The Impact of Women's Health Clinic Closures on Fertility

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Abstract

In recent years, the government of Texas has enacted multiple restrictions and funding limitations on women's health organizations affiliated with the provision of abortion services. These policies have caused numerous clinic closures throughout the state, drastically reducing access to reproductive health care. We study the impact of these clinic closures on fertility rates by combining quarterly snapshots of health center addresses from a network of women's health centers with restricted geotagged data of all Texas birth certificates for 2008–2013. We calculate the driving distance to the nearest clinic for each ZIP-code and quarter, and find that an increase of 100 miles to the nearest clinic results in a 1.2 percent increase in the fertility rate. This increase is driven by a 2.4 percent increase in the fertility rate for unmarried women, while there is no statistically significant change for married women.

JEL codes: H75, I18, J13

Keywords: Family Planning; Contraception; Fertility Rate; Birth Rate; Law; Texas

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Acknowledgements: We are grateful to Elizabeth Ananat, Martha Bailey, Janet Currie, Donna Ginther, Bapu Jena, Ted Joyce, Katy Kozhimannil, Jason Lindo, Michael Richards, Analisa Packham, Daria Pelech, Aaron Schwartz, anonymous reviewers, and seminar and conference participants at the University of Kansas, Iowa State University, West Virginia University, the NBER Summer Institute Children's Workshop, Yale University, the Association for Public Policy Analysis and Management, the Southern Economic Association, Texas A&M University, and KORA (the Danish Institute for Local and Regional Government Research) for their help and comments. We would also like to thank the staff at the Texas Department of State Health Services for providing us with the birth certificate data, and Paul Espinosa, Scott Durham, and Justin Graham at KU IT for managing our HIPAA compliant research server. Partial funding support for this study is from the Department of Economics at the University of Kansas. We have no financial or other conflicts to disclose. All opinions and any errors are our own.

I. Introduction

Women's health care, particularly access to reproductive health care and abortion services, provokes a wide range of reactions across the political spectrum. For example, the 2016 Democratic Party Platform supported "access to quality reproductive health care services, including safe and legal abortion," as part of Democrats' commitment to "protecting and advancing reproductive health, rights, and justice."[1] In contrast, the 2016 Republican Party Platform pledged to "oppose the use of public funds to perform or promote abortion" and asserted "the sanctity of human life."[2] Since January 2017, the current presidential administration and majority-Republican Congress have repeatedly sought to cut funding for women's health organizations that provide abortion services or are associated with organizations that do.[3] This consensus among the President and Congressional leadership has increased the possibility that previous state-level funding cuts to women's health and family planning services could now happen nationwide.

To illuminate the potential consequences of such a national policy, this paper studies one set of previous funding cuts and restrictions that led to clinic closures, namely those of the state of Texas. In particular, we investigate the following question: How does ease of access to women's health and family planning clinics affect the fertility rate? These specialized clinics offer contraceptive and sometimes abortion services, in addition to often serving as a primary

[1] Democratic Party Platform. 2016. https://www.democrats.org/party-platform.

[2] Republican Platform. 2016. https://prod-cdn-static.gop.com/static/home/data/platform.pdf.

[3] For example, the eight-page Health Care Freedom Act spent two and a half pages legislating that certain health care organizations that provide for abortions could not receive federal funds. (*See* Health Care Freedom Act. 2017. https://www.budget.senate.gov/imo/media/doc/HealthCareFreedomAct.pdf.) This sentiment was also mentioned in the summary of the White House's fiscal year 2018 budget. (*See* The White House. 2017. "The President's Fiscal Year 2018 Budget: Overview." https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/budget/fy2018/fact_sheets/2018%20Budget%20Fact%20Sheet_Budget%20Overview.pdf.)

point of access to the health care system (Frost et al. 2012). Therefore, we hypothesize that clinic closures and the resulting increases in driving distance lead to a higher fertility rate, and in this paper seek to identify and to quantify that effect.

Given a change in the fertility rate, we also test whether particular demographic subgroups are driving this overall change. Based on the demographic composition of abortion patients—who may face higher barriers to reproductive health services and therefore approximate the "marginal" patients affected by clinic closures—we hypothesize that any increase in the fertility rate resulting from lack of access to family planning services is concentrated among unmarried women (Jerman et al. 2016). In addition, we predict that decreased access to family planning services affects both white and Hispanic women, affects women of both low and high educational attainment, has some effect on births beyond the first child, and lowers the mean maternal age at birth.[4]

We test our hypotheses using a recent series of politically-motivated public policy changes in Texas. First, in 2011, Texas cut its two-year family planning budget from $111 MM to $38 MM, and gave funding priority to primary care. Consequently, by 2012, 146 clinics had lost state funds, 53 clinics had closed, and 38 clinics had reduced their hours of operation (White et al. 2012).[5] As a result, there were almost 50 percent fewer organizations to help poor women plan their pregnancies,[6] with many basic contraceptive services now out of reach.[7]

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[4] Jerman et al. from the Guttmacher Institute (2016) report that approximately 85 percent of abortion patients nationwide are unmarried. They also report that, in 2008, 37 percent of abortion patients nationwide are white, 25 percent are Hispanic, 39 percent have a high school diploma or less, 61 percent have had at least one previous birth, and 58 percent are in their 20s.

[5] Due to our non-disclosure agreement with the data provider, we are unable to say how many of these overall closures were associated with the provider network we study.

[6] Culp-Ressler, Tara. 2012. "Attacks On Planned Parenthood In Texas Forced At Least 50 Unaffiliated Health Clinics To Close." Think Progress, August 16. http://thinkprogress.org/health/2012/08/16/699031/attacks-on-planned-parenthood-in-texas-forced-at-least-50-unaffiliated-health-clinics-to-close/.

Furthermore, in 2013, Texas excluded provider networks affiliated with abortion providers from the Women's Health Program. This program was largely Medicaid-funded, with the federal government contributing about $30 million per year, or 90 percent of program costs. Due to Texas's action, Texas lost substantial federal funding at the end of 2012.[8] Given that our birth record data extends only through 2013, we observe the effect of clinic closures occurring no later than in the first quarter of 2013. Therefore, our analysis is primarily informative for quantifying the effects of the first Texas policy.

These policy changes and the resulting clinic closures allow us to test the impact of ease of access to care on fertility rates. We follow the approach of Lu and Slusky (2016) by using health center addresses from a particular network of women's health centers to calculate the driving distance to the nearest clinic in that network for each ZIP-code. We also calculate fertility rates for each ZIP-code. Then, using a within estimator, we estimate the impact of a relative change in driving distance on the relative fertility rate. We find that an increase in driving distance to the nearest clinic leads to a statistically significant increase in fertility rates, and that the effect is concentrated among unmarried women.[9]

Clinic closures could affect fertility rates through two complementary mechanisms: (1) lack of access to contraception, with more women having unplanned pregnancies due to using a

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[7] Jones, Carolyn. 2012. "One Year Later, Cuts to Women's Health Have Hurt More Than Just Planned Parenthood." Texas Observer, August 15. http://www.texasobserver.org/one-year-later-cuts-to-womens-health-have-hurt-more-than-just-planned-parenthood/.

[8] Smith, Jordan. 2013. "Fewer Women Served Under Texas Women's Health Program." Austin Chronicle, July 31. http://www.austinchronicle.com/daily/news/2013-07-31/number-of-women-served-under-texas-womens-health-program-drops/.

[9] Our results are robust to using driving time instead of driving distance.

less effective or no method of contraception; and (2) lack of access to abortion.[10] While we are unable to directly disentangle these two mechanisms in this paper, it is important to note that our results are largely driven by changes in access to contraception because the vast majority of clinics that closed during our time period of analysis only provided non-abortion family planning services.[11]

Our paper contributes to and draws on a well-established literature that investigates the impact of proximity to health care providers (or other entities) on health and health care outcomes (e.g., Goodman et al. 1997; Buchmueller et al. 2006; Currie et al. 2010; Anderson and Matsa 2011; Currie et al. 2011; Currie and Walker 2011; Hill 2013; Rossin-Slater 2013; Hill 2014; and Lu and Slusky 2016). This literature validates our methodological approach of estimating the impact of geographic access to a women's health care provider on local behavior, while controlling for time-invariant differences across granular regions.

We also contribute to a literature on public policy and fertility (e.g., Amuedo-Dorantes et al. 2016; Kroeger and La Mattina 2017; Rau et al. 2017) and, more specifically, family planning programs and fertility. Focusing on increases rather than decreases in access to care, Bailey (2012) finds that the introduction of U.S. family planning programs in the 1960s and 1970s was associated with "significant and persistent reductions in fertility" at the county level. Our paper complements and builds on these findings by examining whether reductions in access to care have the opposite effect on fertility rates as increases in access to care. Our findings suggest that the effects are indeed symmetric. We show that even in a much more recent time period, when

[10] The abortion mechanism is consistent with Grossman et al. (2017), who find that an increase in distance to the nearest facility providing abortion services was associated with a decline in abortions between 2012 and 2014 in Texas.

[11] For completeness, we generally refer to access to both contraceptive and abortion services throughout this paper, but our discussion focuses more on access to contraception.

publicly-funded family planning programs have been established for decades and contraceptive use is much more widespread, reduced geographic access to care is an important factor in family planning, especially for unmarried women.

Our results are also consistent with a broader literature on abortion and fertility, including with Coleman and Joyce (2011) and Grossman et al. (2014a), who find that new stringent abortion requirements and restrictions in 2004 and 2013-2014, respectively, reduced abortions in Texas; with Girma and Paton (2013), who find that the 2003 parental consent law had no effect on underage pregnancies; and with Cintina (2017), who finds that increased access to emergency contraception in Washington State reduced the abortion rate. Additionally, Musse (2017) finds that in Nepal, living closer to a clinic that offers pregnancy tests decreased the proportion of women who did not know they were pregnant.

Finally, this paper complements recent work by Stevenson et al. (2016) studying the impact of Texas funding restrictions on contraception and childbirth covered by Medicaid; work by Packham (2017) on family planning funding cuts and teen fertility rates; work by Cunningham et al. (2017) and Quast, Gonzalez, and Ziemba (2017) on abortion clinic closures and abortion rates; work by Fischer, Royer, and White (2017) on the impact of reduced access to abortion and family planning services on fertility rates; and older work by Kearney and Levine (2012). In particular, complementary studies by Stevenson et al. (2016) and Fischer, Royer, and White (2017) find changes in contraceptive use, and Cunningham et al. (2017) and Quast, Gonzalez, and Ziemba (2017) find reductions in abortion. While our results are broadly consistent with these findings, our empirical approach is different. For example, Stevenson et al. (2016) define a binary “treatment” based on the presence of a clinic in a county since the funding restrictions more strongly affected these counties compared to those without a clinic. Packham

(2017), Cunningham et al. (2017), Quast, Gonzalez, and Ziemba (2017), and Fischer, Royer, and White (2017) also all use a county-level approach to study the impact of clinic closures.

Our approach, on the other hand, is substantially more granular because we calculate changes in driving distance to the nearest clinic at the ZIP-code level. This level of granularity is important for examining changes along the intensive margin—i.e., changes in driving distance—for urban and rural residents alike. In particular, our measure is likely to capture more variation in clinic access, both for residents of urban areas, where there may be multiple clinic locations with only some closing over time, and for residents of rural areas, where there may not be a single clinic within an entire county during the time period of analysis.

Additionally, we study the marriage margin and find substantially different effects for married and unmarried women. Among the studies mentioned above, the only one that examines this particular margin is the supplemental analysis of Fischer, Royer, and White (2017), albeit with a less granular approach. Examining heterogeneous outcomes by marital status is important since children born to unmarried mothers are more likely to experience worse economic outcomes.[12] Specifically, children born to unmarried mothers are more likely to grow up in unstable living arrangements, be in poverty, receive less education, and have sex at early ages (McLanahan and Sandefur 1994; Demo and Cox 2000; Haveman, Wolfe and Pence 2001; Thomas and Sawhill 2005). As adults, they are more likely to be idle (neither in school nor employed) and if employed have lower income (McLanahan and Sandefur 1994; Aquilino 1996; Carlson and Corcoran 2001; Musick 2002; Amato 2005). We therefore need to understand

[12] This result has been established using a variety of econometric techniques, such as comparing unmarried mothers who have twins with those who have singletons (Bronars and Grogger 1994) and using availability of funded abortion services as an instrumental variable (Korenman et al. 2001).

whether the policy changes in Texas and the resulting clinic closures have increased the number of children born into adverse economic circumstances.

