14.01	(4.70)	21.34	(7.18)
Birth count	912	(1,069)	648	(746)	2,001	(1,765)
Birth rate	50.66	(11.43)	50.90	(11.44)	45.99	(11.76)
Birth rate girls age 10-19	35.26	(9.61)	36.00	(9.75)	30.61	(9.17)
Mainline protestant share	0.17	(0.08)	0.16	(0.08)	0.19	(0.06)
Evangelical protestant share	0.32	(0.13)	0.33	(0.13)	0.32	(0.12)
Catholic share	0.01	(0.01)	0.01	(0.01)	0.02	(0.02)
Black protestant share	0.14	(0.11)	0.15	(0.11)	0.09	(0.06)
U.S. House GOP vote share	0.39	(0.23)	0.36	(0.24)	0.49	(0.19)
N	137		104		18	

Table A.4: 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	

Appendix A.2 Figures

Figure A.1: CPCs, Abortion Providers and Abortion Rate (NC & SC): 1990

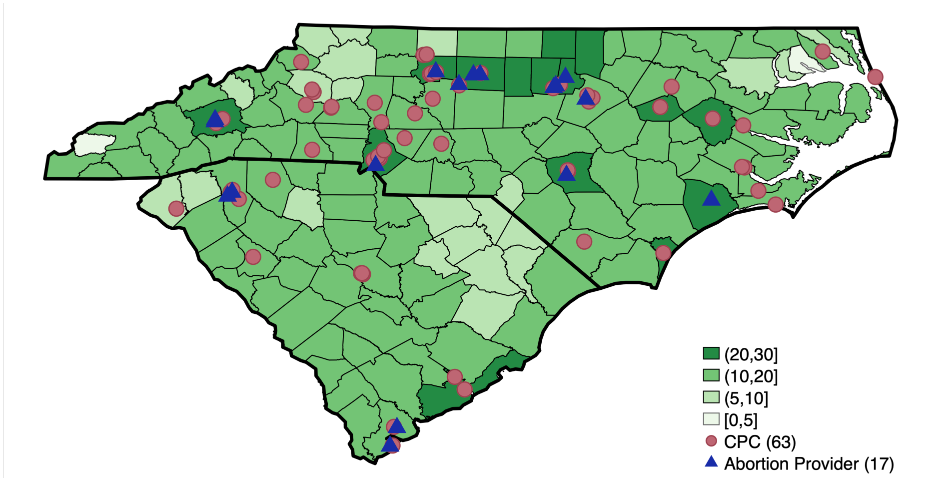


Figure A.2: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2000

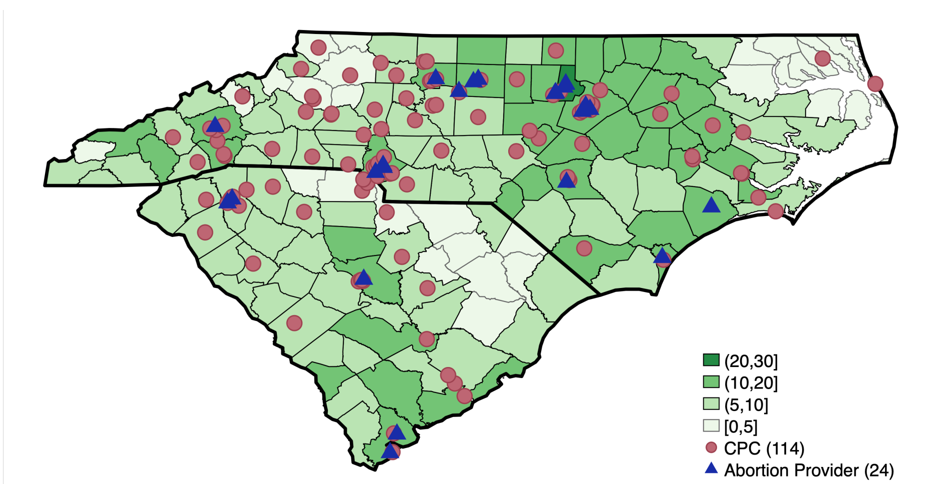


Figure A.3: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2010

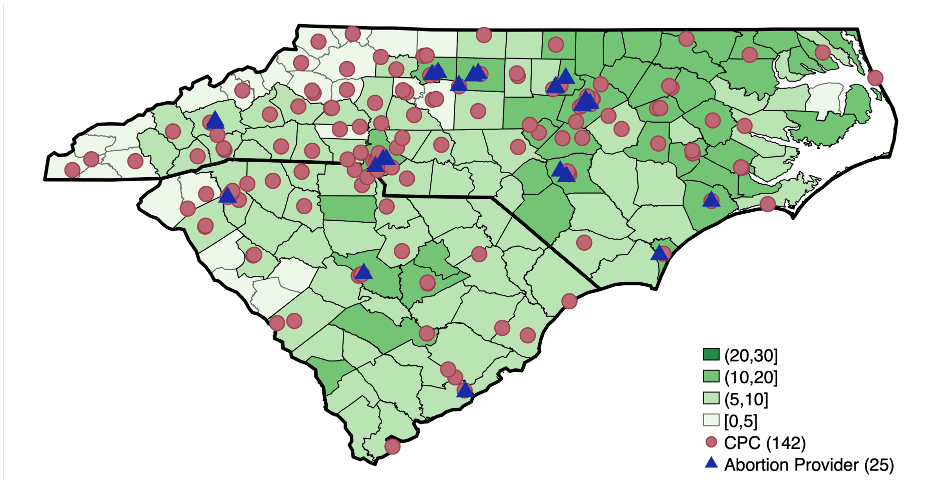


Figure A.4: CPCs, Abortion Providers and Abortion Rate (NC & SC): 2019

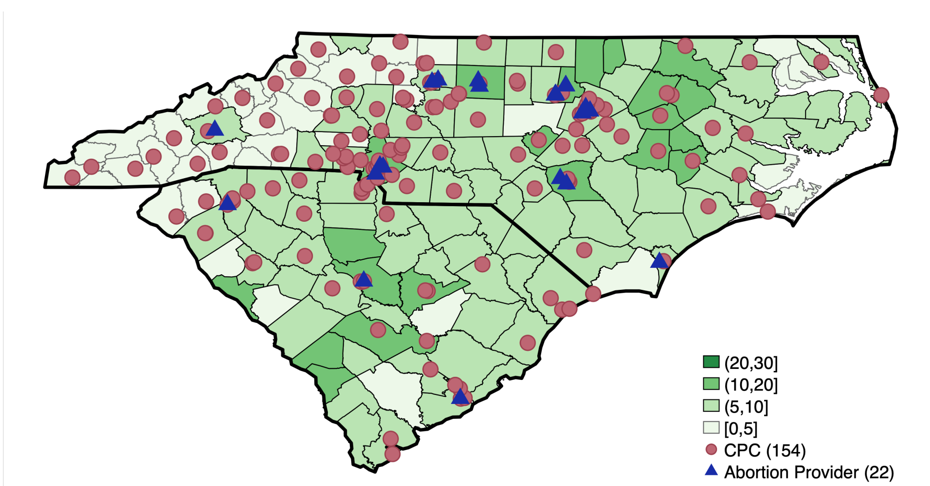
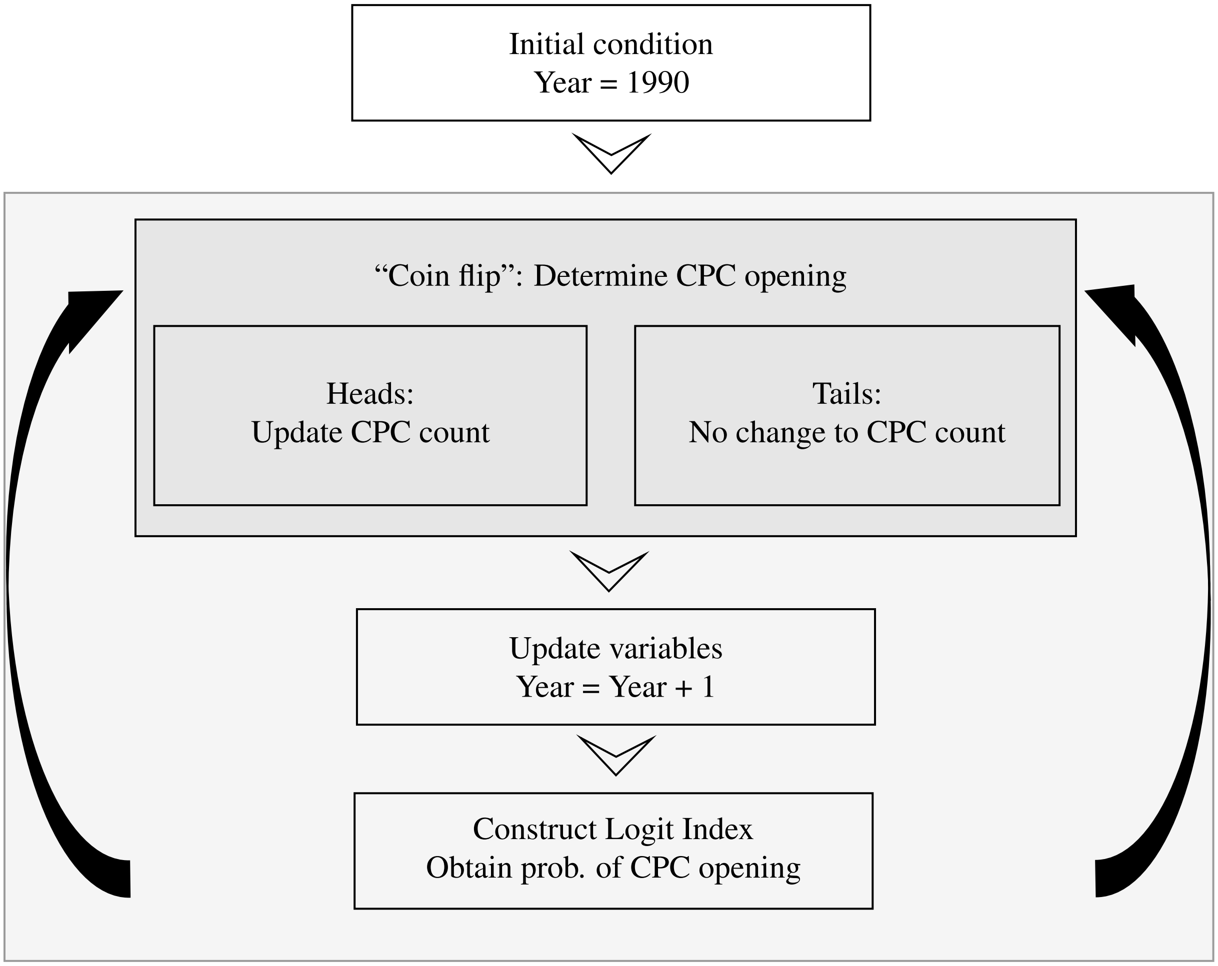


Figure A.5: Instrumental Variables: Simulation Flow Chart



Appendix B. Chapter 2

Appendix B.1 Tables

Table B.1: Municipality Characteristics: All vs. Surveyed (1991-1999 Avg.)

	Collective Municipalities			Indep. Municipalities		
	All Mean/SD	Survey Mean/SD	Diff.	All Mean/SD	Survey Mean/SD	Diff.
Municipal Population	1,169	2,048	-879.21***	9,235	22,045	-12810.50***
	(1,580)	(2,244)	(-14.57)	(19,840)	(60,837)	(-10.36)
Share of Males	0.50	0.50	-0.00**	0.49	0.49	0.00*
	(0.02)	(0.02)	(-2.70)	(0.01)	(0.01)	(2.33)
Pop. Share of Children	0.07	0.10	-0.02***	0.07	0.08	-0.00*
	(0.04)	(0.06)	(-15.68)	(0.03)	(0.04)	(-2.11)
Unemployed Rate	0.03	0.02	0.00***	0.02	0.02	0.00
	(0.02)	(0.01)	(3.34)	(0.01)	(0.01)	(1.58)
Green Party Vote Share	0.05	0.05	-0.00	0.06	0.06	-0.00***
	(0.03)	(0.02)	(-0.53)	(0.03)	(0.03)	(-6.55)
PV Capacity (KW)	0.04	0.05	-0.01	0.33	1.18	-0.85***
	(0.44)	(0.22)	(-0.62)	(2.92)	(8.29)	(-4.96)
No. of PV Installations	0.01	0.02	-0.01**	0.08	0.30	-0.22***
	(0.05)	(0.08)	(-2.87)	(0.42)	(1.78)	(-6.35)
Installed KW's per km^2	0.00	0.00	-0.00	0.01	0.02	-0.01***
	(0.01)	(0.02)	(-0.96)	(0.05)	(0.06)	(-4.46)
Solar Installations per km^2	0.00	0.00	-0.00	0.00	0.00	-0.00***
	(0.00)	(0.01)	(-0.92)	(0.01)	(0.02)	(-6.41)
Installed KW's per 1000 Pop.	0.01	0.01	0.00	0.01	0.01	-0.00
	(0.05)	(0.06)	(0.23)	(0.04)	(0.03)	(-0.69)
Solar Installations per 1000 Pop.	0.00	0.00	0.00	0.00	0.00	-0.00
	(0.02)	(0.02)	(0.58)	(0.01)	(0.01)	(-1.75)
N	4,997	948	5,945	2,821	1,832	4,653

Note: The no. of obs. in the "Collective Municipalities" columns reflects the no. of constituent municipalities.

Appendix B.2 Figures

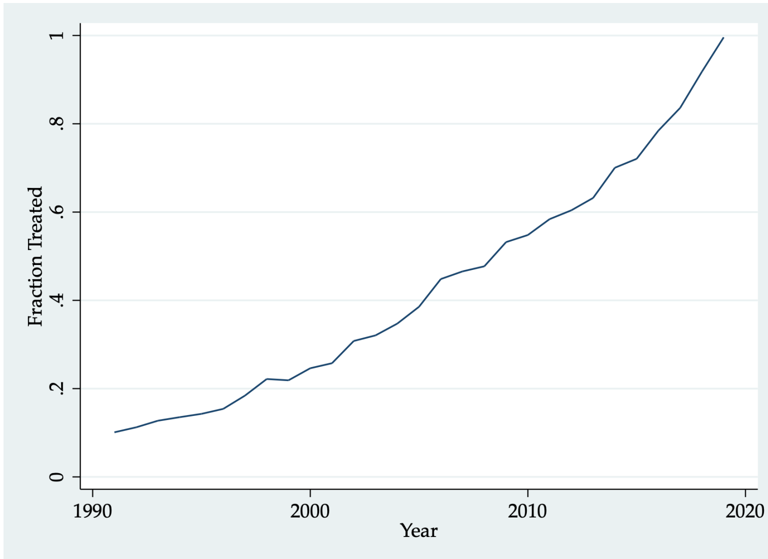


Figure B.1: Share of Municipalities that have Solar Policies

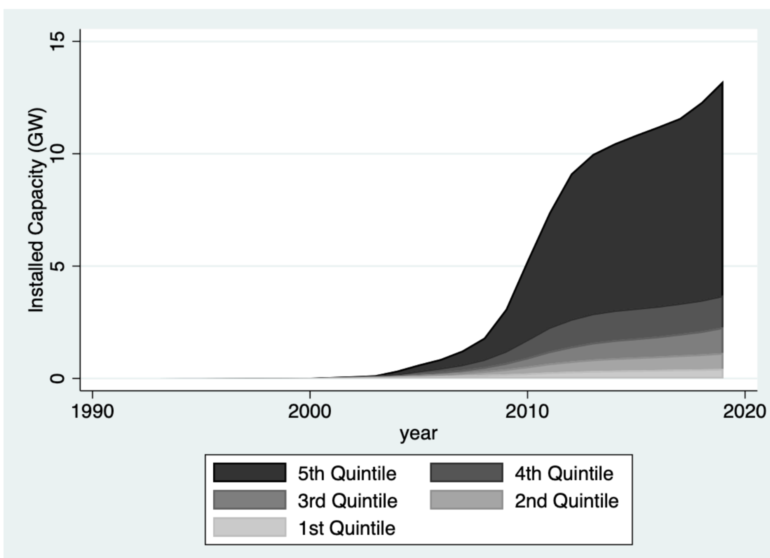


Figure B.2: Evolution of Solar Capacity

Appendix B.3 Survey Distribution and Sampling

The purpose of this Appendix section is to provide a detailed account of how our survey was distributed. Within Germany's federal system of government, the the low level units of local government which are relevant for our study are the Gemeinde and Gemeindeverband, which we generally refer to in the main text as municipalities and collective municipalities, respectively. The registry of local governments maintained by the federal government organizes the units of government with a numbering system known as Amtlichen RegionalschlÃŒssel, or ARS for short.[10] In this system, Gemeindeverband are indicated by 9-digit codes, and individual Gemeinde by 12-digit codes, where the constituent Gemeinde within a Gemeindeverband will share the first 9 digits of their code, distinguished only by the final 3 digits.

As mentioned in the main body of text, Gemeindeverband are often formed for the purpose of centralizing administrative functions for a group of (small) towns. However, the meaning of the term Gemeindeverband varies across states, which have different traditions. Therefore, it is not strictly the case that in every instance where the federal government's registry shows that a Gemeindeverband exists, that the constituent Gemeinde retain no administrative capacity whatsoever. In particular, there are 4 Southern states where this is not the case: Baden-Württemberg, Bavaria, Saxony, and Thuringia. For the states of Baden-WÃŒrttemberg and Saxony, all municipalities belonging to a collective retain enough of their own administrative capacity that for the purposes of this study, the individual municipalities were the appropriate bodies to reach out to with our survey.

Further exceptions are present in the states of Bavaria and Thuringia, though they are less uniform. In Bavaria, out of 982 municipalities within 311 Gemeindeverband, the majority do not retain their own functions, and so we reach out only to the Gemeindeverband office. However, 405 of those municipalities across 126 Gemeindeverband do retain their own offices, in the manner of Baden-Wurttemberg and Saxony, and so we reach out to the individual municipalities. In

[10]This system is similar to the FIPS codes used in US Census data, with the first 2 digits of each code indicating state membership, and subsequent digits indicating region, district, Gemeindeverband, and finally Gemeinde membership.

Thuringia, the vast majority of the 559 municipalities within Gemeindeverband do not retain their own functions, with 6 exceptions. The city of Saaleplatte in the county Weimarer Land is representative of these exceptions; it is a city of 2,862 people, in a Gemeindeverband anchored by the city of Bad Sulza, which has 4,819 people. The other 6 towns in the Gemeindeverband have populations of less than 800 people, so the secondary city of Saaleplatte retains its own administrative function, while the Gemeindeverband deals with the principal city and surrounding small towns.

Table B.6 provides a detailed breakdown by state of the independent and collective municipalities and how they were categorized for the purpose of this study. Figures B.3 and B.4 display the email which was sent to municipalities to invite them to participate in the survey.

Figure B.3: Survey Invitation Letter

Sehr geehrte Damen und Herren,

Wir sind eine Forschergruppe von der Universität Münster und der Georgia State University in den U.S.A. Im Rahmen eines wissenschaftlichen Forschungsprojektes, erstellen wir eine Datenbank von Bauvorschriften auf Ebene der Gemeinden, welche die Anbringung von Photovoltaikanlagen betreffen.

Der Lehrstuhl für Mikroökonomik an der Universität Münster lädt ihre Gemeinde ein, so wie alle Gemeinden in Deutschland, den folgenden Online Fragebogen zu beantworten: LINK.

Die Erforschung der Akzeptanz und Verbreitung von Photovoltaikanlage ist wichtb!ig in Zeiten des Klimawandels und der stetigen Vergünstigung von Solarenergie. Durch ihre Teilnahme helfen sie uns bereits öffentlich zugängliche Daten systematisch zu sammeln und schaffen damit die Voraussetzung für unsere Forschungsarbeit.

Ihre Teilnahme an der Umfrage ist freiwillig. Wir hoffen das ihre Gemeinde die Zeit zur Beantwortung des Fragebogens, circa 10-15 Minuten—je nach Anzahl der relevanten Bauvorschriften in ihrer Gemeinde—zur Verfügung stellen möchtb!e.

Wenn Sie nichtb! alle notwendigen Informationen zur Verfügung haben, um den Fragebogen auszufüllen, bitten wir sie diesen Link an eine andere Person in Ihrer Verwaltung weiterzuleiten. Sie können den Fragebogen kurz ausfüllen oder sich etwas mehr Zeit nehmen, um zusätzliche Details in den Bemerkungsfeldern anzugeben. Sie haben die Möglichkeit den Fragebogen abzubrechen und später an die gleiche Stelle zurückzukommen.

Falls Sie Fragen haben oder uns die Informationen direkt mitteilen möchtb!en, können Sie uns unter +49 XXX XXX XXX anrufen oder sich per Email an uns wenden: sonnenenergie@wiwi.uni-muenster.de für weitere Fragen stehen wir Ihnen gerne zur Verfügung!

Wir danken Ihnen für Ihre Aufmerksamkeit, zählen auf Ihre Teilnahme und verbleiben,

Mit freundlichen Grüssen

Das Projektteam
Prof. Dr. Andreas Löschel, Universität Münster
Dr. Stefano Carattini
Herr Béla Figge
Herr Alexander Gordan

Figure B.4: Survey Invitation Letter (English Translation)

Dear Sir or Madam,

We are a research team at the University of Muenster and Georgia State University in the United States. As part of a scientific research project we are creating a database of building codes at the municipal level insofar as they concern the installation of solar panels.

The Chair of Microeconomics at the University of Muenster is inviting your municipality, and all other municipalities in Germany, to fill out this survey: LINK.

As solar energy becomes cheaper, and mitigating climate change becomes more urgent, identifying potential ways to scale up the adoption of solar energy is crucial. By responding to this survey, you are helping us to systematically collect data that is already publicly available. Your response makes our research project possible.

Participation is voluntary. We hope that your municipality can take the time – around 10-15 minutes - depending on the number of regulations implemented in your municipality.

If you do not have all necessary information at hand to answer the survey, please forward this link to another individual in your administration. You can answer this survey quickly or take a bit more time to leave additional comments. You will be able to pause the survey and return to the same question at a later time.

If you have questions or would like to provide the information directly to us, you can call us at +49 XXX – XXX – XXX or contact us via at email at: sonnenenergie@wiwi.uni-muenster.de. We are happy to answer any questions you may have!

Thank you for taking the time to participate.

Best regards,

The Research Team

Prof. Dr. Andreas Loeschel, University Muenster

Dr. Stefano Carattini

Herr Béla Figge

Herr Alexander Gordan

Table B.2: Municipal Solar Policies Considered in the Survey

Type		Policy	Coverage
Building codes	Ban on solar PV		
			In the entire municipality
			In a part of the municipality
	Regulation of solar PV		
		Street visibility	In the entire municipality
			In a part of the municipality
		Ligh reflection	In the entire municipality
			In a part of the municipality
		Wall/roof integration	In the entire municipality
			In a part of the municipality
	Solar PV is promoted by the municipality		
			In the entire municipality
			In a part of the municipality
Permits	Specific permits for solar PV		
			In the entire municipality
			In a part of the municipality

Table B.3: Keywords for Manual Search of Policies

Search Term	Translation
Bauordnung	Building code
Bausatzung	Building statutes
Bauleitplan	Zoning plan
Gestaltungssatzung	Design statutes
Gestaltungsrichlinie	Design guidelines
Gestaltungsleitfaden	Design guidelines
Baugestaltungsordnung	Building design code
Stadtbildsatzung	Cityscape statutes
Ortsgestaltungssatzung	(place) Design statutes
Abstandsflaechensatzung	Clearance area statutes
Aussenbereichssatzung	Outskirt / exterior statutes

Table B.4: Effect of Any Policy on Solar Adoption

	(1) Log Capacity	(2) Log Installs
all percentile	-0.144	-0.0965
	(0.125)	(0.0819)
20 percentile	-0.101	-0.0546
	(0.0782)	(0.0522)
40 percentile	-0.172	-0.0833
	(0.111)	(0.0687)
60 percentile	-0.176	-0.0809
	(0.119)	(0.0691)
80 percentile	-0.119	-0.0531
	(0.121)	(0.0563)
80_over percentile	-0.113	-0.0448
	(0.167)	(0.0630)
Time-varying controls	Yes	Yes
N	12145	12145
Adj. R^2	0.624	0.646
Adj. within R^2	0.00639	0.00734

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.5: Effect of Permits & Regulations on Solar Adoption

	(1) Log Capacity	(2) Log Installs
all percentile	-0.238	-0.176*
	(0.151)	(0.0962)
20 percentile	-0.177**	-0.106*
	(0.0889)	(0.0593)
40 percentile	-0.261**	-0.134*
	(0.129)	(0.0774)
60 percentile	-0.280**	-0.138*
	(0.137)	(0.0762)
80 percentile	-0.245*	-0.112*
	(0.145)	(0.0642)
80_over percentile	-0.146	-0.0582
	(0.191)	(0.0675)
Time-varying controls	Yes	Yes
N	9523	9523
Adj. R^2	0.627	0.651
Adj. within R^2	0.0105	0.0111

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.6: Survey Distribution, by State

State	(1)	(2)	(3)	(4)	(5)
Schleswig-Holstein	86	1020	84	86 (4)	84 (2)
Lower Saxony	292	653	116	292 (1)	116
North Rhine Westphalia	396	0	0	396	0
Hesse	423	0	0	423	0
Rhineland-Palatinate	42	2262	139	42	139
Baden-WÃŒrttemberg	190	911 (911)	270	1,101 (3)	0
Bavaria	1,074	982 (405)	311	1,479	185
Saarland	52	0	0	52	0
Brandenburg	146	271	52	146	52
Mecklenburg	40	686	76	40 (1)	76
Saxony	238	181 (181)	71	419 (3)	0
Saxony-Anhalt	104	114	18	104	18
Thuringia	105	559 (6)	88	111 (1)	88
Germany (sans Berlin, Bremen, and Hamburg)	3,188	7,639 (1,503)	1,225	4,691 (13)	758 (2)

(1) 12-digit ARS codes not belonging to a Gemeindeverband); (2) number of municipalities that do belong to a Gemeindeverband, and in parentheses the number that are, for the purpose of this study, treated as independent; (3) number of Gemeindeverband (9-digit ARS codes); (4) number of effectively independent municipalities, which is the sum of the first column and the parenthetical values of the second column, and in parentheses the number for which contact information could not be gathered; (5) the number of effective Gemeindeverband, which is the value of the third column less those whose constituent municipalities are all treated as independent municipalities, and in parentheses again the number for which contact information could not be gathered.