Our overall finding of a negative relationship between the fertility rate and access to contraceptive and abortion services is also consistent with the mechanisms underlying changes in education, career, and fertility trends among women (see, e.g., Goldin 2014 and Goldin 2015) and specifically increased maternal age (Matthews and Hamilton 2016). However, the effects that we find for this particular policy context potentially represent backtracking from the general progress in women's empowerment that has resulted from family planning.

II. Data

This paper uses two primary data sources: (1) quarterly snapshots of clinic addresses from a network of women's health and family planning clinics, and (2) birth certificates from Texas. These data sets are supplemented with several other sources, including the coordinates of ZIP-code centroids, a ZIP-code to ZIP-code Tabulation Area (ZCTA) mapping, and total population and population by demographic subgroups at the ZCTA level.

The primary exogenous variable—driving distance to the nearest clinic—is calculated from end-of-quarter snapshots of clinic locations between Q3 2007 and Q1 2013, from a network of women's health and family planning clinics. This nonprofit network was one of the largest recipients of funding from both the Texas Department of State Health Services (DSHS)'s Family Planning Program and the Women's Health Program. Its clinics provide a range of family planning and reproductive health care services, and its patient mix is very similar to that of clinics receiving federal funding under Title X.[13]

[13] Fowler et al. (2011) report that Title X patients are approximately 90% female, 25% ages 15-19, 30% ages 20-24, 20% ages 25-29, and 25% ages 30 and over.

As described in further detail below, we use these end-of-quarter snapshots to calculate the driving distance from each ZIP-code centroid to the nearest clinic at the end of each quarter.[14] These driving distances are then assigned to the period of time three to four quarters before each birth to approximate a mother's access to care before and in the early phases of her pregnancy.

The primary outcome variable—the general fertility rate[15] (hereafter referred to as simply the "fertility rate") in each quarter in each ZIP-code—is calculated from a restricted version of all administrative birth certificates from the DSHS's Vital Statistics office for 2008–2013.[16] The restricted version contains two variables essential to our analysis: the mother's ZIP-code and the child's birthdate, a combination of which allows each birth to be matched to the appropriate driving distance to the nearest clinic. We also observe demographic variables, including the mother's age, race, ethnicity, educational attainment, marital status, and number of prior live births.

We supplement these two primary data sets with four other data sets. To calculate the distance from each ZIP-code to the nearest clinic, we use ZIP-code centroid coordinates from SAS. To calculate the fertility rate in each ZIP-code in each quarter per population subgroup, we

[14] The network that we study includes clinics throughout the U.S. Therefore, the nearest clinic may be located in a neighboring state (i.e., Texas, New Mexico, Colorado, Kansas, Oklahoma, Arkansas, Louisiana, or Arizona) for some women.

[15] The general fertility rate (GFR) is defined as the number of children born to women ages 15-49 over a given time period, divided by the number of women in the population ages 15-49, and then multiplied by 1,000 to scale it to be per 1,000 women. The GFR is typically calculated on an annual basis. In this study, we multiply our quarterly fertility rates by 4 in order to make them comparable to other GFRs.

[16] We do not expect Krieger et al. (2016)'s finding of an inverse relationship between state funding for abortion and infant deaths to affect our results. Specifically, we use births (regardless of how long the newborn lives) to calculate the birth rate, while they focus on infant mortality before age 1. A change in the infant death rate should not have any effect on the fertility rate as we are calculating it.

first map the mother's ZIP-code to a ZCTA[17] using the crosswalk for 2011 (i.e., the midpoint of our data set) from UDS Mapper,[18] and then match each ZCTA with its population (total and by subgroup) from 2008–2012 from the U.S. Census's 5-year estimates.[19]

We also include the county-level unemployment rate as a control in our regressions, since there is a strong negative link between unemployment rates and fertility (Ananat et al. 2013; Currie and Schwandt 2014; Buckles et al. 2017). Analogous to how we assign driving distance to each ZCTA-quarter, we calculate the mean monthly unemployment rate for nine and twelve months before the last month of each quarter.[20]

III. Methodology

The methodology in this paper is analogous to that of Lu and Slusky (2016), which uses a within estimator to study the impact of changes in driving distance to the nearest clinic on the incidence of preventive care. More broadly, by constructing a continuous measure of driving distance that proxies for access to care, our analysis fits within a longstanding literature on the effects of the time price of health care (e.g., Acton 1975; Coffey 1983; Vistnes and Hamilton 1995; Clarke 1998; Lourenço and Ferreira 2005; Jeuland et al. 2010; Brent 2017). Our results are consistent with the broad consensus in this literature that demand for health care is indeed sensitive to non-monetary costs, such as travel time.

[17] This is necessary because some ZIP-codes such as post office boxes have official populations of 0.

[18] The U.S. Census does not provide a formal crosswalk.

[19] Our results are robust to using quarterly population levels for each ZCTA, using a linear interpolation between the 2000 Census and the midpoints of the Census's 5-year population estimates for 2007-2011 through 2012-2016.

[20] Our results are robust to using alternative measures to control for local labor market conditions, such as the annual county-level employment-to-population ratio from the BEA and the annual ZCTA-level share of tax returns that report receiving unemployment benefits.

We first construct several key variables. For each Texas ZIP-code and quarter, we calculate the geodesic (i.e., crow-flies) distance from the ZIP-code centroid to each clinic in our primary clinic location data set using the Haversine formula. Then, for the clinic that has the shortest geodesic distance from a given ZIP-code centroid, we calculate the driving distance, using Google Maps.[21]

We map each mother's ZIP-code of residence to the corresponding ZCTA because some ZIP-codes have no official population. We then aggregate the number of births by ZCTA and quarter, match each ZCTA with its population from the U.S. Census's 5-year estimates, and calculate the quarterly fertility rate for each ZCTA. Our measures are generally consistent with the literature, and the 5-year population estimates are a reasonable proxy for mid-period population since the population remained relatively stable between 2008 and 2012. Additionally, our results are robust to using other, count-based specifications that do not require population estimates.

For each ZCTA, we then use the driving distance data from the ZIP-code of the same name.[22] We estimate driving distance around the time of conception as follows: first we assign each birth to the end-of-quarter date (e.g., February 12 is assigned to March 31), and then we calculate the mean of driving distance lagged three quarters (e.g., June 30 of the previous year) and driving distance lagged four quarters (e.g., March 31 of the previous year). This approach provides a reasonable estimate of the mean driving distance during the period shortly before (e.g., when a woman may be seeking contraceptives) and after conception (e.g., when a woman

[21] Lu and Slusky (2016) looked at the impact of driving distance increases on preventive care rates also used several alternative measures of clinic proximity and found comparable results.

[22] This is partly out of convenience and partly because ZIP-codes always map to ZCTAs of the same name if those ZCTAs exist. I.e., there is never a case where X → Y but Y → A. If X → Y, then Y → Y.

may be seeking an abortion). While we use the mean of driving distance lagged three and four quarters as our main measure of driving distance around the time of conception, our results are also robust to using the driving distance lagged four quarters.

Our primary econometric specification is within-ZCTA, over-time:

$$y_{zt} = \beta_0 + \beta_1 \frac{dist_{z,t-3} + dist_{z,t-4}}{2} + \beta_2 \frac{UR_{z,t-3} + UR_{z,t-4}}{2} + \boldsymbol{\beta}_3 \boldsymbol{\zeta}_z + \boldsymbol{\beta}_4 \mathbf{q}_t + \boldsymbol{\beta}_5 \boldsymbol{r}_t + \varepsilon_{zt}$$

where the unit of analysis is ZCTA *z* in quarter-year *t*. *y* is a measure of the fertility rate, and *dist* is the driving distance from a ZCTA to the nearest clinic. *UR* refers to the county-level unemployment rate (BLS 2016), which we use to control for the effects of the regional labor market on the fertility rate. Similar to our calculation of driving distance around the time of conception, this labor market measure is incorporated as the mean of the unemployment rate lagged three and four quarters.[23]

$\boldsymbol{\zeta}$, $\mathbf{q}$, and $\mathbf{r}$ are ZCTA, quarter, and year fixed effects. We cluster standard errors by county, which is generally more conservative than clustering by more granular geographies and because there are likely across-ZCTA, within-county correlations that should be accounted for. Our main sample is all ZCTAs with a population greater than 0.

This empirical approach is then applied to demographic subgroups, including by age group, marital status, ethnicity, and educational attainment.[24] We also examine fertility rates by birth parity and quartiles of the unemployment rate. These subgroup analyses supplement the main analysis by providing a clearer picture of who is most affected by clinic closures that lead to higher fertility.

[23] Since the unemployment rate is reported on a monthly basis, we assign the unemployment rate in the last month of a quarter as the end-of-quarter unemployment rate.

[24] Hicks-Courant and Schwartz (2016)'s fascinating result that family planning clinics are associated with a lower high school dropout rate does not directly relate to our analysis, since we study women ages 18 and over, for whom educational attainment is relatively stable.

We interpret our estimates as causal for two primary reasons. First, our use of ZCTA fixed effects controls for time-invariant differences across ZCTAs in unobservable characteristics, such as attitudes toward family planning that could correlate with clinic closures. Second, based on the policy context and empirical evidence, we argue that the changes in driving distance over time are sufficiently exogenous to produce robust estimates. Specifically, we observe that the majority of clinic closures occurred during the quarter in which the 2011 funding cut took effect. This timing strongly suggests that most of the clinic closures we study were largely affected by the funding cut. Furthermore, following Lahey (2014)'s approach, we confirm that we cannot predict whether a clinic will experience a subsequent closure using 2007 fertility rates, ZCTA population for females ages 15-49, or the pre-policy-change trend in fertility rates. Based on these analyses, we conclude that the closures from politically-motivated funding cuts during our time frame are sufficiently uncorrelated with previous values of our outcome variables and with population that we can consider them exogenous and move forward with our analysis.

IV. Results

IV.A Summary Statistics: Demographic Characteristics

Table 1 shows summary statistics at the ZCTA-quarter level.[25] The mean male population count is approximately equal to the mean female population count.[26] Among females, nearly half are ages 15-49. Among these women of reproductive age, about half are married, and about one-third are Hispanic and one-third are non-Hispanic white (NHW). Of the female adult population

[25] There are 22 quarters (Q3 2008 – Q4 2013) of data and 1,870 ZCTAs with nonzero population. This yields 22 * 1,870 = 41,140 observations for the primary regressions below.

[26] The male population is relevant for calculating the crude birth rate (which is defined as births per total population) and ensuring our results are robust to this measure. If the population were substantially imbalanced (e.g., in North Dakota), then the results may not be robust. In our case, however, as shown in the appendix, the results are robust to using the crude birth rate.

(ages 18 and over), roughly comparable shares do not have a high school diploma, only have a high school diploma, have some college but not a bachelor's degree, and have at least a bachelor's degree (Panel A).

Among women with births, nearly all are ages 15-49, the majority are married, half are Hispanic, and less than one-third are non-Hispanic white (NHW) women. Across the different educational categories, the mean number of births across ZCTA-quarters is comparable. Finally, about 40 percent of births are first births, and about one-third are second births (Panel B).

Mean fertility rates vary across ZCTAs for each subgroup of women. The number of ZCTAs varies by subgroup since we cannot calculate a fertility rate if there are no women of reproductive age in a given subgroup and ZCTA. To facilitate comparisons across related subgroups (e.g., fertility rates among women ages 18-plus with varying levels of educational attainment), the rightmost column recalculates the overall fertility rate for the relevant age range and for the same set of ZCTAs as used in the primary specification. Overall, fertility rates are higher among married women, Hispanic women, and women with lower educational attainment (Panel C).

The mean maternal age at birth is 26.5 years, and the mean unemployment rate around the time of conception is 6.9 percent, though there is wide variation in both variables. The mean driving distance to the nearest clinic around the time of conception was 42.7 miles, and the mean change in driving distance over the course of the sample period was an increase of 15.3 miles. Again, as with many of the variables, this measure also varies widely, with some ZCTAs experiencing a distance *decrease* by up to 17.3 miles and some experiencing an increase by almost 300 miles (Panel D).[27,28]

[27] While an event study graph would likely be useful here, our data is not conducive. Not only is the treatment continuous as opposed to discrete, but many ZCTAs are affected by multiple closures, which makes it ambiguous

IV.B Summary Statistics: Clinical Data

Figure 1 shows the relative[29] number of clinics in Texas in this network for each quarter between Q3 2007 and Q1 2013, normalizing the number on October 1, 2007 (the start date of our clinic data set) to 100. While a small share of clinics closed prior to the 2011 budget cut, Figure 1 shows that the overwhelming majority of closures occurred during the quarter in which the funding cut took effect. Specifically, we observe a 19% drop in the number of clinics in this network between June 30, 2011, and September 30, 2011. The timing of this precipitous drop is consistent with our expectation that the majority of clinic closures during our study period were largely driven by budget cuts, which took effect on September 1, 2011 (White et al. 2015; Stevenson et al. 2016).

Figure 2 provides a visualization of the effect of clinic closures on Texas women's changes in driving distance. The shaded ZCTAs indicate the change in driving distance to the nearest clinic over time, using the earliest and latest data available to us on clinic addresses. In Panel A, we see that while a handful of ZCTAs experienced small decreases in driving distance, the overwhelming majority saw driving distance increase. Some areas, particularly in the west, north, and southeast of Texas, experienced driving distance increases of greater than 100 miles, and as high as 280 miles. Panel B shows the same result but at a larger scale for Texas's five largest metropolitan areas (in decreasing order by population). Here we see variation within cities, where some ZCTAs in Dallas/Ft. Worth/Arlington (DFW), Houston, San Antonio, and Austin saw small increases (0-20 miles) while others saw minimal if any change. El Paso,

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when to define "event-time zero". These heavily affected ZCTAs play an important role in our results. Therefore, focusing on ZCTAs only affected by one closure would not be comparable.

[28] The mean increase in driving distance is consistent with Gerdts et al. (2016), which surveyed Texas-resident women seeking abortions and found that clinic closures increased driving distance.

[29] The number of clinics is calculated relative to October 1, 2007, which is normalized to 100.

however, saw enormous increases in driving distance (over 100 miles) for all of its ZCTAs, which resulted from closures of all of the El Paso clinics in the network we study.[30]

IV.C Impact of Driving Distance on Fertility Rate

Table 2 presents our main regression results, which restrict the sample to ZCTAs with a non-zero population of women ages 15-49. We gradually add each control and set of fixed effects. First, the pooled OLS specification of fertility rate on driving distance shows a strong, positive causal relationship, with a 100-mile[31] increase in the distance to the nearest clinic raising the fertility rate by approximately 3.2 children per 1,000 women ages 15-49 (column 1). Adding year and quarter fixed effects makes minimal difference (column 2). Adding ZCTA fixed effects in column (3) substantially reduces the magnitude of the coefficient of interest. An increase in distance of 100 miles to the nearest clinic now leads to a statistically significant coefficient of 0.727 children per 1,000 women ages 15-49, but the estimate is substantially more precise. In relative terms, this coefficient represents an increase of approximately 1.2 percent from a sample mean rate of 62.44 children per 1,000 women ages 15-49. This change in the coefficient magnitude is as expected, given the large cross-sectional differences across ZCTAs in Texas, and suggests that ZCTAs that experienced larger increases in driving distance were also those that would have experienced relatively larger increases (or relatively smaller decreases) in fertility even in the absence of clinic closures. For instance, it is plausible that clinics were more likely to close in areas that already had a more negative overall attitude toward family planning. ZCTA

[30] If we exclude El Paso, then the key coefficient of interest is no longer statistically significant. It is, however, close in magnitude to our main result and the same sign, which alleviates potential concerns that clinic closures had a different effect on fertility rates in the rest of Texas than in El Paso.

[31] This is the same unit used in Lu and Slusky (2016). The raw coefficient would be for 1 mile, which is not particularly meaningful. 100 miles represents a severe, though not implausible, increase in driving distance resulting from the only clinic in a particular geography closing. Lu and Slusky (2016) also tested multiple nonlinear functions of driving distance and found comparable results.

fixed effects control for the time-invariant portion of these differences, and therefore will be included in all other estimations in this paper. Overall, the positive coefficient shown in column (3) is consistent with Bailey (2012)'s result that there is a negative relationship between the fertility rate and public funding for family planning. Our result, though, is from the opposite direction, showing that removing access to family planning services raises the fertility rate.

Column (4) additionally controls for the unemployment rate. While the coefficient on this additional variable is negative and statistically significant (consistent with Currie and Schwandt 2014), the main "driving distance" coefficient of interest is virtually unchanged. Therefore, for most of the results below, we will always include the local unemployment rate as a control.

Finally, the table includes a count model, specifically a fixed effect Poisson. This alternative specification is appropriate because the count of births in each ZCTA in each quarter is discrete and nonnegative (see Simcoe 2008). To implement this model, we first limit the sample to ZCTAs that record at least one birth during the sample period, which slightly reduces the total number of ZCTAs and produces OLS results that are comparable to our main finding (column 5). We then apply the fixed effect Poisson model (average marginal effects shown in log points in column 6) and find that births increase by 1.2 percent for every 100-mile increase, which is identical to the result found from OLS on the fertility rate.[32,33]

IV.D Placebo Test

Table 3 checks the validity of our result by including a control for the driving distance to

[32] The Poisson regression does not explicitly use population weights because maximum likelihood estimation of the Poisson regression is already equivalent to generalized weighted least squares (see Charnes, Frome, and Yu 1976).

[33] Our results are also robust to not weighting by ZCTA population; to alternative measures of the fertility rate, such as the crude birth rate; and to alternative nonlinear econometric specifications, such as a more general fixed effect negative binomial specification (see Allison and Waterman 2002). They are also robust to a nonlinear function of driving distance, such as dummy variables for each 50-mile category, a quadratic specification, and an exponential specification.

the nearest clinic in the quarter after the quarter of birth. Including all ZCTAs, as shown in column (1), provides only a marginally statistically significant result because driving distance is highly persistent over time, since the majority of ZCTAs were not affected by a clinic closure. Therefore, the other columns of this table consider only the ZCTAs where the driving distance to the nearest clinic changed between 2007 and 2013. For each minimum threshold of driving distance (e.g., changed by more than 0 miles, changed by more than 10 miles, etc.), we first re-estimate the main result and then additionally control for the distance after birth. For each threshold, the main coefficient of interest is still statistically significant both alone (even-numbered columns) and when the additional control is added (odd-numbered columns starting with (3)). Moreover, the coefficient on driving distance in the quarter after birth is always statistically insignificant.

IV.E Subgroup Analysis

Table 4 shows results from an investigation into whether the fertility increase reported in Table 2 is driven by changes for married or unmarried mothers.[34] We expect the effect to be different based on the substantial literature showing that access to contraception and abortion strongly affects unmarried women (e.g., Goldin and Katz 2002; Bailey 2006; Ananat and Hungerman 2012). Column (1) repeats our main result, excluding the ZCTAs that do not have at least one birth to a married woman and one birth to an unmarried woman at some point during the sample period.[35] Since this restriction only applies to a few low-population ZCTAs, the results are almost identical to our main specification. Columns (2) and (3) then stratify by marital

[34] Unfortunately, we cannot track mothers across births, nor do we know how long mothers are married, so we cannot assess to what degree pregnancy is influencing marriage rates. Still, the results are so stark that we are not concerned overall.

[35] We will re-estimate our main result for each subset of ZCTAs considered in each table. While this will produce slightly different versions of our primary estimate, each version will be comparable to the rest of the estimates in the table.

status and show, respectively, that an increase of 100 miles to the nearest clinic results in a statistically insignificant change in the fertility rate for unmarried women and a 2.4 percent increase in the fertility rate for married women. These two coefficients are also statistically significantly different from each other at the 5% level.

Our finding of differential effects by marital status—with the effects concentrated among unmarried women—differs from recent literature on the impact of reduced access to abortion and family planning services. Specifically, Fischer, Royer, and White (2017) find no effect for unmarried mothers but an increase in fertility for married mothers. Given that in 2008 and 2014, approximately 85 percent of women obtaining abortions were unmarried, we believe our results to be more plausible (Jerman et al. 2016). Additionally, our results potentially have less measurement error than others in the literature since we implement a more granular, ZIP-code level analysis.

Table 5 further unpacks the 1.2 percent increase in the fertility rate shown in Table 2. Here, we look at the teen (or adolescent) fertility rate, which is defined as births to mothers ages 15-19 divided by the population of women ages 15-19.[36] We limit the analysis here to ZCTAs that have at least one woman between the ages of 15-19. Column (1) repeats our main regression on this (large) subset and finds comparable results. Column (2) then looks at the teen fertility rate in OLS. This result is much noisier, having a different sign and only being statistically significant at the 10% level.

Columns (3) and (4) therefore re-estimate the results using only the 285 ZCTAs that have at least 5 teen births in each quarter. This is intended to address the concern that perhaps the teen pregnancy results are inconclusive due to the larger amount of left censoring at 0 than in the

[36] See http://data.worldbank.org/indicator/SP.ADO.TFRT.

main regressions.

The result in column (3) for these ZCTAs with women ages 15-49 shows a 1.4 percent increase, comparable to our main result. Column (4), focusing on the teen rate, does find a much more consistent result of a relative increase of 1.1 percent, though it is only statistically significant at the 5% level, unlike the main findings of this paper. Our results are therefore broadly in agreement with Packham (2017), who found an increase in the teen fertility rate as a result of clinic closures.

Table 6 shows the impact of an increase in distance on the age of the mother. If women were having the same number of children as before but having them earlier, then the age of mothers should be decreasing. Column (1) repeats the main regression for ZCTAs with at least one birth (and therefore at least one data point on the age of the mother). Column (2) shows that an increase of 100 miles in driving distance to the nearest clinic leads to a decrease in the age of the mother by 0.09 years, or approximately one month.[37]

V. Robustness checks

The appendices contain results and discussion of several robustness checks. They are discussed here briefly. First, as described above, we unsuccessfully attempt to predict changes in driving distance using pre-determined characteristics and trends. We also check our results for potential differences when stratifying by the distance to the Mexican border. This stratification addresses the potential concern that women near the border could access pharmaceuticals in Mexico either for contraception or to induce abortion, whereas those living farther from the border could not (Grossman et al. 2014b; Grossman et al. 2015). If so, we would expect a smaller coefficient for ZCTAs near the border and a larger coefficient for those farther from the

[37] Other stratifications, such as by ethnicity or educational attainment, do not produce results that are statistically significantly different across groups. See Appendix A for details.

border. However, we find the opposite to be true, with ZCTAs near the border having a larger and more precise estimate. This is likely due to the fact that El Paso County, which is a main source of variation in driving distance, is also very close to the border, which makes it difficult to effectively test this question.

In addition, we rerun our analysis for larger levels of geographical aggregation, specifically at the county and commuting zone levels. As expected, these results are substantially noisier than the results at the ZCTA level, though the coefficients are of a similar sign and magnitude.

Our results are also robust to clustering the standard errors at a greater level of aggregation than counties, including commuting zones, BEA economic areas, and core-based statistical areas. When we cluster standard errors at a *smaller* level of aggregation, by ZCTA, we find that the standard errors actually increase relative to our main specification. While uncommon, this is possible if standard errors are more negatively correlated at the ZCTA level than the county level (Cameron and Miller 2015). We continue to cluster the standard errors at the county level in our main specifications because there are likely across-ZCTA, within-county correlations that should be accounted for.

Finally, we implement a robustness check that additionally controls for whether the county had Medicaid Managed Care (MMC), which other researchers have found to affect birth outcomes and fertility (Aizer, Currie, and Moretti 2007; Kuziemko, Meckel, Rossin-Slater 2013).[38] We find no effect of controlling for MMC on our main result. However, this is partially

[38] The names of the counties that changed to MMC before 2007 are from Kuziemko, Meckel, Rossin-Slater (2013). The names of the counties from the Medicaid Rural Service Areas that changed to MMC in 2012 (per https://hhs.texas.gov/sites/default/files/documents/services/health/medicaid-chip/programs/star-plus/starplus-mrsa-regions-map-with-mcos.pdf) are from https://hhs.texas.gov/sites/default/files//documents/laws-regulations/reports-presentations/2017/medicaid-chip-perspective-11th-edition/11th-edition-complete.pdf.

due to the fact that the rural counties that experienced MMC expansions in 2012 have low populations and therefore have a limited impact on the overall result in our population-weighted regression framework.