Appendix B.4 Building the Dataset

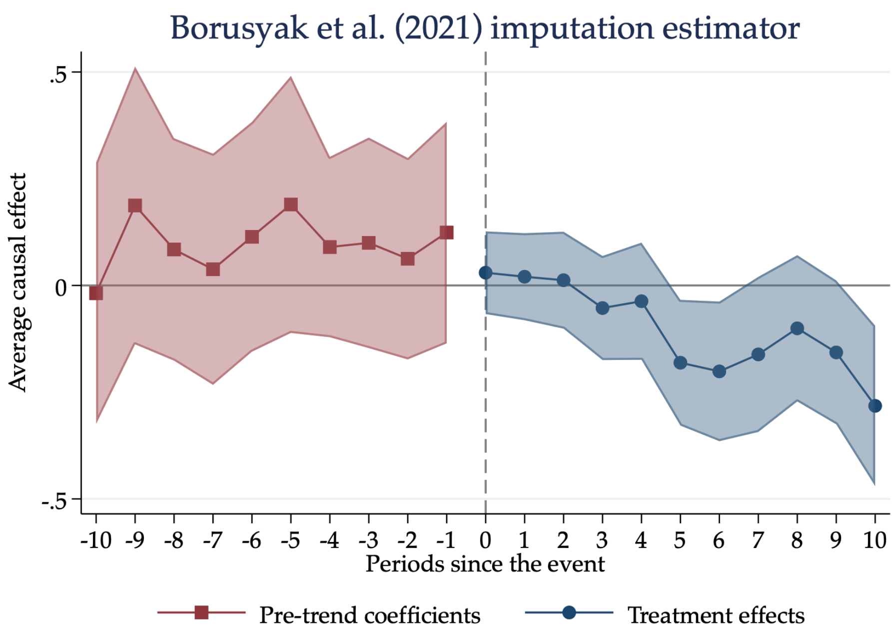
This section describes how we built our main dataset, covering both the inclusion of data on solar installations and the definition of German municipalities over time.

We start with the data on solar installations. As mentioned in the main body of paper, our analyses rely on the MaStR database for information about solar installations at the municipal level. However, we note here that for the purpose of confidently matching the solar data to the information that we collected from municipalities on solar policies and control data, we also rely on the predecessor of the MaStR database, the Erneuerbare-Energien-Gesetz (EEG) database. While the EEG database only covers installations from before 2016, it does include in its public version information on exact addresses of all solar installations, and not only the largest ones as it is the case for the MaStR database. Exact addresses can be easily converted to latitude and longitude using a geocoding service offered by the German government and improve the reliability of the match with the other data used in the analyses. Since the shapefiles use the same registry of municipalities that we used to construct the mailing list for the survey on solar policies, this strategy ensures proper matching between data sources. Furthermore, since municipality definitions can change over time, using a single registry ensures that a fixed set of municipality definitions are used throughout the analysis, which are separately described in the following section.

Then, we describe how we approach the structure of municipalities in Germany over time. The municipality definitions used throughout the text are the definitions which were current as of June 2019, when the survey was first being designed and fielded. However, municipality definitions are not fixed over time, since municipalities sometimes go through administrative mergers or separations. In order to conduct our panel data investigation, which brings together data on solar installations, municipal policies, and demographic information, all covering multiple decades, we need to use a consistent set of municipality definitions over time. We are able to do this by making use of the full record of changes in municipality definitions and mergers over time since 2007, provided by the Federal government.

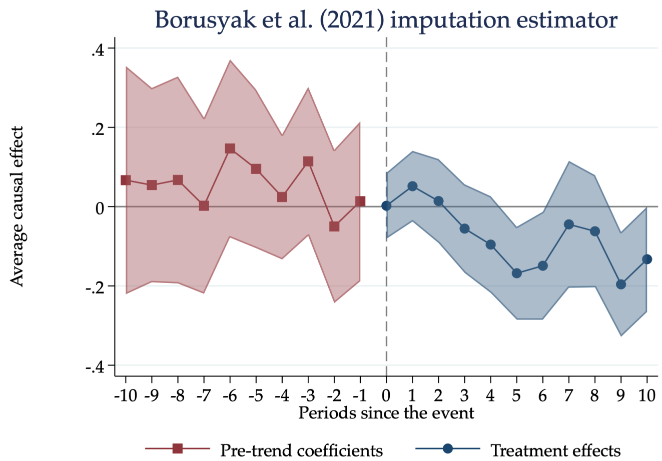
Appendix B.5 Event Study: All Solar Policies

Figure B.5: Event Analysis: Effect of All Solar Policies on (log) Installations



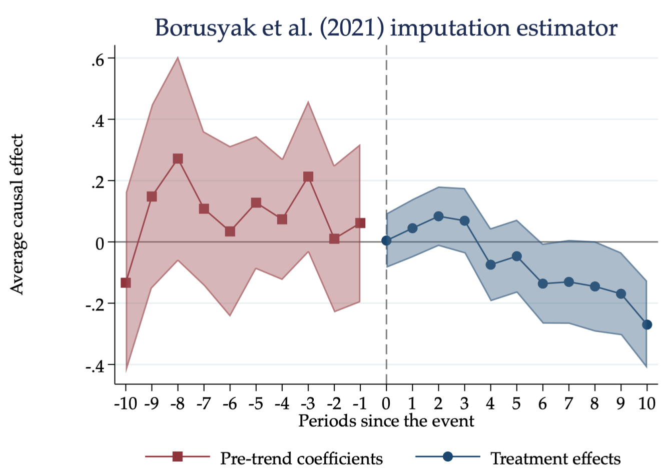
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.6: Event Analysis: Effect of All Solar Policies on (log) Installations Below the 20th Percentile of Capacity



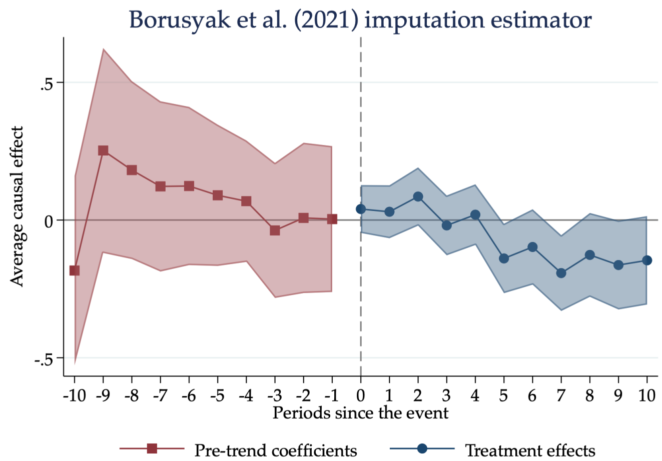
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.7: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity



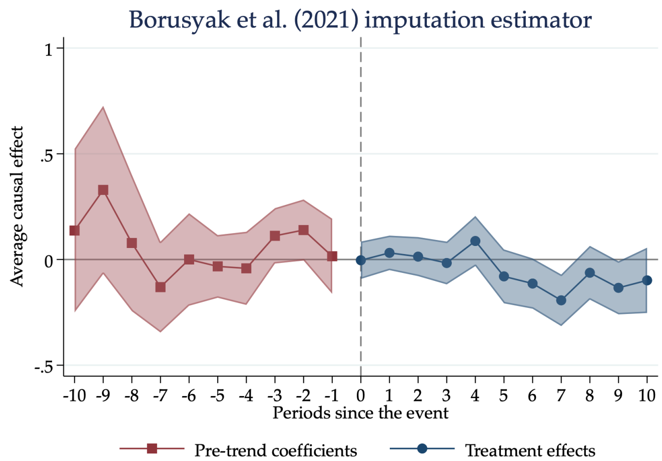
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.8: Event Analysis: Effect of All Solar Policies on (log) Installations at 40th to 60th Percentile of Capacity



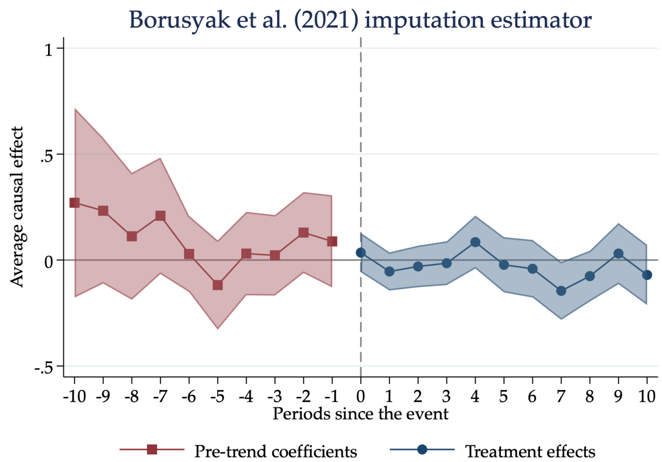
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.9: Event Analysis: Effect of All Solar Policies on (log) Installations at 60th to 80th Percentile of Capacity



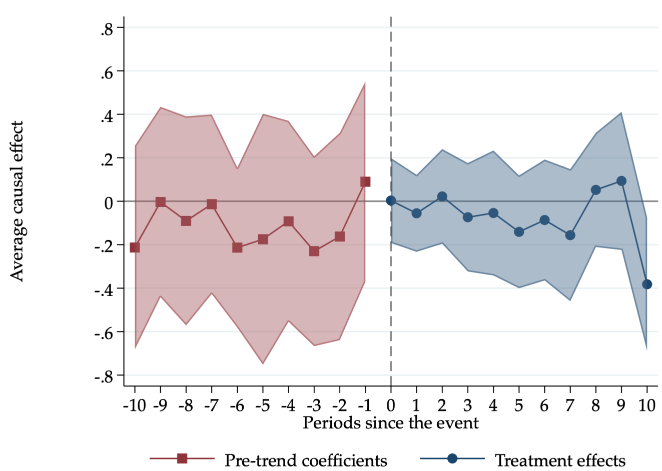
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.10: Event Analysis: Effect of All Solar Policies on (log) Installations Above the 80th Percentile of Capacity



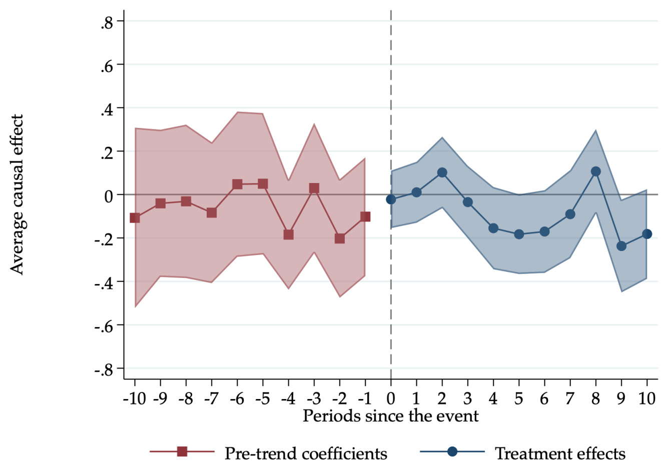
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.11: Event Analysis: Effect of All Solar Policies on (log) Capacity



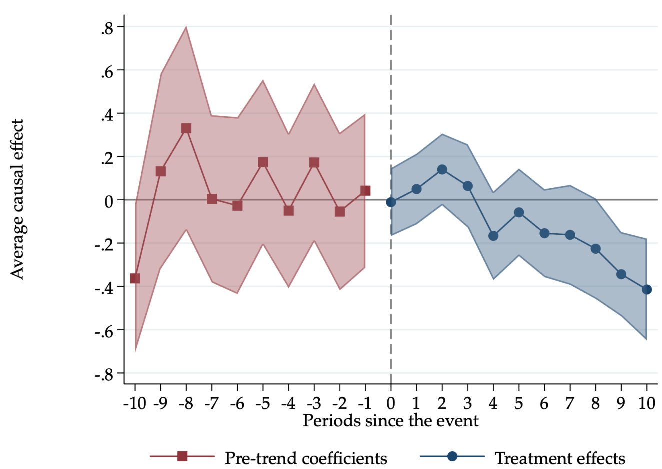
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.12: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity



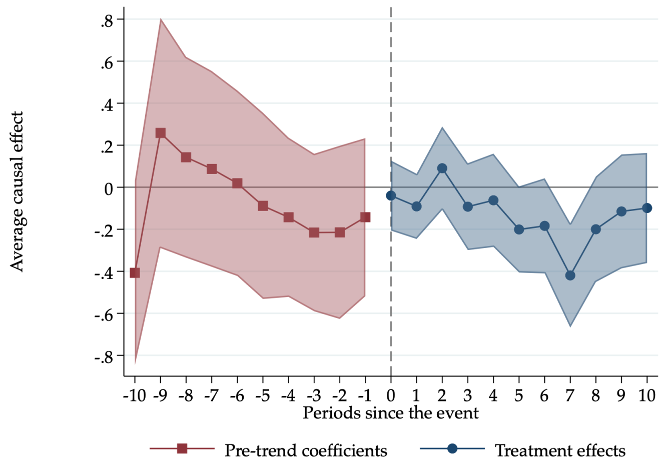
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.13: Event Analysis: Effect of All Solar Policies on (log) Capacity at 20th to 40th Percentile of Capacity



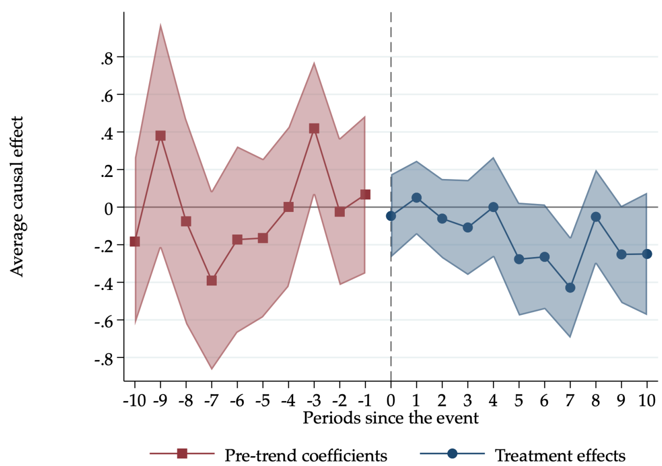
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.14: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity



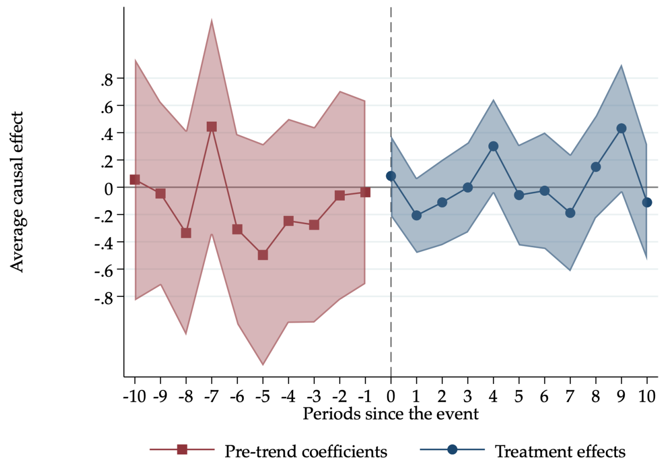
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.15: Event Analysis: Effect of All Solar Policies on (log) Capacity at 60th to 80th Percentile of Capacity



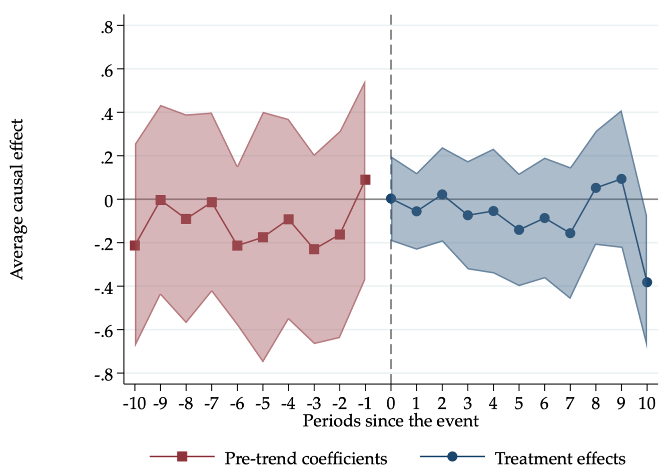
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.16: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity



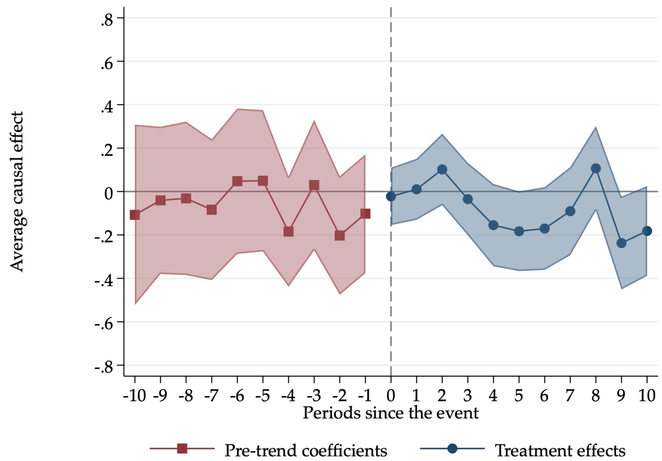
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.17: Event Analysis: Effect of All Solar Policies on (log) Capacity



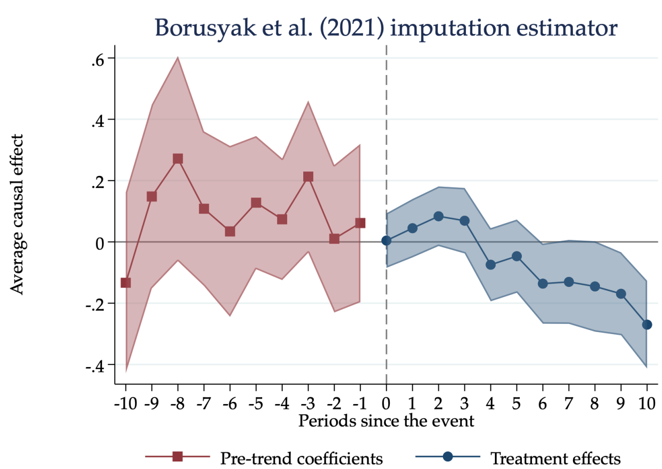
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.18: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity



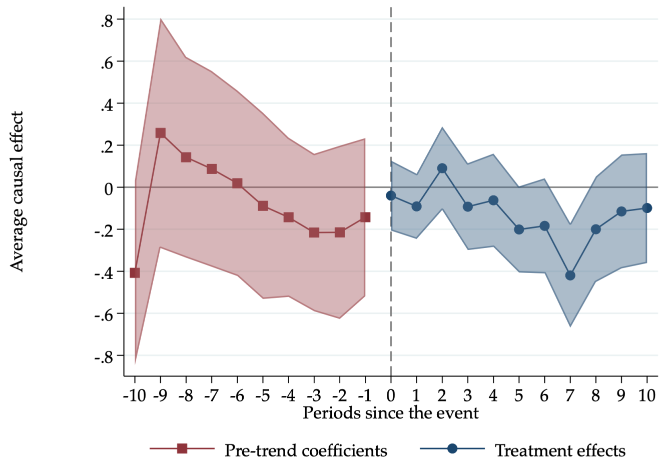
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.19: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity



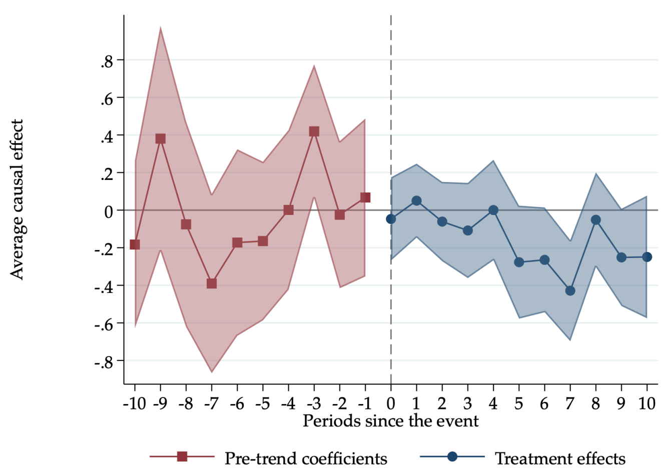
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.20: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity



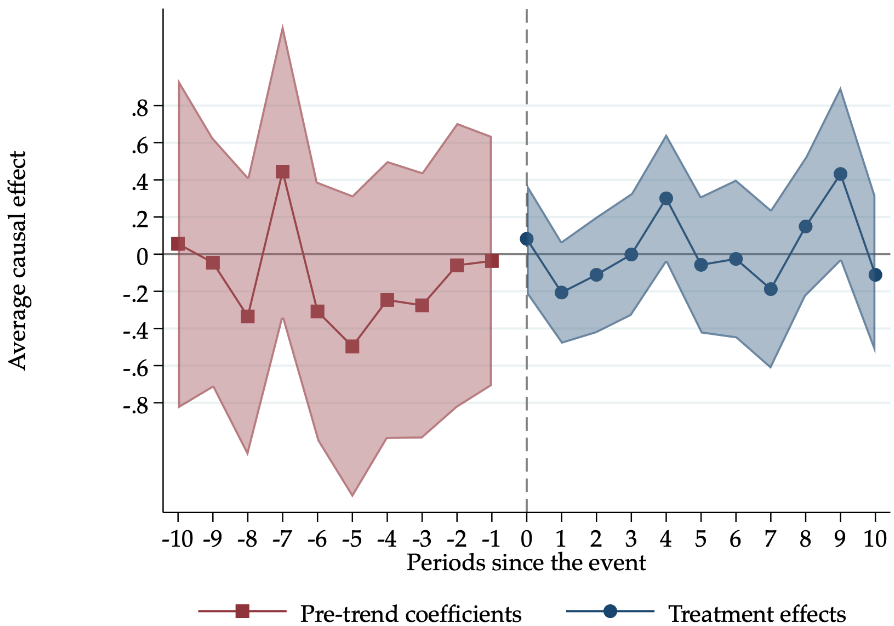
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.21: Event Analysis: Effect of All Solar Policies on (log) Capacity at 60th to 80th Percentile of Capacity



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

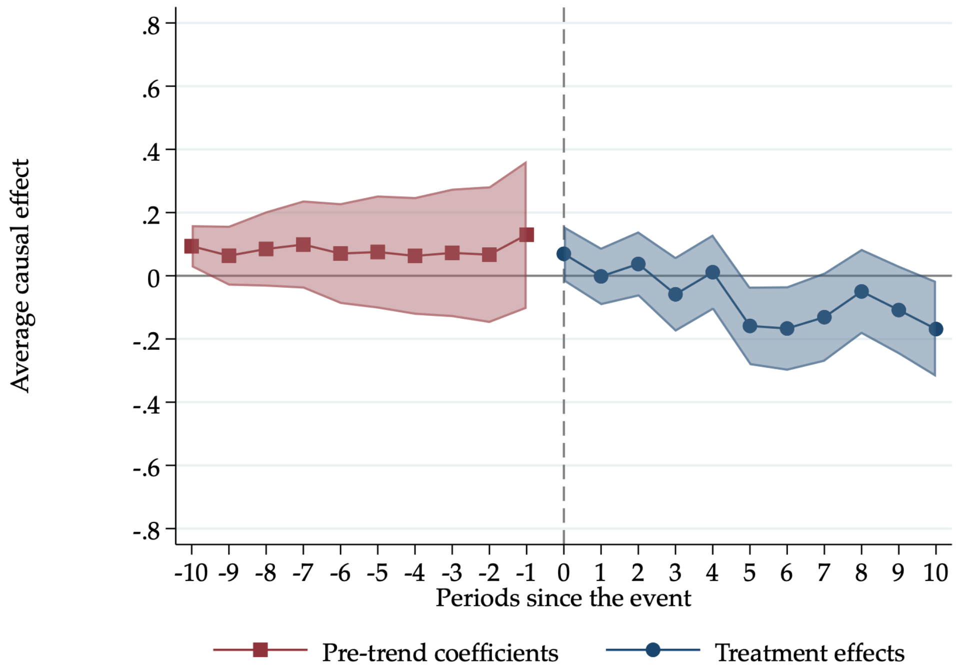
Figure B.22: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

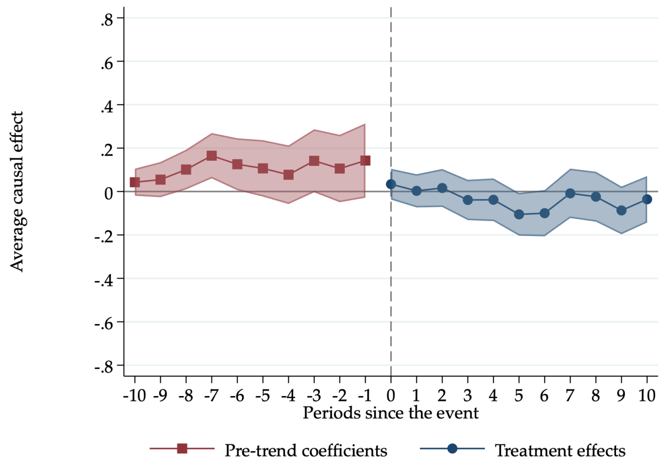
Appendix B.6 Event Study: No Covariates

Figure B.23: Event Analysis: Effect of All Solar Policies on (log) Installations (No Covariates)