VI. Discussion

Our results show that increases in driving distance to the nearest clinic lead to statistically significant increases in the fertility rate on the order of 1 to 2 percent, and that this increase is robust to a variety of specifications and sample restrictions.

Based on our main results, a back-of-the-envelope calculation indicates that these clinic closures led to an additional 690 births in Texas each year, mostly to unmarried women.[39] Monea and Thomas (2011) estimate that the mean taxpayer cost of a publicly-subsidized unintended pregnancy in 2001 was $9,000, or about $12,000 in 2016 dollars. This alone would suggest an additional total public cost of more than $8 million per year. Further considering the approximately $10,000 per year in costs of raising a child for a single mother would suggest that the total direct costs of these extra children are comparable to the approximately $65 million in annual funding cut by Texas or lost in federal matching.[40] In addition, these estimates do not even take into account any indirect costs, such as to women's labor force productivity, the mental wellbeing of unintended children, and the additional economic consequences as described above of children born to unmarried women. Furthermore, if clinic closures lead to more closely-spaced pregnancies, then that can also have adverse consequences since larger spacing between births has a positive effect on outcomes such as educational attainment (Black et al. 2005; Buckles and Munnich 2012).

[39] 690 children = 3,315 women ages 15-49 / ZCTA * 1,870 ZCTAs * 15.3 miles increase in driving distance * (0.727 children / 1,000 women) / "100 miles" * "100 miles" / 100 "1 miles" * "1,000 women" / 1,000 "1 women".

[40] See http://www.cnpp.usda.gov/tools/CRC_Calculator/default.aspx.

VII. Conclusion

In recent years, a primary cause of women's health clinic closures is the loss of public funding. Funding-related clinic closures, such as those in Texas, decrease women's ease of access to care—in the current analysis, we focus on increases in their driving distance to the nearest clinic, but closures could have indirect effects as well, such as overcrowding or increased fees at remaining clinics.[41] Our analysis shows that these clinic closures lead to higher fertility rates, likely through the combined effects of reduced access to contraception and abortion services. Furthermore, we find that fertility increases are concentrated among unmarried women and among women having their first or second child.

This paper expands on Lu and Slusky (2016) by using comprehensive administrative data that covers all ZIP-codes in Texas during 2007-2013, and by focusing on a direct consequence of family planning clinic closures, namely fertility rates. An increase in fertility rates resulting from decreased access to family planning services can be interpreted as an increase in the number of unplanned pregnancies. When considering the impact of funding cuts, it is important to consider the effects of an increase in the number of unplanned pregnancies. Furthermore, funding cuts may actually lead to increases in future state outlays from decreased tax revenues (e.g., unplanned pregnancies may affect women's educational investments and subsequent earnings) and increased public expenditures (e.g., education and health care spending) on the additional children born.

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[41] See, e.g., Conde (2012), Ku et al. (2012), White et al. (2012), and Zuzek (2013).

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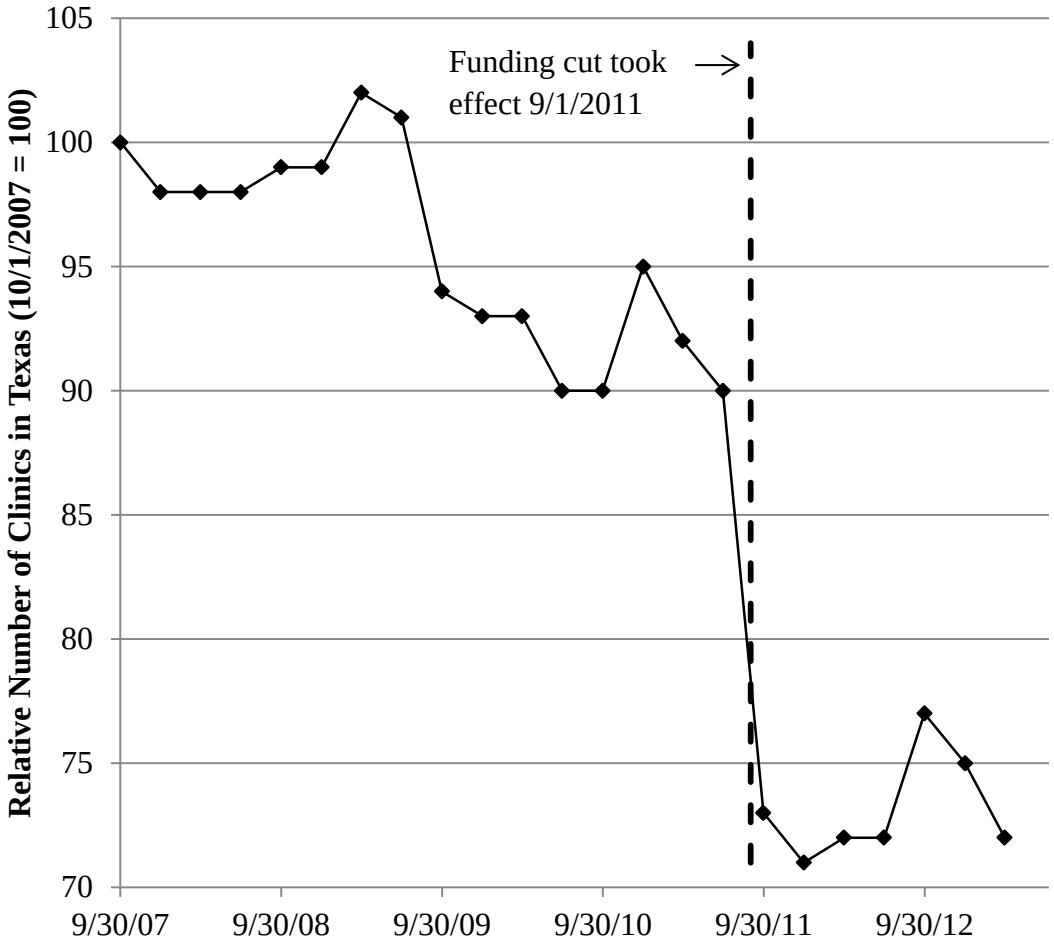
Figures

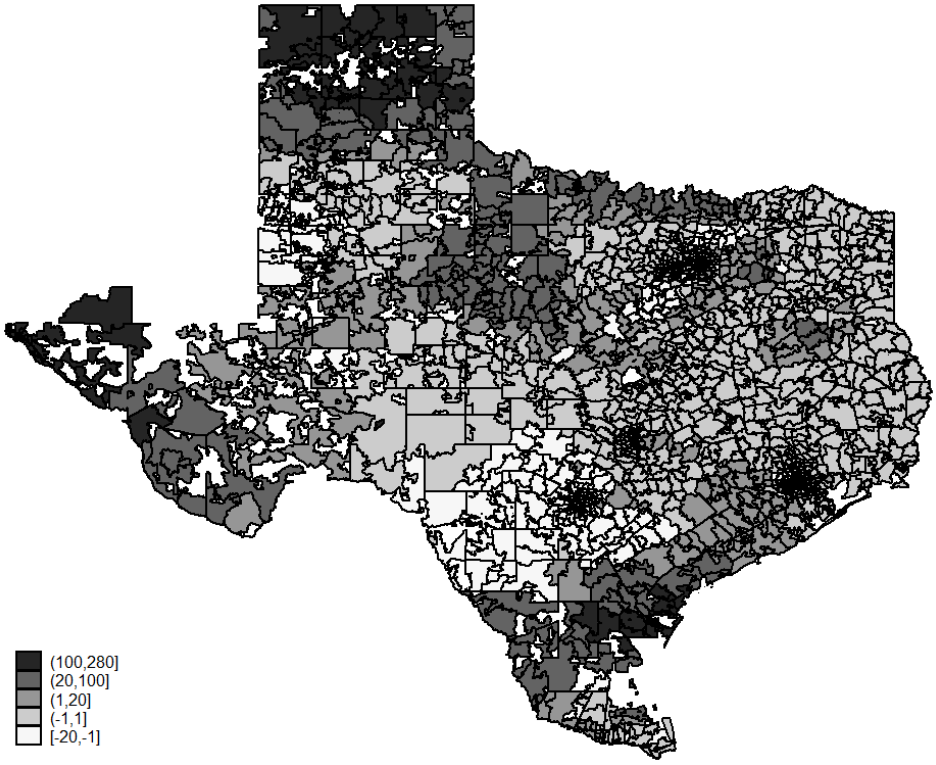
Figure 1: Relative Number of Clinics in Texas



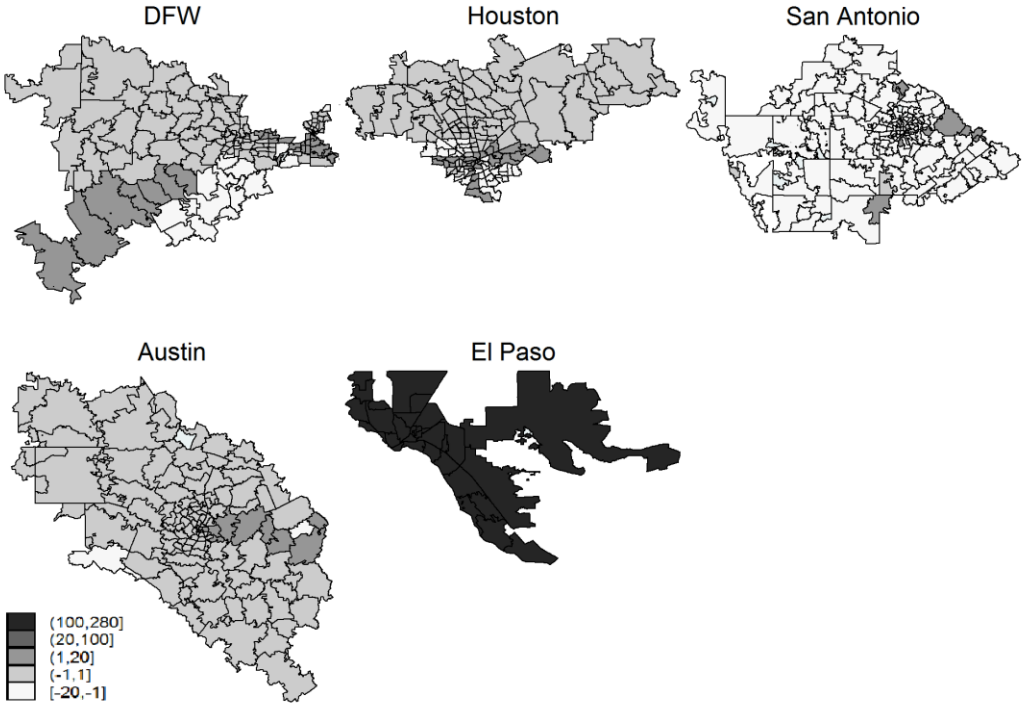
Note: Number of clinics is relative to October 1, 2007, which is normalized to 100.

Figure 2: Change in Driving Distance from October 1, 2007, to March 31, 2013

Panel A



Panel B



Tables

Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) % of total
		(N = 41,140 ZCTA-Quarters)	
Panel A: Count of population that is…			
Female	6,771	8,347	50%
Female & Age 15-19	486	670	4%
Female & Age 15-49	3,315	4,291	25%
Female & Age 15-49 & Married	1,630	2,176	12%
Female & Age 15-49 & Not Married	1,684	2,256	13%
Female & Age 18+ & <HS diploma	1,081	1,539	8%
Female & Age 18+ & HS diploma	1,395	1,518	10%
Female & Age 18+ & Some College	1,752	2,083	13%
Female & Age 18+ & ≥Bachelor's	1,263	1,956	9%
Female & Age 15-44 & Hispanic	1,164	2,176	9%
Female & Age 15-44 & Non-Hispanic White	1,144	1,636	9%
Panel B: Count of births to mothers who are…			
Age 15-19	6.04	9.85	12%
Age 15-49	51.74	71.23	99.8%
Age 15-49 & Married	29.79	42.60	57%
Age 15-49 & Not Married	21.95	33.81	42%
Age 18+ & <HS diploma	12.56	23.91	24%
Age 18+ & HS diploma	13.70	20.88	26%
Age 18+ & Some College	13.79	19.73	27%
Age 18+ & ≥Bachelor's	11.29	21.62	22%
Age 15-44 & Hispanic	25.31	49.72	49%
Age 15-44 & Non-Hispanic White	17.72	25.49	34%
Having their 1st child	20.01	27.49	39%
Having their 2nd Child	15.98	22.08	31%
Having their 3rd+ Child	15.74	23.60	30%

Panel C: Fertility rate for mothers who are…	Mean	ZCTAs	Comparison
Age 15-49	62.44	1,870	15-49: 62.44
Age 15-19	49.67	1,725	15-49: 62.45
Age 15-44	72.59	1,862	15-49: 62.44
Age 15-49 & Married	73.08	1,785	15-49: 62.50
Age 15-49 & Not Married	52.23	1,785	15-49: 62.50
Age 18+ & <HS diploma	50.43	1,662	18+: 39.97
Age 18+ & HS diploma	42.62	1,662	18+: 39.97
Age 18+ & Some College	34.14	1,662	18+: 39.97
Age 18+ & ≥Bachelor's	38.82	1,662	18+: 39.97
Age 15-44 & Hispanic or NHW	74.43	1,621	15-44: 72.46
Age 15-44 & Hispanic	86.79	1,621	15-44: 72.46
Age 15-44 & Non-Hispanic White (NHW)	61.88	1,621	15-44: 72.46

Panel D: Other (weighted by population)	Mean	SD	Min	Max
Mother's age (years)	26.5	2.9	15.0	47.0
Unemployment rate (%, 9-12 months ago)	6.9	2.1	1.8	19.5
Driving distance (miles, 9-12 months ago)	42.7	44.6	0.3	289.9
Change in driving distance (miles)	15.3	43.4	-17.3	276.9

Notes: The unit of analysis in this table is a ZCTA-quarter. Each mean corresponds to a particular subgroup's population count or fertility rate, across all ZCTAs and quarters of data. Panel D is weighted by the population of females ages 15-49 in each ZCTA. For the unemployment rate and the driving distance to the nearest clinic, the means is taken across ZCTAs and quarters of the mean 9 and 12 months before the birth quarter, as described in the methodology section above.

Table 2: Main Result of Impact of Driving Distance on Fertility Rate

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49	(3) Fertility Rate 15-49	(4) Fertility Rate 15-49	(5) Fertility Rate 15-49	(6) Poisson for Births to Women 15-49
Driving Distance - 100 mi	3.199**	3.501**	0.727***	0.753***	0.753***	0.0121***
	(1.519)	(1.499)	(0.218)	(0.209)	(0.209)	(0.00314)
Unemployment Rate				-1.135***	-1.134***	-0.0165***
				(0.154)	(0.154)	(0.00247)
Observations	41,140	41,140	41,140	41,140	41,008	41,008
R-squared	0.005	0.035	0.101	0.104	0.104	
Number of ZCTA			1,870	1,870	1,864	1,864
Mean	62.44	62.44	62.44	62.44	62.45	
Year Fixed Effects		X	X	X	X	X
Quarter Fixed Effects		X	X	X	X	X
ZCTA Fixed Effects			X	X	X	X

Notes: Robust standard errors clustered at the county level in parentheses. OLS results in columns (1)-(5) are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Impact of Driving Distance on Fertility Rate, Controlling for Driving Distance After Birth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Absolute Change in Distance > (Miles)	-∞	0	0	10	10	25	25	50	50	100	100
Driving Distance - 100 mi	0.514*	0.907***	0.618*	0.946***	0.807***	1.095***	1.080***	1.282***	1.246***	0.777**	0.783**
	(0.310)	(0.264)	(0.342)	(0.244)	(0.286)	(0.261)	(0.265)	(0.408)	(0.407)	(0.339)	(0.363)
Driving Distance - 100 mi, quarter after birth	0.514		0.648		0.426		0.0727		0.226		-0.0704
	(0.534)		(0.544)		(0.548)		(0.377)		(0.442)		(0.352)
Obs.	41,140	26,334	26,334	10,758	10,758	5,830	5,830	3,740	3,740	2,552	2,552
R-squared	0.105	0.113	0.114	0.086	0.086	0.099	0.099	0.114	0.114	0.131	0.131
Number of ZCTA	1,870	1,197	1,197	489	489	265	265	170	170	116	116
Mean	66.61	63.83	63.83	66.95	66.95	68.47	68.47	69.35	69.35	66.61	66.61

Notes: The dependent variable in all regressions is the general fertility rate for all women 15-49. Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. The absolute change in distance is calculated as the magnitude of the difference in lagged driving distance corresponding to Q3 2008 and Q4 2013. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of Driving Distance on Fertility Rate by Marital Status

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49 Married	(3) Fertility Rate 15-49 Not Married
Driving Distance - 100 mi	0.755*** (0.209)	0.177 (0.374)	1.297*** (0.347)
Observations	39,270	39,270	39,270
R-squared	0.120	0.072	0.066
Number of ZCTA	1,785	1,785	1,785
Weight	Population Female 15-49	Population Female 15-49 Married	Population Female 15-49 Not Married
Mean	62.50	73.08	52.23

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one married woman and one unmarried woman between the ages of 15 and 49. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Impact of Driving Distance on the Teen Fertility Rate

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-19	(3) Fertility Rate 15-49	(4) Fertility Rate 15-19
Restricted to ZCTA with:	Women 15-19	Women 15-19	At least 5 teen births (i.e., 15-19) in each quarter	At least 5 teen births (i.e., 15-19) in each quarter
Driving Distance - 100 mi	0.752*** (0.212)	-0.626* (0.332)	1.036*** (0.300)	0.715** (0.330)
Observations	37,950	37,950	6,270	6,270
R-squared	0.123	0.095	0.336	0.270
Number of ZCTA	1,725	1,725	285	285
Mean	62.45	49.67	71.59	66.94

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Impact of Driving Distance on Mother's Age

	(1) Fertility Rate 15-49	(2) Mother's Age (Years)
Driving Distance - 100 mi	0.797***	-0.0910***
	(0.212)	(0.0172)
Observations	37,290	37,290
R-squared	0.123	0.081
Number of ZCTA	1,864	1,864
Mean	62.68	27.25

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one birth. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Appendix A: Additional Results

Below are additional stratifications of our primary analysis. None show as stark differences as the one by marital status that is shown in the main body of the text.

Table A1 repeats the same process but now stratifying by educational attainment. Given that the Census's population variables for educational attainment are for women ages 18 and over, we limit this section of the analysis to births to women 18 and older. Column (1) shows our main result for the subset of ZCTAs that have at least one woman aged 18 or older in each educational category. While the magnitude of this coefficient is different from our main result (since we are excluding those below 18 but adding back those above 49), the relative magnitude is the same percentage increase that we discussed previously.

Columns (2)–(5) then look at the change in the fertility rate for women ages 18 and above with and without a high school diploma. The effect appears to be largest among those with a high school diploma but no further education, and also large and statistically significant for those with some college but no four-year degree. Unlike in Table 4, though, the coefficients are not statistically significantly different from each other, in part because they are substantially noisier.

Table A2 stratifies our regression by ethnicity, focusing on women ages 15-44 to be consistent with how the Census population data by ethnicity is reported. Column (1) repeats our main result for ZCTAs that had at least one birth to a Hispanic woman age 15-44 and one to a non-Hispanic white woman age 15-44. Column (2) then further excludes women who are neither Hispanic nor non-Hispanic white. Both results are comparable in percentage terms to our main results.

Columns (3)–(4) then look at the effects of an increase in driving distance on the fertility rates for Hispanic and non-Hispanic white women. As with the education results, all of the

coefficients are positive, but there is a large difference in magnitude. Given the noisiness of these estimates, however, the difference between them is not statistically significant.

The results by ethnicity do not show statistically significant differences. This is surprising, given Slusky (2017)'s result that the impact of clinic closures on preventive care rates does vary substantially by ethnicity. It suggests that there may be different sensitivites to changes in access to care, depending on the type of care that is involved.

The results stratifying by education and by ethnicity produce less stark constrasts than those by marital status. The educational results show an effect on those with an intermediate level of educational attainment—high school graduates and those with some college education. It is possible that women who are high school dropouts already had minimal access to reproductive health services and/or resource constraints such that an increased driving distance did not make a difference to them. Similarly, college graduates are able to drive farther and consequently may be less sensitive to an increase in driving distance relative to all other women.

Table A3 breaks down the impact of the fertility increase shown in Table 2 by order of birth. This analysis helps disentangle whether the overall fertility increase is driven by women having additional children beyond their planned number of children, or by women having the same number of children as they had planned, but at younger ages.

Column (1) repeats our main results but only for ZCTAs that have at least one first birth (i.e., to a mother that has no previous live births), one second birth (i.e., to a mother that has exactly one previous live birth), and one third or higher birth (i.e., to a mother that has at least two previous live births). As this is the overwhelming majority of ZCTAs, the result is effectively unchanged from our main specification.

Columns (2) and (3) then repeat the strategy of the previous tables for each type of birth.

Here, we do not have Census population data by the number of previous live births, so the denominator is the entire ZCTA population (i.e., the means sum to the mean in column (1) in Table 2). We see here a substantial increase in the number of first and second children (1.9 percent and 2.2 percent, respectively) but an insubstantial and statistically insignificant change for third children. These first two coefficients are statistically significantly different from the one in column (3) at the 1% level, but are not statistically significantly different from each other.

Table A4 contains the result of regressions of each age-specific fertility rate on driving distance. The results appear to overwhelmingly be driven by those aged 20-29, which is consistent with our results from above showing that the effect is concentrated among those who are not married and therefore tend to be younger. Table A5 then repeats the method of Table 5 by only looking at ZCTAs that have at least five births in each age category. The results are comparable to Table 5 and Table A4, with a positive and strongly statistically significant result for teens, and a much larger result for those aged 20-29. Table A6 then applies this method (i.e., restricting to ZCTAs that have at least five births in each education category) to the subpopulations in Table A1, finding comparable results by educational attainment.

Table A7 presents additional sensitivities on the differential effects by educational attainment, as previously shown in Table A1. A possible issue with the results above is that the Census only provides ZCTA population estimates by educational attainment for those 18 and over, forcing us to include women past reproductive age in the denominator of our birth rates. That said, the first column of Table A1 shows that the main result is consistent even with the expanded denominator, and so the potential bias caused by this factor is likely not substantial. Given that older women are more likely to be high school dropouts (Park, Noel, and McFarland, 2015), it is possible that our coefficient estimate for high school dropouts could be negatively

biased. To address this potential concern, Table A7 focuses on the 623 ZCTAs that have at least one birth in each quarter at each educational attainment level and then uses the log of births as opposed to the fertility rate. Our results here are broadly similar, with the main effect (a 1% increase in the fertility rate with a p-value of 0.001) being driven by those with a high school diploma but no college education (a 5% increase, p-value 0.003).[42]

Table A1: Impact of Driving Distance on Fertility Rate by Educational Attainment

	(1) Fertility Rate 18+	(2) Fertility Rate 18+ <HS diploma	(3) Fertility Rate 18+ HS diploma	(4) Fertility Rate 18+ Some College	(5) Fertility Rate 18+ ≥Bachelor's
Driving Distance - 100 mi	0.568*** (0.140)	-0.116 (0.703)	1.897** (0.800)	1.132*** (0.343)	0.807 (0.517)
Observations	36,564	36,564	36,564	36,564	36,564
R-squared	0.123	0.175	0.076	0.048	0.041
Number of ZCTA	1,662	1,662	1,662	1,662	1,662
Weight	Population Female 18+	Population Female 18+ <HS diploma	Population Female 18+ HS diploma	Population Female 18+ Some College	Population Female 18+ ≥Bachelors
Mean	39.97	50.43	42.62	34.14	38.82

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one woman 18 and older in each educational category. *** p<0.01, ** p<0.05, * p<0.1

[42] In this specification, there is a statistically significant negative coefficient (i.e., distance increases lead to lower birth rates) for those with less than a high school degree. However, the p-value is only 0.02, which would fail a standard Bonferroni correction given that four hypotheses are being tested here.