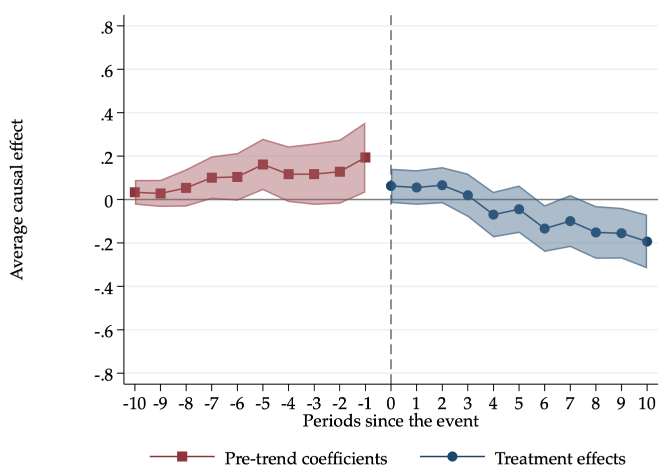
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.24: Event Analysis: Effect of All Solar Policies on (log) Installations Below the 20th Percentile of Capacity (No Covariates)



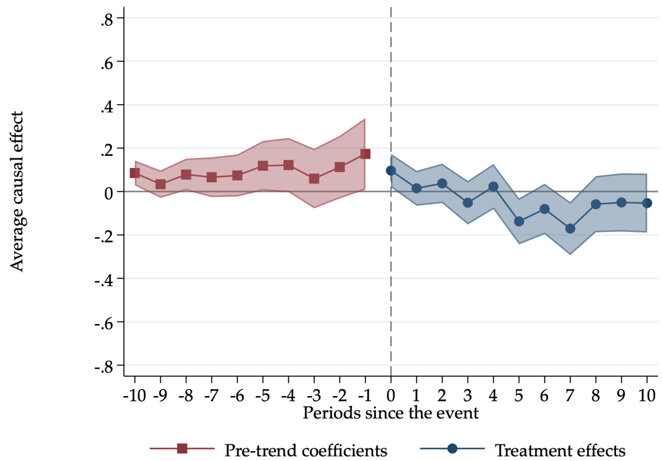
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.25: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity (No Covariates)



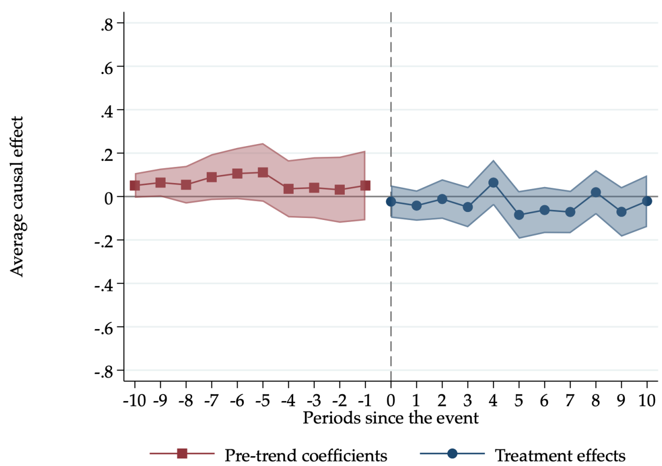
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.26: Event Analysis: Effect of All Solar Policies on (log) Installations at 40th to 60th Percentile of Capacity (No Covariates)



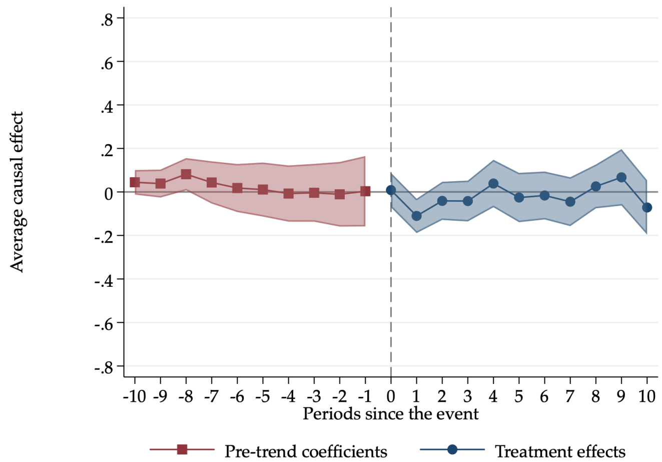
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.27: Event Analysis: Effect of All Solar Policies on (log) Installations at 60th to 80th Percentile of Capacity (No Covariates)



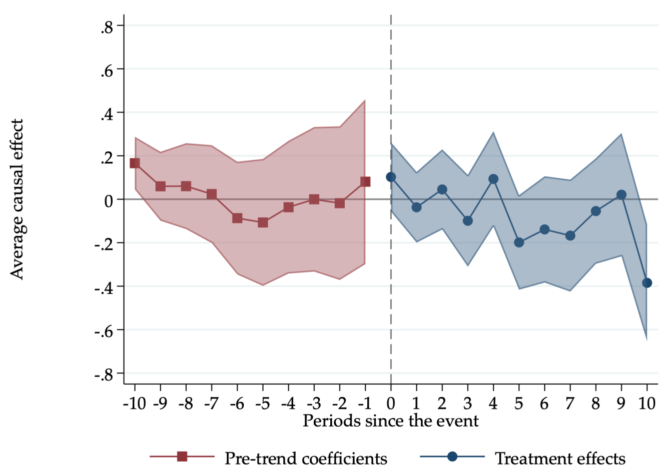
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.28: Event Analysis: Effect of All Solar Policies on (log) Installations Above the 80th Percentile of Capacity



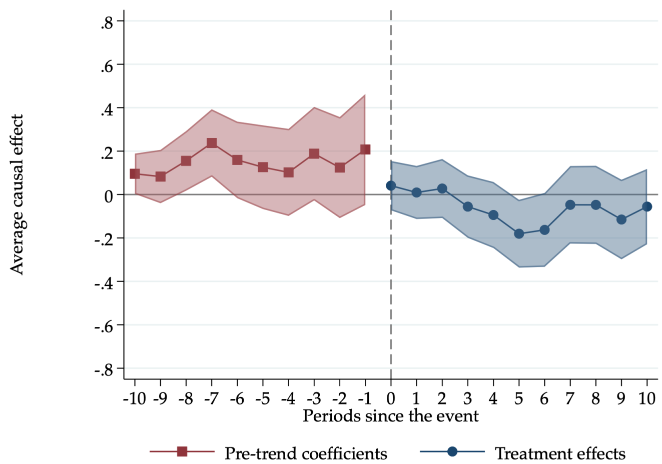
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.29: Event Analysis: Effect of All Solar Policies on (log) Capacity



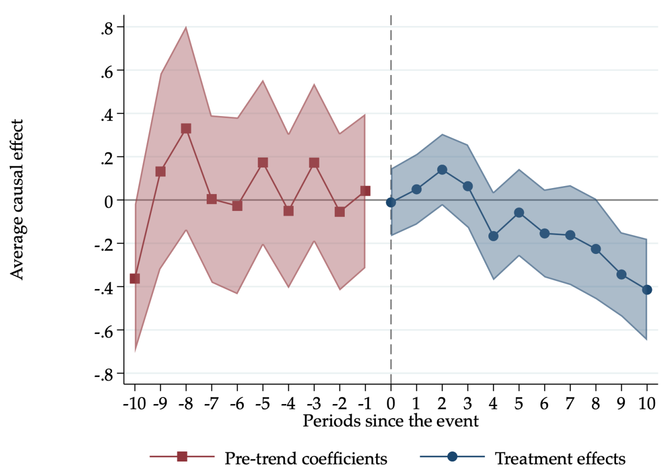
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.30: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity (No Covariates)



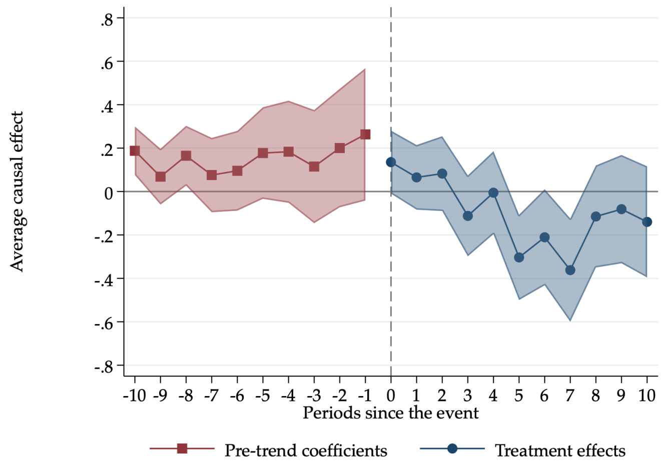
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.31: Event Analysis: Effect of All Solar Policies on (log) Capacity at 20th to 40th Percentile of Capacity



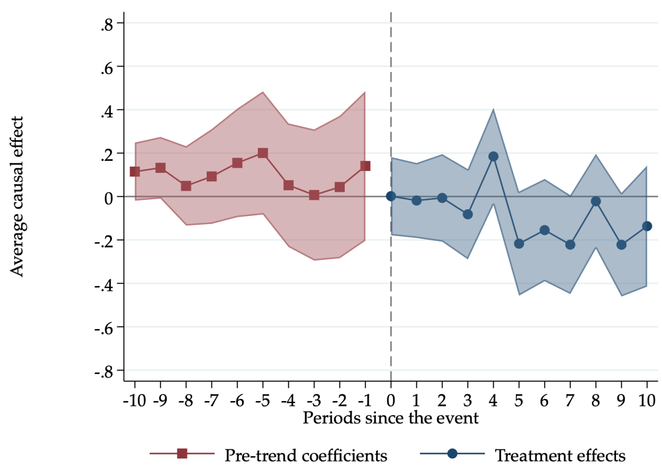
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.32: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity (No Covariates)



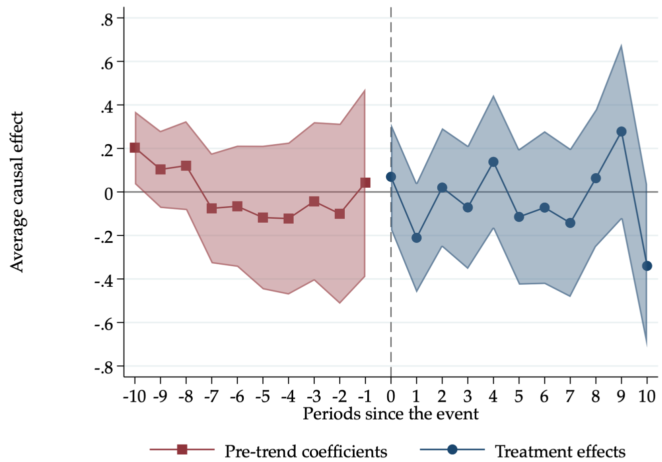
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.33: Event Analysis: Effect of All Solar Policies on (log) Capacity at 80th to 80th Percentile of Capacity



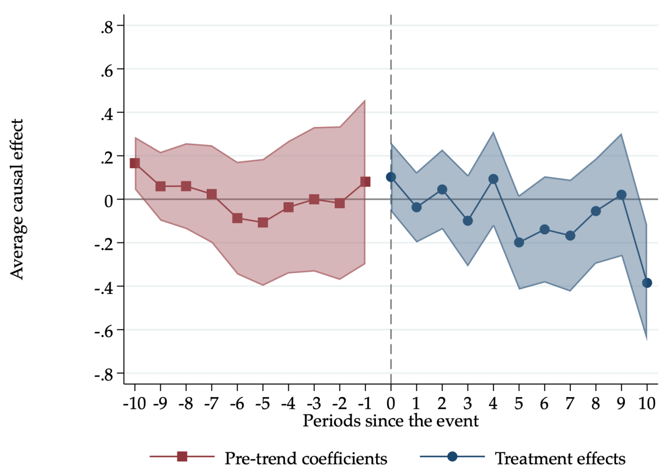
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.34: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity (No Covariates)



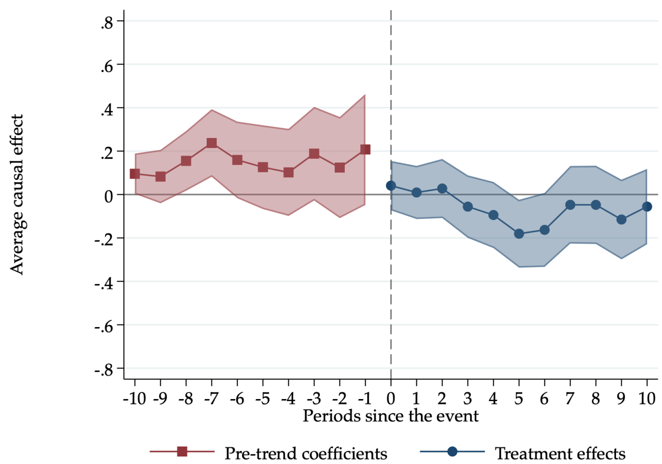
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.35: Event Analysis: Effect of All Solar Policies on (log) Capacity (No Covariates)