Table A2: Impact of Driving Distance on Fertility Rate by Ethnicity

	(1) Fertility Rate 15-44	(2) Fertility Rate 15-44 Hispanic & Non-Hispanic White	(3) Fertility Rate 15-44 Hispanic	(4) Fertility Rate 15-44 Non- Hispanic White
Driving Distance - 100 mi	0.852*** (0.247)	0.953*** (0.313)	1.095** (0.494)	4.364* (2.361)
Observations	35,662	35,662	35,662	35,662
R-squared	0.127	0.124	0.110	0.027
Number of ZCTA	1,621	1,621	1,621	1,621
Weight	Population Female 15-44	Population Female 15-44 Hispanic & Non- Hispanic White	Population Female 15-44 Hispanic	Population Non- Hispanic White
Mean	72.46	74.43	86.79	61.88

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one woman 18 and older in each ethnicity category. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Impact of Driving Distance on Fertility Rate by Parity

	(1) Fertility Rate 15-49 1st Child	(2) Fertility Rate 15-49 2nd Child	(3) Fertility Rate 15-49 3rd+ Child
Driving Distance - 100 mi	0.448*** (0.0810)	0.430*** (0.0952)	-0.126 (0.120)
Observations	41,140	41,140	41,140
R-squared	0.058	0.031	0.046
Number of ZCTA	1,870	1,870	1,870
Mean	24.15	19.29	18.99

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Impact of Driving Distance on Fertility Rate by Age Category

	(1)	(2)	(3)	(4)
	Fertility Rate 15-49	Fertility Rate 15-19	Fertility Rate 20-29	Fertility Rate 30-49
Driving Distance - 100 mi	0.749***	-0.607*	4.238***	-0.472**
	(0.212)	(0.328)	(0.535)	(0.192)
Observations	36,806	36,806	36,806	36,806
R-squared	0.127	0.097	0.072	0.068
Number of ZCTA	1,673	1,673	1,673	1,673
Weight	Population Female 15-49	Population Female 15-19	Population Female 20-29	Population Female 30-49
Mean	62.49	49.89	115.8	38.24

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have positive population in each of the three age categories. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Impact of Driving Distance on Fertility Rate by Age Category for High Birth ZCTAs

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-19	(3) Fertility Rate 20-29	(4) Fertility Rate 30-49
Driving Distance - 100 mi	1.147***	0.861***	4.583***	-0.514**
	(0.271)	(0.289)	(0.675)	(0.202)
Observations	6,160	6,160	6,160	6,160
R-squared	0.356	0.281	0.265	0.171
Number of ZCTA	280	280	280	280
Weight	Population Female 15-49	Population Female 15-19	Population Female 20-29	Population Female 30-49
Mean	71.74	67.07	133	38.68

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least five births in each quarter in each age category. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Impact of Driving Distance on Fertility Rate by Education for High Birth ZCTAs

	(1) Fertility Rate 18+	(2) Fertility Rate 18+ <HS diploma	(3) Fertility Rate 18+ HS diploma	(4) Fertility Rate 18+ Some College	(5) Fertility Rate 18+ ≥Bachelors
Driving Distance - 100 mi	0.437***	-0.232	1.811**	0.749**	0.526
	(0.123)	(0.706)	(0.833)	(0.341)	(0.364)
Observations	6,666	6,666	6,666	6,666	6,666
R-squared	0.256	0.308	0.150	0.112	0.103
Number of ZCTA	303	303	303	303	303
Weight	Population Female 18+	Population Female 18+ <HS diploma	Population Female 18+ HS diploma	Population Female 18+ Some College	Population Female 18+ ≥Bachelors
Mean	43.27	53.69	47.10	37.08	41.21

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least five births in each quarter in each educational attainment category. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Impact of Driving Distance on Log Births by Education

	(1) Ln(Births to Women 18+)	(2) Ln(18+ <HS diploma)	(3) Ln(18+ HS diploma)	(4) Ln(18+ Some College)	(5) Ln(18+ ≥Bachelors)
Driving Distance - 100 mi	0.0114*** (0.00348)	-0.0442** (0.0188)	0.0454*** (0.0148)	0.0140** (0.00563)	0.0108 (0.0113)
Observations	13,706	13,706	13,706	13,706	13,706
R-squared	0.205	0.169	0.108	0.085	0.052
Number of ZCTA	623	623	623	623	623
Weight	Population Female 18+	Population Female 18+ <HS diploma	Population Female 18+ HS diploma	Population Female 18+ Some College	Population Female 18+ ≥Bachelors

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one birth in each quarter in each educational attainment category. *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Robustness Checks

Appendix B discusses additional robustness checks. First, we address the potential concern that our source of quasi-experimental variation (i.e., abortion policy-driven clinic closures) may not be sufficiently exogenous to be used to produce robust estimates. Following Lahey (2014)'s approach, we attempt to use the fertility rate in the fall of 2007 and the ZCTA population for women ages 15-49 to predict whether a ZCTA will experience a subsequent closure. We also attempt to use the trend in the fertility rate between Q3 2007 and Q3 2009 (before most of the closures and before the policy changes of interest) to predict subsequent closures. The reasoning is that a significant relationship could suggest differential pre-trends between affected and unaffected ZCTAs and therefore pose a potential threat to exogeneity. We implement these checks for several different dependent variables: First, we calculate the maximum one-quarter driving distance change for each ZCTA, which has a mean of about 15 miles for the full period between Q3 2007 and Q1 2013. In addition, we define multiple different "closure" dummies, based on different cutoffs of this variable (30, 50, and 70 miles). Table B1 shows the results of this analysis.

Regardless of which measure is used, we see no statistically significant relationship between the fertility rate, population, or fertility trend at the start of our data and any future change in driving distance or closure. This allows us to conclude that the closures from politically-motivated funding cuts during our time frame are sufficiently uncorrelated with previous values of our outcome variables and with population that we can consider them exogenous and move forward with our analysis.

In Table B2, we regress the fertility rate on driving distance not just for the mean of three and four quarters before birth but also, separately, for three through five quarters before birth, to

validate our main measure of driving distance around the time of conception.[43]

All of the coefficients are directionally consistent and statistically significant at the 1% level, and we cannot reject a null hypothesis that the coefficients are equal to each other across specifications. The consistency of these results confirms the robustness of our estimates to varying measures of driving distance.

Column (1) is the main result from Table 2 above. The second column repeats this analysis for the ZCTAs that have a positive population of women age 15-44 (dropping only 8 ZCTAs), finding an identical result. Column (3) then repeats the analysis for the fertility rate for women 15-44, finding a larger coefficient but a comparable 1.2 percent increase, off of a sample mean fertility rate of 72.59 per 1,000 women age 15-44.

Column (4) repeats the analysis for only the 1,511 ZCTAs that have at least one woman in each five-year reproductive age category (i.e., 15-19, 20-24, 25-29, 30-34, 35-39, 40-45, and 45-49), finding a virtually identical result to column (1). We then compare column (4) to column (5), which uses the total fertility rate (TFR) as a dependent variable, as in Chatterjee and Vogl (2016).[44] While the magnitude of the coefficient is different, it represents a 1.5 percent increase, which is directionally consistent and roughly comparable to our main result in column (1).

Table B3 uses alternative measures of the fertility rate to show that our main results from above are consistent.

Table B4 then combines Table 4 and Table B2 to show how different lags of driving distance affect the fertility rates for women who are married (Panel A) or not married (Panel B).

[43] Recall we are measuring from the end of each quarter, so that for some of the births the driving distance is for almost one quarter less, for a given ZCTA-quarter observation. E.g., 3 and 4 quarters represents 6-12 months before birth, and 5 quarters represents 12-15 months before birth.

[44] The total fertility rate is calculated by summing all of the age-specific general fertility rates (e.g., births to mothers ages 15-19 divided by 1,000 women ages 15-19) and then multiplying by five (i.e., the number of years per age category). It gives the total number of children expected to be born to a woman over her lifetime.

We see from Panel A that none of the coefficients are statistically significant at the 5% level, nor can we reject a null hypothesis that they are equal to each other.

In Panel B, all of the coefficients are statistically significant at the 1% level and show that increases in driving distance lead to increases in the fertility rate among unmarried women. While the effects appear to be strongest 3 and 4 quarters before birth, we cannot reject that the coefficients in columns (1) through (4) are equal to each other.

In Table B5, we re-estimate our main regression without weighting by ZCTA population. While our coefficient loses its statistical significance when including all ZCTAs, dropping the 15 percent of ZCTAs with population below 500 individuals restores it. This is likely because low-population ZCTAs can have an extremely wide range of fertility rates, which would cause our results to be extremely noisy.

In Table B6, we use alternative measures of the fertility rate, such as the crude birth rate, and alternative nonlinear econometric specifications, such as a more general fixed effect negative binomial specification (see Allison and Waterman 2002). Some of these alternative specifications have the added benefit of not using population counts and being unweighted, allowing us to check the robustness of our results on that dimension. Many also are on slightly different subsamples due to limitations of the particular specification. All of these produce comparable results of an increase in the fertility rate on the order of 1.0-1.4 percent.

Table B7 uses driving time instead of driving distance. We find that a 100-minute increase in the driving time increases the fertility rate by a comparable 1.4 percent and is statistically significant at the 1% level.

Table B8 uses a nonlinear function of driving distance, such as dummy variables for each 50-mile category, a quadratic specification, and an exponential specification. For the dummy

variables, all of the coefficients are positive and jointly statistically significant at the 1% level. While they are suggestive that there is a greater effect of having a very large increase in driving distance (greater than 200 miles), the coefficients are not statistically significantly different from each other. For the quadratic specification, the coefficients are positive and jointly significant at the 1% level. The exponential coefficient is also significant at the 1% level, again suggesting that the fertility effects of clinic closures increase disproportionately as the change in driving distance increases.

Table B9 repeats the primary specification of this paper but interacts distance with quartiles of the unemployment rate. All of the coefficients are still positive, with some variation in magnitude. None are statistically significantly different from each, but together they are jointly significant at the 1% level, as shown by the F-statistic at the bottom of the table. Table B9 also repeats the analysis instead using the employment-to-population ratio from the Bureau of Economic Analysis (BEA). The advantage of this alternative approach is that while the LAUS unemployment rates are interpolated,[45] the BEA data comes from administrative records. One disadvantage is that this data is only annual, and not quarterly, and so matches more poorly with the timing of our primary clinic data. We have therefore chosen to use the data from the calendar year before the birth year, though that may be anywhere from a few months to almost a full year before the birth. The results are comparable with the main results of the paper, but generally somewhat smaller in magnitude. This is potentially because women's labor decisions around pregnancy and children are more linked to labor force participation than to the unemployment rate, and the employment-to-population ratio incorporates labor force participation as well.

[45] See http://www.bls.gov/lau/laumthd.htm.

Again, all of the interacted coefficients are jointly statistically significant but not statistically significantly different from each other.

Table B10 considers what happens if we ignore clinic closures in El Paso. Since all of the El Paso clinics in the network that we study close (see Lu and Slusky 2016) and there are no other nearby in-network clinics, this area is the source of a substantial amount of our variation in driving distance. To account for this, we assign all El Paso County ZCTAs the distance they had at the start of our time frame, effectively ignoring any closures. (Adjacent counties are sufficiently close to other clinics that the closest clinic was not affected by these closures.) With this change, our main result is no longer statistically significant on its own. It is, however, close in magnitude to our main result and the same sign, which alleviates potential concerns that clinic closures had a different effect on fertility rates in the rest of Texas than in El Paso.

Table B11 stratifies the main regression by the distance to the Mexican border.[46] This addresses the potential concern that women near the border could access pharmaceuticals in Mexico either for contraception or to induce abortion, whereas those living farther from the border could not (Grossman et al. 2014b; Grossman et al. 2015). We would therefore expect a smaller coefficient for those ZCTAs near the border and a larger one for those farther from the border. However, we find the opposite to be true, with ZCTAs near the border having a larger and more precise estimate. This is likely due to the fact that El Paso County, which is a main source of variation in driving distance, is also very close to the border, which makes it difficult to effectively test this question.

Table B12 uses alternative measures to control for the local labor market situation, such as the annual county employment-to-population ratio from the BEA and the annual ZCTA share

[46] This is calculate as the minimum crow-fly distance between the ZCTA centroid and each coordinate of the Mexican border found in the TIGER/Line Shapefiles.

of tax returns that report receiving unemployment benefits.[47] Regardless of which metric is used, our results are consistent and not statistically significantly different from each other.

Table B13 shows results if we cluster at a greater level of aggregation than counties. This is because adjacent counties may be affected by the same closure and so are potentially not independent observations. Our main results are robust to each alternative level of clustering, whether we use commuting zones, BEA economic areas, or core-based statistical areas (i.e., metropolitan and micropolitan statistical areas).

Table B14 includes several other additional checks. First, it compares the main result (Column 1), clustering at the county level, to the result when clustering at the ZCTA level. Unexpectedly, the standard error increases at lower level of aggregation, resulting in the main result no longer being statistically significant. While uncommon, this is possible (see Cameron and Miller 2015) if standard errors are more negatively correlated at the ZCTA level than the county level. Given the argument made above for clustering at the county level and not at the ZCTA level, we believe that the county level clustering is less biased.

Table B14 also includes our results at greater levels of aggregation, namely at the county and commuting zone level. As expected, these results are substantially noisier than the results at the ZCTA level, though the coefficients are of a similar sign and magnitude.

Finally, Table B14 also includes the results of a regression that controls for whether the county had Medicaid Managed Care (MMC), which other researchers have shown has an impact on birth outcomes and fertility (see Aizer, Currie, and Moretti, 2007; Kuziemko, Meckel, Rossin-

[47] Our measure here is the number of returns in each ZCTA (aggregated from the ZIP-code level) reporting unemployment benefits divided by the total number of returns in that ZCTA. Unfortunately, the data for 2008 is missing the variable for number of returns reporting unemployment benefits, but has the total amount of benefits reported for each ZIP-code. Therefore, we use the 2007 and 2009 data (both of which contain the number of returns and the total amount) to calculate a mean amount per return and then use this to calculate the approximate number of returns in each ZIP-code that claim unemployment benefits.

Slater, 2013). [48] We find no effect of controlling for MMC on our main result. However, this is partially due to the fact that the rural counties that were expanded to in 2012 have low populations and so in our weighted regression framework will not have much impact on the overall result.

Figure B1 and Table B15 stratify the analysis by closures that happened before the funding cuts in 2011 versus closures that happened afterwards. Figure B1 repeats Figure 2 but for each time period. Unlike in Figure 1, where it is obvious that the majority of the closures happened after June 2011, here the difference is not easy to see.

Table B15 then repeats our main result but stratifies by births occurring in 2007-2010 and births in 2010-2013. The reason for including 2010 and 2011 births, even though they will mostly be unaffected by the closures in 2011, is to provide a "pre-period" for the affected ZCTAs. The results show that while there is more precision in the estimate for 2007-2010, both are positive and statistically significant at the 10% level, and we cannot reject the null hypothesis that they are equal to each other.

Finally, Table B16 considers whether controlling for changing population levels biases our results. While the Census does not provide 1-year averages for ZCTA-level population, it does provide 5-year averages for the years 2010-2016. From the midpoints of each of these intervals (i.e., 2008-2014), and from the Census's 2000 ZCTA population data, we interpolate quarterly population levels for each ZCTA. These interpolated values can then be used to recalculate the fertility rate for women ages 15-49, reweight the regressions, or both. As shown

[48] The names of the counties that changed to MMC before 2007 are from Kuziemko, Meckel, Rossin-Slater (2013). The names of the counties from the Medicaid Rural Service Areas that changed to MMC in 2012 (per https://hhs.texas.gov/sites/default/files/documents/services/health/medicaid-chip/programs/star-plus/starplus-mrsa-regions-map-with-mcos.pdf) are from https://hhs.texas.gov/sites/default/files//documents/laws-regulations/reports-presentations/2017/medicaid-chip-perspective-11th-edition/11th-edition-complete.pdf.

in Table B16, our estimates are larger in magnitude using these more granular population levels, suggesting that, if anything, using constant population levels biases our results toward zero. These results also remain robust to weighting with the constant or quarterly population, and to removing the earliest birth cohorts that make use of the 2000 Census data.

Table B1: Attempting to Predict Clinic Closures

Panel A: Using 2007 Fertility Rates

	(1) Maximum Distance Change	(2) Closure if Delta Distance > 30 mi	(3) Closure if Delta Distance > 50 mi	(4) Closure if Delta Distance > 70 mi
Fertility Rate 15-49	0.119 (0.0825)	0.00100 (0.000639)	0.000375 (0.000356)	0.000319 (0.000346)
Observations	1,870	1,870	1,870	1,870
R-squared	0.004	0.008	0.001	0.001

Panel B: Using ZCTA Population for Females 15-49

	(1) Maximum Distance Change	(2) Closure if Delta Distance > 30 mi	(3) Closure if Delta Distance > 50 mi	(4) Closure if Delta Distance > 70 mi
ZCTA Population	0.000767 (0.00128)	-2.87e-07 (5.15e-06)	-9.06e-08 (4.98e-06)	7.07e-07 (4.93e-06)
Observations	1,870	1,870	1,870	1,870
R-squared	0.007	0.000	0.000	0.000

Panel C: Using the Change in Fertility Rates between Q3 2007 and Q3 2009 [49]

	(1) Maximum Distance Change	(2) Closure if Delta Distance > 30 mi	(3) Closure if Delta Distance > 50 mi	(4) Closure if Delta Distance > 70 mi
Fertility Rate 15-49 change	0.00363 (0.0236)	-2.46e-05 (0.000296)	0.000168 (0.000211)	0.000136 (0.000186)
Observations	1,870	1,870	1,870	1,870
R-squared	0.000	0.000	0.000	0.000

Notes: Robust standard errors clustered at the county level in parentheses. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

[49] Here the maximum distance change is only for Q3 2009 to Q1 2013 (after the timeframe used to calculate the trend in the fertility rate).

Table B2: Impact of Driving Distance on Fertility Rate

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49	(3) Fertility Rate 15-49	(4) Fertility Rate 15-49
Driving Distance Mean of 3 and 4 quarters before birth - 100 mi	0.839*** (0.213)			
Driving Distance 3 quarters before birth - 100 mi		0.808*** (0.223)		
Driving Distance 4 quarters before birth - 100 mi			0.775*** (0.181)	
Driving Distance 5 quarters before birth - 100 mi				0.633*** (0.185)
Observations	39,270	39,270	39,270	39,270
R-squared	0.094	0.094	0.094	0.094
Number of ZCTA	1,870	1,870	1,870	1,870
Mean	62.14	62.14	62.14	62.14

Notes: Robust standard errors clustered at the county level in parentheses. All regressions contain birth year, birth quarter, and ZCTA fixed effects. Results are for quarters that have at least five past quarters of driving distance data. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B3: Alternative Measures of the Fertility Rate

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49	(3) Fertility Rate 15-44	(4) Fertility Rate 15-49	(5) TFR (Total Fertility Rate)
Restricted to ZCTA with:	Women 15-49	Women 15-44	Women 15-44	Women in each age category	Women in each age category
Driving Distance - 100 mi	0.753***	0.753***	0.885***	0.750***	34.2***
	(0.209)	(0.209)	(0.243)	(0.211)	(8.97)
Observations	41,140	40,964	40,964	33,242	33,242
R-squared	0.104	0.102	0.101	0.132	0.071
Number of ZCTA	1,870	1,862	1,862	1,511	1,511
Mean	62.44	62.44	72.59	62.53	2273

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that meet the criteria described in the table header. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B4: Impact of Driving Distance on Fertility Rate by Marital Status and Lag

Panel A: Married

	(1) Fertility Rate 15-49 Married	(2) Fertility Rate 15-49 Married	(3) Fertility Rate 15-49 Married	(4) Fertility Rate 15-49 Married
Driving Distance Mean of 3 and 4 quarters before birth - 100 mi	0.441 (0.358)			
Driving Distance 3 quarters before birth - 100 mi		0.292 (0.362)		
Driving Distance 4 quarters before birth - 100 mi			0.533* (0.316)	
Driving Distance 5 quarters before birth - 100 mi				0.623* (0.374)
Observations	37,485	37,485	37,485	37,485
R-squared	0.065	0.064	0.065	0.065
Number of zip	1,785	1,785	1,785	1,785
Weight	Population Female 15-49 Married	Population Female 15-49 Married	Population Female 15-49 Married	Population Female 15-49 Married
Mean	72.70	72.70	72.70	72.70

Panel B: Not Married

	(1) Fertility Rate 15-49 Not Married	(2) Fertility Rate 15-49 Not Married	(3) Fertility Rate 15-49 Not Married	(4) Fertility Rate 15-49 Not Married
Driving Distance Mean of 3 and 4 quarters before birth - 100 mi	1.267***			
	(0.334)			
Driving Distance 3 quarters before birth - 100 mi		1.348***		
		(0.348)		
Driving Distance 4 quarters before birth - 100 mi			1.049***	
			(0.280)	
Driving Distance 5 quarters before birth - 100 mi				0.723***
				(0.211)
Observations	37,485	37,485	37,485	37,485
R-squared	0.064	0.064	0.064	0.063
Number of zip	1,785	1,785	1,785	1,785
Weight	Population Female 15-49 Not Married	Population Female 15-49 Not Married	Population Female 15-49 Not Married	Population Female 15-49 Not Married
Mean	52.02	52.02	52.02	52.02

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have at least one married woman and one unmarried woman between the ages of 15 and 49. *** p<0.01, ** p<0.05, * p<0.1

Table B5: With and Without Weights

	(1) Fertility Rate 15-49 Weighted	(2) Fertility Rate 15-49 Unweighted	(3) Fertility Rate 15-49 Weighted	(4) Fertility Rate 15-49 Unweighted	(5) Fertility Rate 15-49 Weighted	(6) Fertility Rate 15-49 Unweighted
Driving Distance - 100 mi	0.753***	1.478	0.754***	1.181**	0.743***	1.162**
	(0.209)	(1.522)	(0.209)	(0.599)	(0.209)	(0.507)
Observations	41,140	41,140	35,288	35,288	31,878	31,878
R-squared	0.104	0.002	0.129	0.008	0.140	0.050
Number of ZCTA	1,870	1,870	1,604	1,604	1,449	1,449
Weight	Population Female 15-49		Population Female 15-49		Population Female 15-49	
Mean	62.44	62.44	62.41	62.62	62.43	61.17
Population			>500	>500	>1,000	>1,000

Notes: Robust standard errors clustered at the county level in parentheses. All regressions contain birth year, birth quarter, and ZCTA fixed effects. Results in columns (3)–(6) are limited to ZCTAs that have at least the population indicated in the last row. *** p<0.01, ** p<0.05, * p<0.1

Table B6: Impact of Driving Distance on Alternative Measures and Specifications

	(1) Crude Birth Rate	(2) Fertility Rate 15-49	(3) Ln(Births to Women 15-49)
Driving Distance - 100 mi	0.182***	0.814***	0.00987***
	(0.0531)	(0.220)	(0.00347)
Observations	41,140	30,228	30,228
R-squared	0.120	0.146	0.126
Number of ZCTA	1,870	1,374	1,374
Clusters	County	County	County
Weight	Population	Population Female 15-49	Population Female 15-49
Mean	15.43	62.74	

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. The dependent variable in Column (1) – the crude birth rate – is defined as births per 1,000 individuals in the population (of any age and gender). Columns (2) and (3) are limited to ZCTAs with at least one birth in each quarter to avoid ln(0). *** p<0.01, ** p<0.05, * p<0.1

Table B7: Impact of Driving Time on Fertility Rate

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49
Driving Distance - 100 mi	0.753***	
	(0.209)	
Driving Time - 100 minutes		0.899***
		(0.280)
Observations	41,140	41,140
R-squared	0.104	0.101
Number of ZCTA	1,870	1,870
Mean	62.44	62.44

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B8: Non-Linear Functions of Driving Distance

	(1) Linear	(2) Buckets	(3) Quadratic	(4) Exponential
Driving Distance - 100 mi	0.753***		0.599	0.142***
	(0.209)		(1.855)	(0.0284)
Driving Distance 50-100 miles - 100 mi		0.427		
		(0.939)		
Driving Distance 100-150 miles - 100 mi		0.459		
		(0.926)		
Driving Distance 150-200 miles - 100 mi		0.793		
		(1.043)		
Driving Distance 200-250 miles - 100 mi		2.553		
		(3.318)		
Driving Distance 250-300 miles - 100 mi		2.049***		
		(0.378)		
Driving Distance - 100 mi squared			0.0586	
			(0.643)	
Observations	41,140	41,140	41,140	41,140
R-squared	0.104	0.104	0.104	0.104
Number of ZCTA	1,870	1,870	1,870	1,870
Mean	62.44	62.44	62.44	62.44
F-stat for joint significance of driving distance coefficients		8.561***	16.29***	
P-value of F-stat		0.000	0.000	