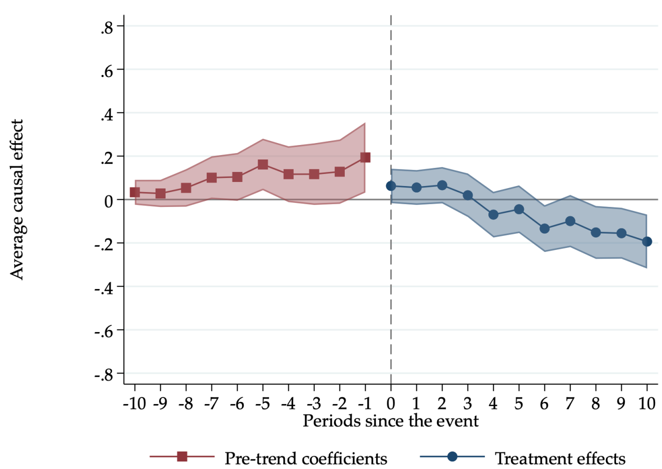
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.36: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity



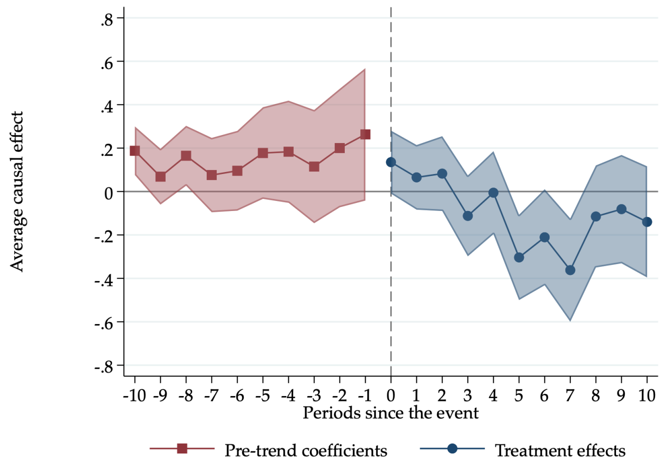
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.37: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity (No Covariates)



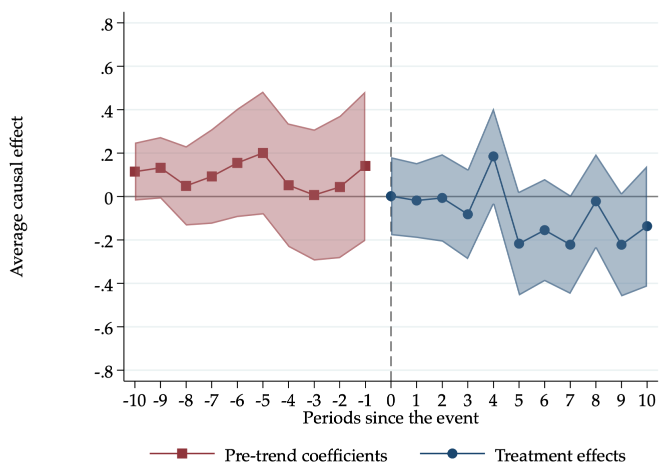
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.38: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity (No Covariates)



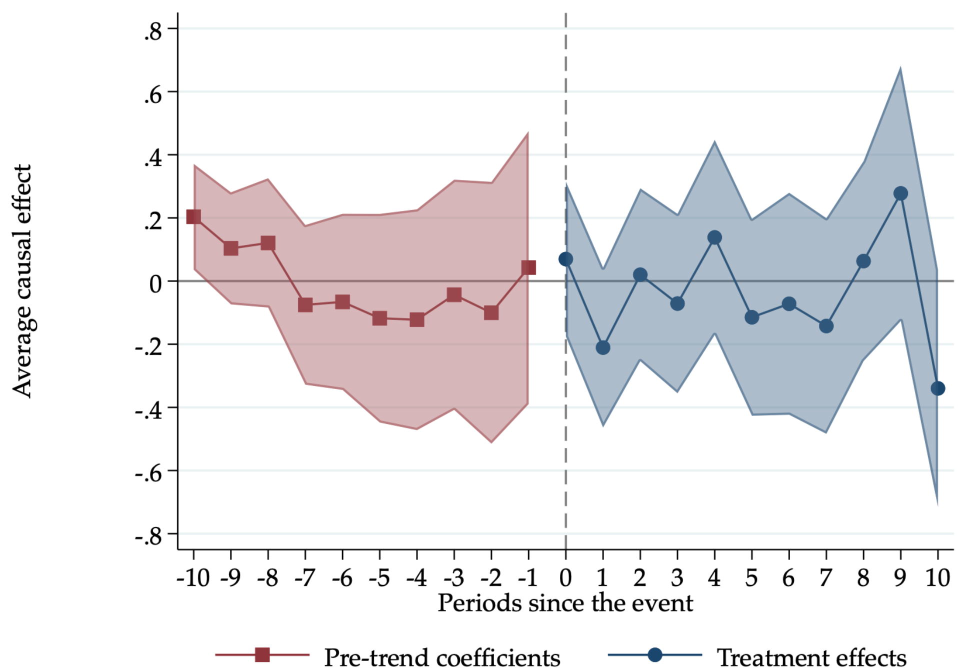
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.39: Event Analysis: Effect of All Solar Policies on (log) Capacity at 60th to 80th Percentile of Capacity (No Covariates)



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

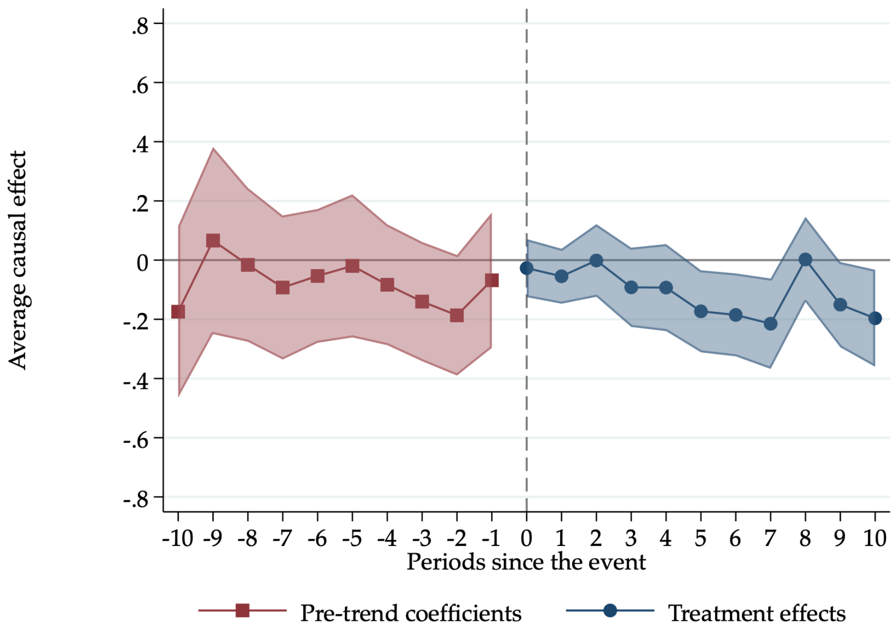
Figure B.40: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity (No Covariates)



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

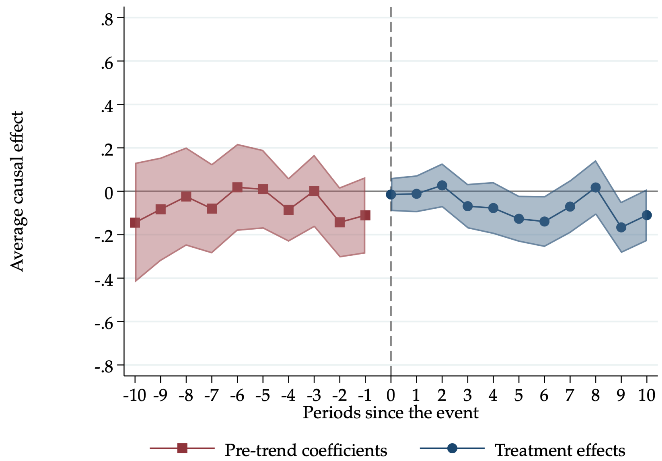
Appendix B.7 Event Study: Permits and Regulations

Figure B.41: Event Analysis: Effect of All Solar Policies on (log) Installations



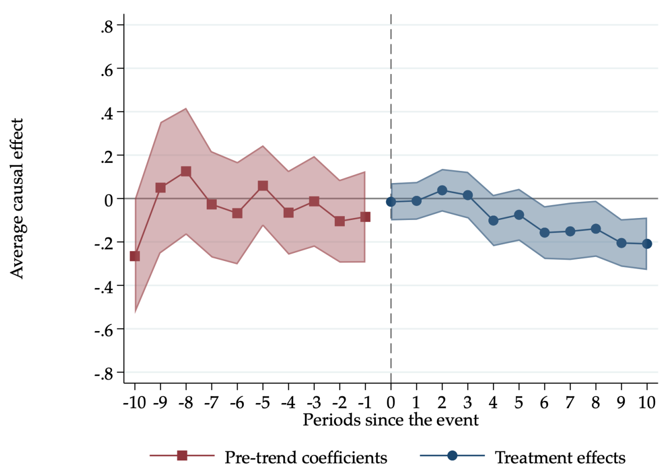
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.42: Event Analysis: Effect of All Solar Policies on (log) Installations Below the 20th Percentile of Capacity



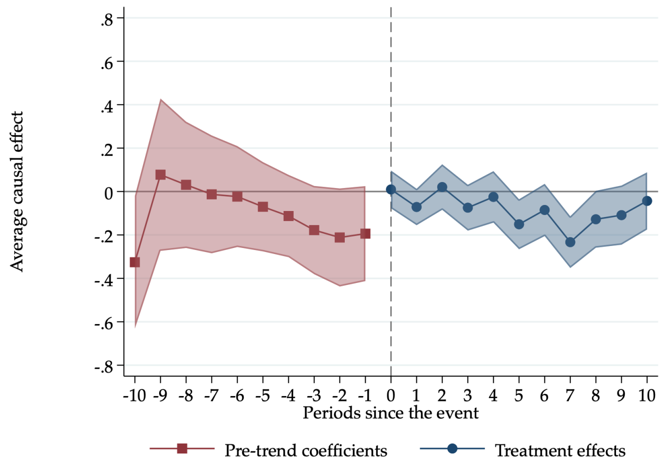
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.43: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity



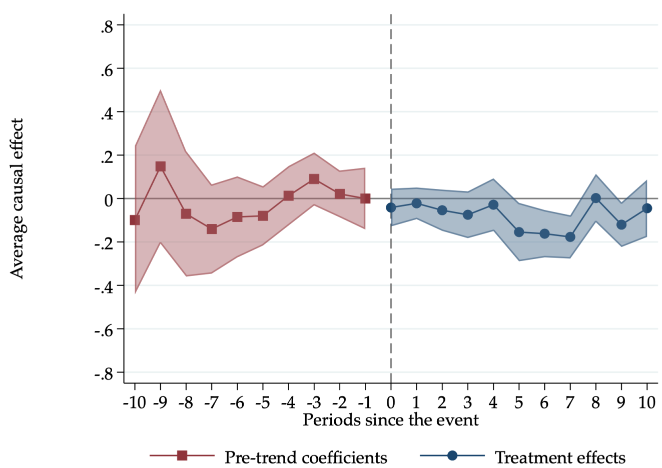
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.44: Event Analysis: Effect of All Solar Policies on (log) Installations at 40th to 60th Percentile of Capacity



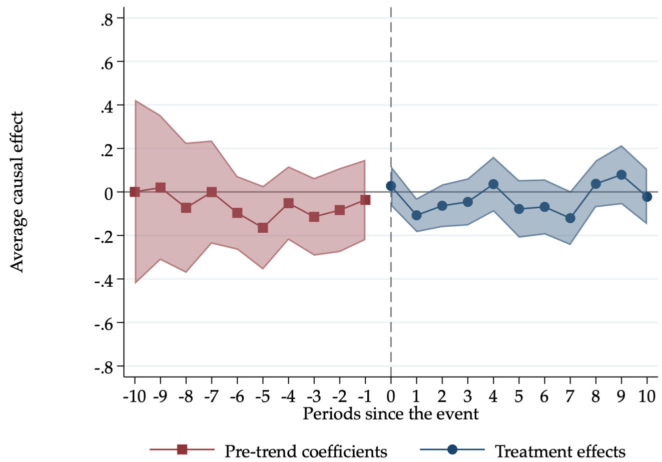
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.45: Event Analysis: Effect of All Solar Policies on (log) Installations at 60th to 80th Percentile of Capacity



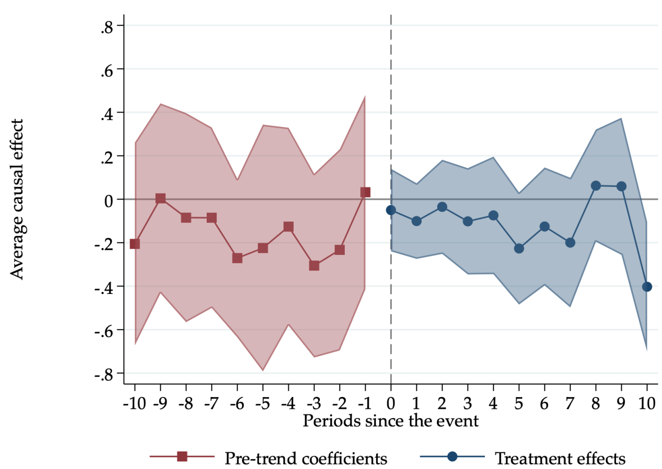
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.46: Event Analysis: Effect of All Solar Policies on (log) Installations Above the 80th Percentile of Capacity