Notes: The dependent variable in all regressions is the general fertility rate for all women 15-49. Robust standard errors clustered at the county level in parentheses. The outcome variable for all columns is the fertility rate for all women 15-49. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B9: Impact of Driving Distance on Fertility by Status of the Labor Market

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49	(3) Fertility Rate 15-49	(4) Fertility Rate 15-49
Distance interacted with		Unemployment Rate		Employment to Population Ratio
Driving Distance - 100 mi	0.753*** (0.209)		0.579*** (0.208)	
Unemployment Rate	-1.135*** (0.154)			
Employment to Population Ratio			36.31** (16.50)	
Driving Distance - 100 mi * 1st quartile		1.988** (0.831)		1.654 (1.485)
Driving Distance - 100 mi * 2nd quartile		0.928* (0.528)		0.601*** (0.184)
Driving Distance - 100 mi * 3rd quartile		0.984** (0.488)		2.737*** (1.023)
Driving Distance - 100 mi * 4th quartile		0.533** (0.224)		1.420 (1.129)
Observations	41,140	41,140	41,140	41,140
R-squared	0.104	0.101	0.102	0.101
Number of ZCTA	1,870	1,870	1,870	1,870
Mean	62.44	62.44	62.44	62.44
F-stat for joint significance of driving distance coefficients		4.503***		3.353**
P-value of F-stat		0.00157		0.0107

Notes: Robust standard errors clustered at the county level in parentheses. All regressions contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B10: Ignoring Closures in El Paso County

	(1) Fertility Rate 15-49 Main Regression	(2) Fertility Rate 15-49 Adding clinics back to El Paso
Driving Distance - 100 mi	0.753*** (0.209)	
Driving Distance - 100 mi with no closures in El Paso County		0.578 (1.040)
Observations	41,140	41,140
R-squared	0.104	0.104
Number of ZCTA	1,870	1,870
Mean	62.44	62.44

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B11: Stratifying by Distance to the Mexican Border

	(1) Fertility Rate 15-49 Main Regression	(2) Fertility Rate 15-49 Border Distance < 50 miles	(3) Fertility Rate 15-49 Border Distance > 50 miles
Driving Distance - 100 mi	0.753*** (0.209)	1.101*** (0.300)	0.220 (1.076)
Observations	41,140	7,392	33,748
R-squared	0.104	0.177	0.087
Number of ZCTA	1,870	336	1,534
Mean	62.44	68.78	60.48

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results in columns (2) and (3) are for ZCTAs stratified by distance to the Mexican border as indicated in the table header. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B12: Alternative Measures of Local Labor Market Conditions

	(1) Fertility Rate 15-49	(2) Fertility Rate 15-49	(3) Fertility Rate 15-49	(4) Fertility Rate 15-49
Driving Distance - 100 mi	0.723*** (0.219)	0.747*** (0.210)	0.571*** (0.209)	0.712*** (0.200)
Unemployment Rate		-1.117*** (0.157)		
Employment-to-Population Ratio			37.61** (16.74)	
IRS ZCTA-Level Unemployment Benefits Rate				-0.829*** (0.288)
Observations	33,528	33,528	33,528	33,528
R-squared	0.128	0.132	0.129	0.131
Number of ZCTA	1,524	1,524	1,524	1,524
Mean	62.52	62.52	62.52	62.52

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results are for ZCTAs that have data on all three measures of the local labor market. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B13: Clustering at Levels of Aggregation Larger than Counties

Clustering by:	(1) County	(2) Commuting Zone	(3) BEA Economic Area	(4) County	(5) CBSA 2013	(6) County	(7) CBSA 2003
Driving Distance - 100 mi	0.727***	0.727***	0.727***	0.744***	0.744***	0.745***	0.745***
	(0.218)	(0.177)	(0.194)	(0.215)	(0.168)	(0.214)	(0.161)
Observations	41,140	41,140	41,140	30,316	30,316	29,788	29,788
R-squared	0.101	0.101	0.101	0.122	0.122	0.123	0.123
Number of ZCTA	1,870	1,870	1,870	1,378	1,378	1,354	1,354
Clusters	254	62	14	127	68	121	67
Mean	62.44	62.44	62.44	62.43	62.43	62.42	62.42

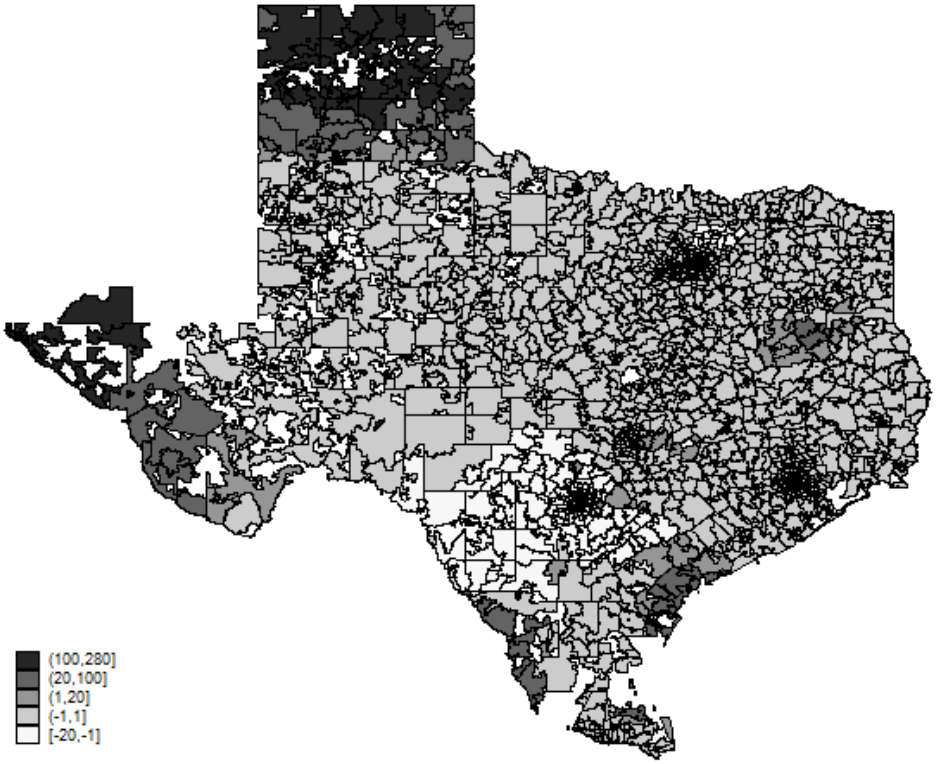
Notes: The dependent variable in all regressions is the fertility rate for all women 15-49. Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Results in columns (4)–(7) are for ZCTAs that part of a CBSA in either 2013 or 2003 as indicated. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B14: Additional Checks

	(1)	(2)	(3)	(4)	(5)
Unit of analysis	ZCTA	ZCTA	County	Commuting Zone	ZCTA
Clustering by	County	ZCTA	County	Commuting Zone	County
Driving Distance - 100 mi	0.753***	0.753	0.634*	0.678**	0.766***
	(0.209)	(0.666)	(0.333)	(0.307)	(0.210)
County has Medicaid Managed Care					0.754
					(0.580)
Observations	41,140	41,140	6,604	1,612	41,140
R-squared	0.101	0.101	0.472	0.707	0.101
Number of Units	1,870	1,870	254	62	1,870
Mean	62.44	62.44	62.89	62.89	62.89

Notes: The dependent variable in all regressions is the fertility rate for all women 15-49. Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. Driving distance for counties and commuting zones is calculated as a population weighted mean of the driving distance for the ZCTAs within each area. The unemployment rate for each commuting zone is calculated analogously. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Figure B1: Change in Driving Distance for Specific Years
Panel A: October 1, 2007, to June 30, 2011



Panel B: June 30, 2011, to March 31, 2013

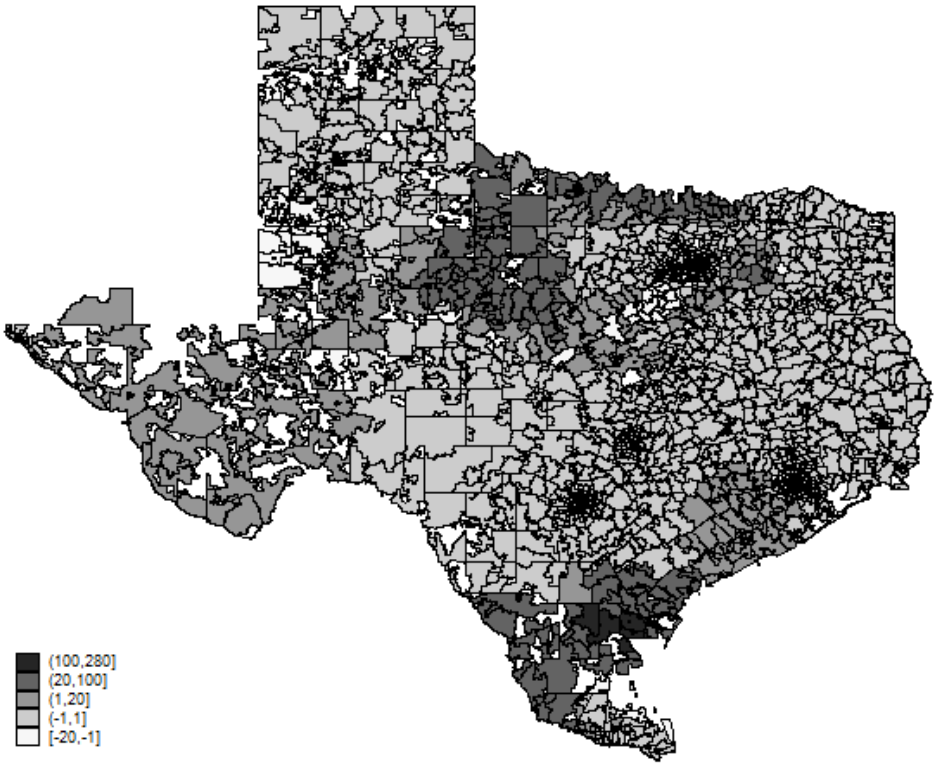


Table B15: Impact of Driving Distance on Fertility Rate for Specific Years

Birth Years	(1) 2007-2013	(2) 2007-2010	(3) 2011-2013
Driving Distance - 100 mi	0.753***	0.657***	1.591*
	(0.209)	(0.142)	(0.899)
Observations	41,140	18,700	22,440
R-squared	0.101	0.091	0.111
Number of ZCTA	1,870	1,870	1,870
Mean	62.44	63.89	61.23

Notes: The dependent variable in all regressions is the fertility rate for all women 15-49. Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. All regressions are weighted by the population of females ages 15-49. *** p<0.01, ** p<0.05, * p<0.1

Table B16: Impact of Driving Distance on Fertility Rate, Quarterly Population

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Fertility Rate 15-49	Fertility Rate 15-49, Quarterly Population	Fertility Rate 15-49, Quarterly Population	Fertility Rate 15-49, Quarterly Population	Fertility Rate 15-49, Quarterly Population
Birth Years	2008Q2-2013	2008Q2-2013	2009Q3-2013	2008Q2-2013	2009Q3-2013
Driving Distance - 100 mi	0.730***	1.356***	1.673***	1.369***	1.666***
	(0.215)	(0.322)	(0.371)	(0.310)	(0.362)
Observations	38,324	38,324	31,356	38,324	31,356
R-squared	0.125	0.140	0.126	0.740	0.748
Number of ZCTA	1,742	1,742	1,742	1,742	1,742
Weight	Population Female 15-49	Population Female 15-49	Population Female 15-49	Quarterly Female Population 15-49	Quarterly Female Population 15-49
Mean	62.53	62.09	61.24	61.99	61.11

Notes: Robust standard errors clustered at the county level in parentheses. All regressions control for the county-level unemployment rate and contain birth year, birth quarter, and ZCTA fixed effects. *** p<0.01, ** p<0.05, * p<0.1