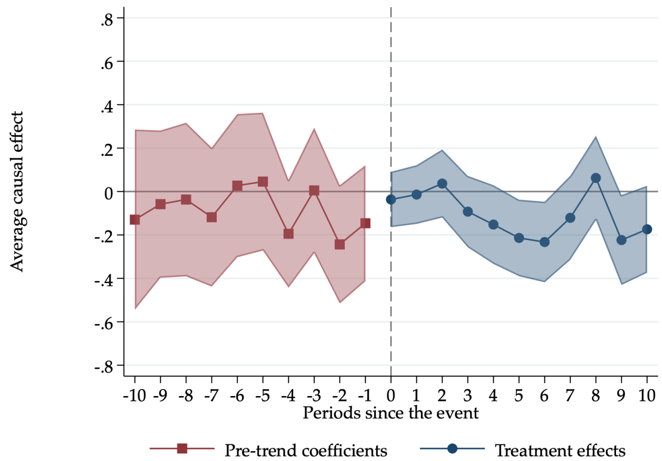
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.47: Event Analysis: Effect of All Solar Policies on (log) Capacity



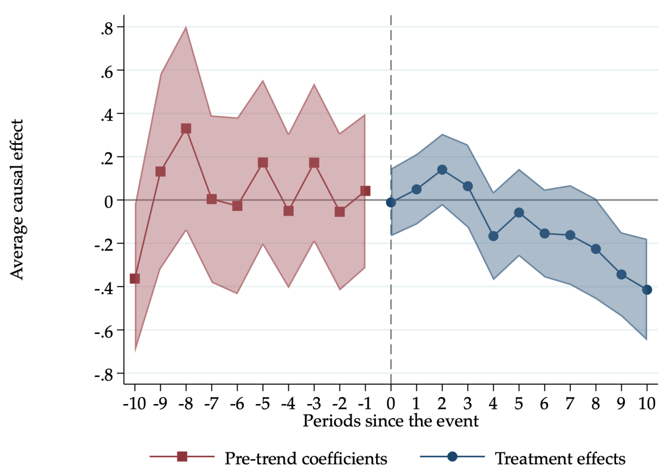
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.48: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity



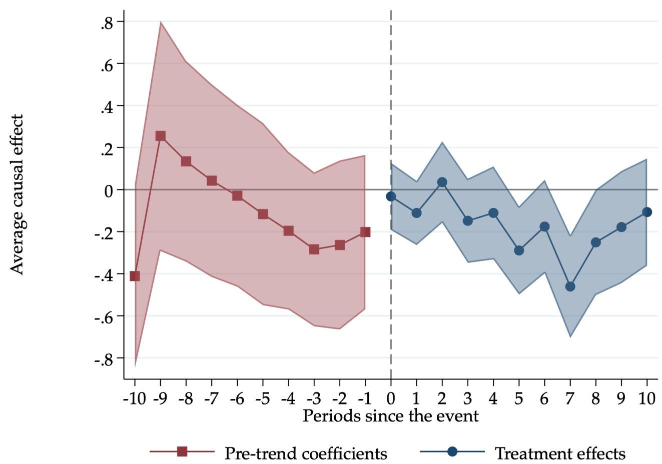
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.49: Event Analysis: Effect of All Solar Policies on (log) Capacity at 20th to 40th Percentile of Capacity



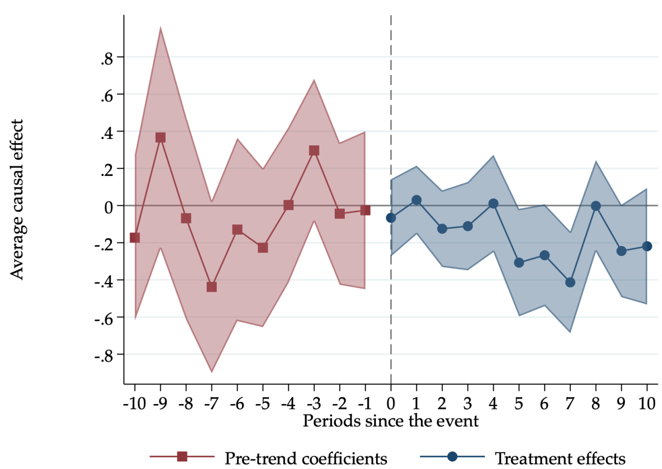
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.50: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity



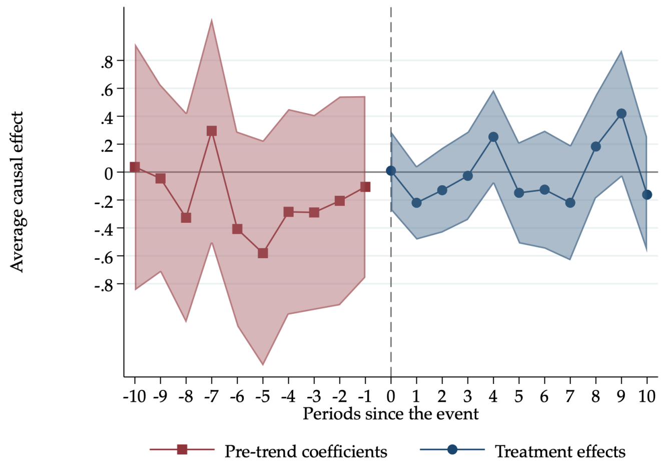
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.51: Event Analysis: Effect of All Solar Policies on (log) Capacity at 80th to 80th Percentile of Capacity



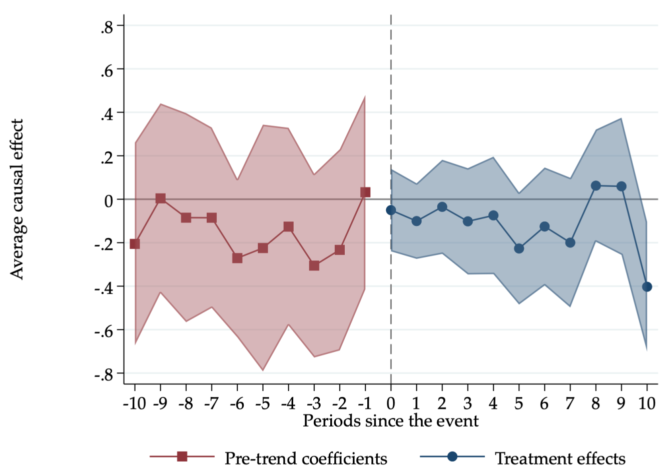
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.52: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity



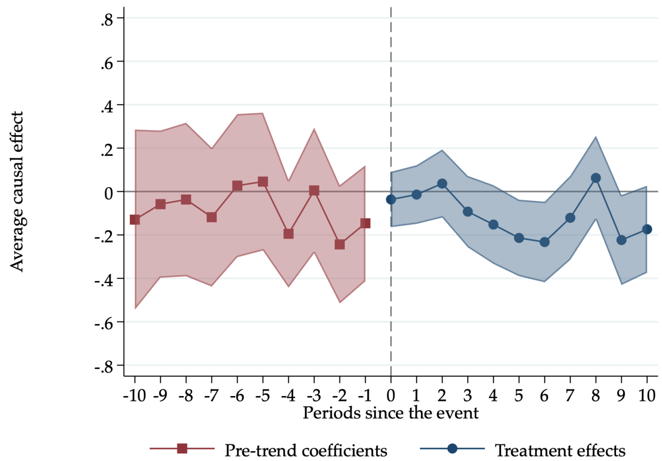
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.53: Event Analysis: Effect of All Solar Policies on (log) Capacity



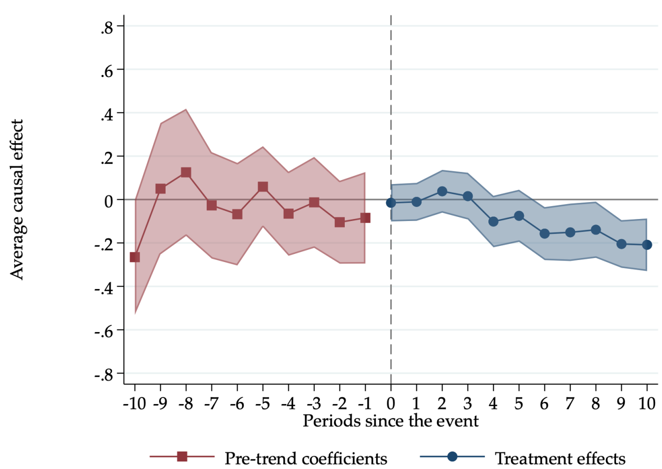
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.54: Event Analysis: Effect of All Solar Policies on (log) Capacity Below the 20th Percentile of Capacity



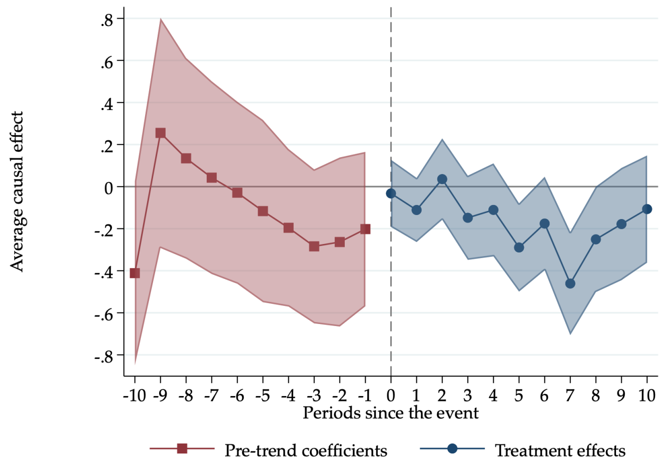
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.55: Event Analysis: Effect of All Solar Policies on (log) Installations at 20th to 40th Percentile of Capacity



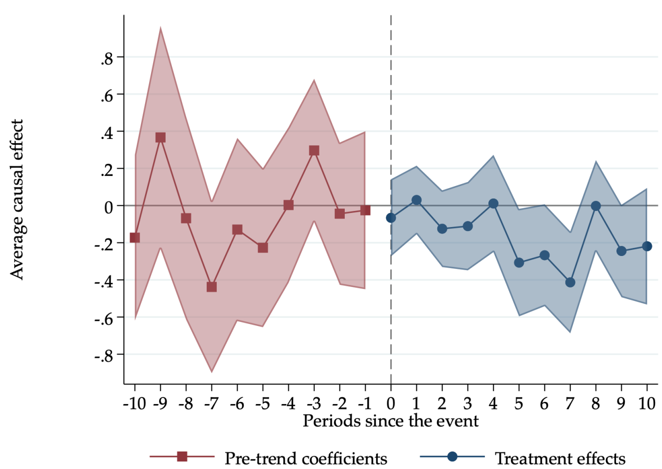
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.56: Event Analysis: Effect of All Solar Policies on (log) Capacity at 40th to 60th Percentile of Capacity



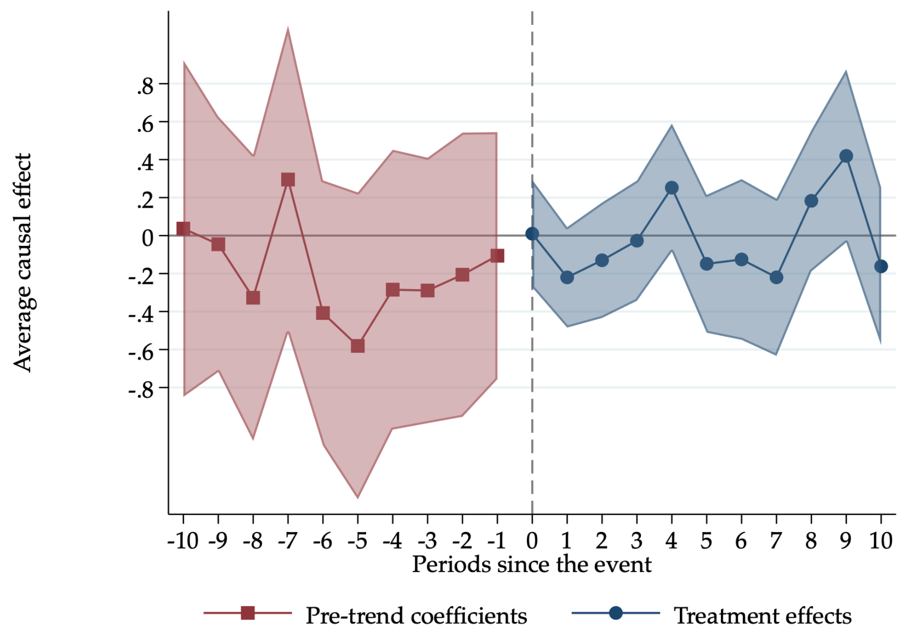
Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.57: Event Analysis: Effect of All Solar Policies on (log) Capacity at 60th to 80th Percentile of Capacity



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Figure B.58: Event Analysis: Effect of All Solar Policies on (log) Capacity Above the 80th Percentile of Capacity



Borusyak et al. (2021) imputation estimator. 95 percent confidence intervals indicated by shaded area.

Appendix B.8 Continuous Treatment

Our main specification studies the treatment effect of a municipal solar policy as a canonical binary policy effect. In reality, some municipalities implement solar policies that apply only to a subset of the total land area of the municipality. Therefore, our analyses include an additional set of estimations where we account for area-specific policies using a continuous variable.

The treatment variable of interest takes value zero if no solar policy is in place, one if the municipality implemented a policy that applies to its entire land area, and a value corresponding to the share of the total urban area that is treated if the policy is spatially targeted.

This continuous treatment variable relies on land use categorization data,[11] in which urban land with many buildings that may have rooftop solar installed is categorized as either "continuous urban fabric" (Durchgängig städtische Prägung) or "discontinuous urban fabric" (Nich durchgängig städtische Prägung). Our treatment intensity measure is thus the fraction of the total urban fabric which is covered by the policy. The values corresponding to the share of the total land area that is treated are constructed using the detailed policy documents, maps, and shapefiles provided by the municipalities.

The two-way fixed effect estimation using the continuous treatment variable identifies an average causal response (ACR), which captures a weighed average of causal responses to a unit change in treatment (Angrist and Imbens, 1995). Intuitively, this can be though of as a treatment dose. Callaway and Sant'Anna, 2021 discuss the implications of identifying the ACR in a generalized difference-in-differences framework. They show that a stronger parallel trend assumption needs to hold in a scenario with multiple time periods and staggered adoption of continuous treatments. This stronger assumption restricts paths of treated potential outcomes by treatment dose group: All dose groups treated at a particular time need to follow the same path of potential outcomes at every dose. We believe that our argument in support of the parallel trend assumption in the binary treatment case extends to the continuous case. Moreover, it is plausible that, for example, a ban of

[11] Specifically, on the CORINE Land Cover (CLC) database, 2018 edition, maintained by Germany's geodesy agency (Bundesamt für Kartographie und Geodäsie.)

solar installations that applies to 60 percent of an urban area implies a solar capacity trajectory not substantially different from a ban that applies to 30 percent of an area. In other words, we expect a reduction in capacity twice as large in the case of a 60 percent area ban compared to the ban on solar in 30 percent of the urban area.

Appendix B.9 Additional Tables & Figures

Table B.7: Effect of Any Policy on Solar Adoption (2000-2019)

	(1) Log Capacity	(2) Log Installs
all percentile	-0.0421	-0.0216
	(0.107)	(0.0641)
20 percentile	-0.0219	-0.00546
	(0.0662)	(0.0451)
40 percentile	-0.0890	-0.0535
	(0.0830)	(0.0539)
60 percentile	-0.0857	-0.0499
	(0.0898)	(0.0574)
80 percentile	0.00777	0.0112
	(0.0914)	(0.0472)
80_over percentile	-0.126	-0.0334
	(0.142)	(0.0548)
Time-varying controls	Yes	Yes
N	22296	22296
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Adj. R^2	0.660	0.685
Adj. within R^2	0.00556	0.00654

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.8: Effect of Permits & Regulations on Solar Adoption, Matching on 1995 Control Variables

	(1) Log Capacity	(2) Log Installs
all percentile	-0.00836	-0.0216
	(0.0963)	(0.0584)
20 percentile	-0.0237	-0.0109
	(0.0593)	(0.0398)
40 percentile	-0.0773	-0.0445
	(0.0763)	(0.0476)
60 percentile	-0.0886	-0.0358
	(0.0856)	(0.0503)
80 percentile	-0.0131	-0.00417
	(0.0826)	(0.0402)
80_over percentile	-0.0258	-0.00919
	(0.125)	(0.0451)
Time-varying controls	Yes	Yes
N	34384	34384
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Adj. R^2	0.620	0.647
Adj. within R^2	0.00366	0.00426

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Figure B.59: Effect of Permits & Regulations on Solar Adoption for 1st Quintile Installations, Over 78 Permutations Removing 2 States

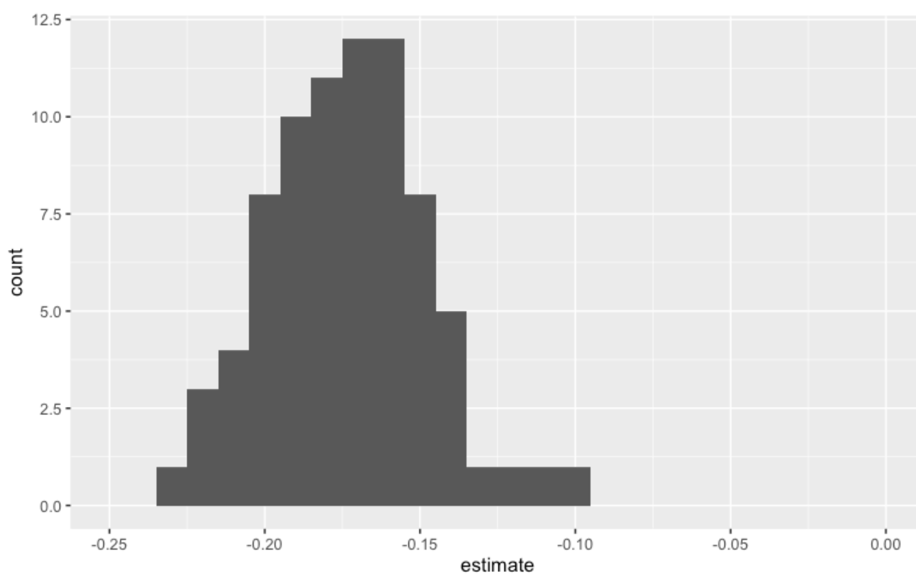


Table B.9: Effect of Any Policy on Solar Adoption, Exact Match on Historical Status of Municipality

	(1) Log Capacity	(2) Log Installs
all percentile	-0.153	-0.108*
	(0.0970)	(0.0591)
20 percentile	-0.106*	-0.0673*
	(0.0601)	(0.0399)
40 percentile	-0.154**	-0.0853*
	(0.0768)	(0.0483)
60 percentile	-0.178**	-0.0866*
	(0.0860)	(0.0514)
80 percentile	-0.151*	-0.0716*
	(0.0840)	(0.0410)
80_over percentile	-0.194	-0.0739
	(0.127)	(0.0468)
Time-varying controls	Yes	Yes
N	34369	34369
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Adj. R^2	0.620	0.645
Adj. within R^2	0.00609	0.00885

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.10: Effect of Any Policy on Solar Adoption, Treatment Intensity

	(1) Log Capacity	(2) Log Installs
all percentile	-0.213*	-0.152*
	(0.125)	(0.0833)
20 percentile	-0.152*	-0.0954*
	(0.0845)	(0.0549)
40 percentile	-0.237**	-0.143**
	(0.110)	(0.0679)
60 percentile	-0.249**	-0.134*
	(0.123)	(0.0694)
80 percentile	-0.211*	-0.0956*
	(0.121)	(0.0561)
80_over percentile	-0.325*	-0.118*
	(0.176)	(0.0638)
Time-varying controls	Yes	Yes
N	33169	33169
Adj. R^2	0.617	0.643
Adj. within R^2	0.00691	0.0104

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.11: Effect of Permits & Regulations on Solar Adoption, Treatment Intensity

	(1) Log Capacity	(2) Log Installs
all percentile	-0.361**	-0.254**
	(0.169)	(0.104)
20 percentile	-0.246***	-0.149**
	(0.0928)	(0.0621)
40 percentile	-0.366***	-0.195**
	(0.138)	(0.0824)
60 percentile	-0.400***	-0.204**
	(0.146)	(0.0805)
80 percentile	-0.344**	-0.150**
	(0.157)	(0.0679)
80_over percentile	-0.309	-0.108
	(0.206)	(0.0721)
Time-varying controls	Yes	Yes
N	9523	9523
Adj. R^2	0.627	0.651
Adj. within R^2	0.0118	0.0124

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.12: Effect of Permits & Regulations on Solar Adoption, Including Multiple Policies

	(1) Log Capacity	(2) Log Installs
All installations	-0.233	-0.148
	(0.142)	(0.0912)
1 quintile	-0.129	-0.0687
	(0.0869)	(0.0588)
2 quintile	-0.217*	-0.0994
	(0.122)	(0.0749)
3 quintile	-0.261**	-0.116
	(0.129)	(0.0737)
4 quintile	-0.180	-0.0742
	(0.143)	(0.0659)
5 quintile	-0.114	-0.0326
	(0.177)	(0.0656)
Time-varying controls	Yes	Yes
N	9390	9390
Adj. R^2	0.620	0.642
Adj. within R^2	0.0118	0.0124

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.13: Effect of Permits & Regulations on Solar Adoption, Removing Bavaria and Baden-Württemberg

	(1) Log Capacity	(2) Log Installs
All Installations	-0.349	-0.263**
	(0.227)	(0.130)
1 quintile	-0.207*	-0.121
	(0.120)	(0.0796)
2 quintile	-0.360**	-0.177*
	(0.172)	(0.104)
3 quintile	-0.373**	-0.168*
	(0.183)	(0.0987)
4 quintile	-0.322*	-0.148**
	(0.180)	(0.0720)
5 quintile	-0.228	-0.109
	(0.277)	(0.0833)
Time-varying controls	Yes	Yes
N	4915	4915
Adj. R^2	0.565	0.602
Adj. within R^2	0.00778	0.00847

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.14: Effect of Permits & Regulations on Solar Adoption, with False Discovery Rate q-values

	(1) Log capacity	(2) Log installs
All installations	-0.235	-0.143
	(0.176)	(0.176)
1 quintile	-0.135	-0.0716
	(0.186)	(0.245)
2 quintile	-0.185	-0.0785
	(0.176)	(0.247)
3 quintile	-0.235	-0.0943
	(0.176)	(0.244)
4 quintile	-0.153	-0.0633
	(0.245)	(0.247)
5 quintile	-0.112	-0.0282
	(0.507)	(0.608)
Time-varying controls	Yes	Yes
N	9019	9019
Adj. R^2	0.614	0.634
Municipality FE	Yes	Yes
Year FE	Yes	Yes

q-values computed across all 12 estimates

Table B.15: Effect of any Solar Policy on Solar Adoption (1:1 match)

	(1) Log Capacity	(2) Log Installs
any percentile	-0.144	-0.0965
	(0.125)	(0.0819)
20 percentile	-0.101	-0.0546
	(0.0782)	(0.0522)
40 percentile	-0.172	-0.0833
	(0.111)	(0.0687)
60 percentile	-0.176	-0.0809
	(0.119)	(0.0691)
80 percentile	-0.119	-0.0531
	(0.121)	(0.0563)
80 over percentile	-0.113	-0.0448
	(0.167)	(0.0630)
Time-varying controls	Yes	Yes
N	12145	12145
Adj. R^2	0.624	0.646
Adj. within R^2	0.00639	0.00734

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.16: Effect of Permits & Regulations on Solar Adoption (1:1 match)

	(1) Log Capacity	(2) Log Installs
all percentile	-0.209	-0.141
	(0.141)	(0.0865)
20 percentile	-0.136*	-0.0783
	(0.0811)	(0.0535)
40 percentile	-0.179	-0.0794
	(0.112)	(0.0680)
60 percentile	-0.236*	-0.102
	(0.124)	(0.0701)
80 percentile	-0.153	-0.0692
	(0.135)	(0.0629)
80_over percentile	-0.131	-0.0399
	(0.172)	(0.0638)
Time-varying controls	Yes	Yes
N	11133	11133
Year FE	0.613	0.634
Municipality FE	0.0107	0.0144

Standard errors clustered at the municipality-level.
Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.17: Bans

	(1) Log Capacity	(2) Log Installs
All installations	0.503*	0.300**
	(0.269)	(0.148)
1 quintile	0.353***	0.234***
	(0.123)	(0.0844)
2 quintile	0.399**	0.260**
	(0.195)	(0.130)
3 quintile	0.200	0.141
	(0.248)	(0.155)
4 quintile	0.388	0.174
	(0.236)	(0.107)
5 quintile	0.619*	0.224*
	(0.364)	(0.131)
Time-varying controls	Yes	Yes
N	6131	6131
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Adj. R^2	0.665	0.690
Adj. within R^2	0.0774	0.0970

Standard errors clustered at the municipality-level.

Significance levels: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

References

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Vita

Béla Figge is a Ph.D. Candidate in the Economics Department of the Andrew Young School of Policy Studies at Georgia State University. He is expected to graduate in the Summer of 2022. He holds an undergraduate degree in Economics from Bennington College and pursued graduated studies at the University of Mannheim. Béla's doctoral studies were supported by the Andrew Young School Dean's Fellowship and by the Georgia State University Second Century Initiative Graduate Fellowship. He worked at Georgia Policy Labs from 2017 to 2022. His research interests are in applied microeconomics, with a focus on labor, health and environmental economics.