The Impact of Women's Health Clinic Closures on Fertility

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Abstract

The government of Texas recently enacted multiple restrictions and funding limitations on women's health organizations that provide abortion services or are associated with those that do. These policies have caused numerous clinic closures throughout the state, drastically reducing access to care. We study the impact of these clinic closures on fertility 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 2007–2013. We calculate the driving distance to the nearest clinic for each ZIP code, and find that an increase of 100 miles to the nearest clinic results in a 1.2 percent increase in the birth rate. This increase is driven by fertility changes for unmarried women and those having their first or second child. It also reduces average maternal age.

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I. Introduction

How does ease of access to women's health and family planning clinics affect fertility? While these specialized clinics typically provide a wide range of health servicesand often serve as a primary point of access to the health care system for women who may lack alternatives (Frost et al. 2012), they also offer contraceptive and abortion services. Therefore, we hypothesize that clinic closures and the resulting increases in driving distance lead to a higher birth rate, and in this paper seek to identify and to quantify that increase.

We test this hypothesis using a recent series of politically motivated public policy changes in Texas. 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). As a result, there were almost 50% fewer organizations to help poor women plan their pregnancies,[1] with many basic contraceptive services now out of reach.[2]

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% of program costs. Due to Texas's action, Texas lost substantial federal funding at the end of 2012.[3]

[1] 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/.

[2] 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/.

[3] 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/.

These cuts and the resulting clinic closures allow us to test the impact of ease of access on birth rates. We follow the approach of our previous work (Lu and Slusky 2016) by using health center addresses from a network of women's health centers to calculate the driving distance to the nearest clinic for each ZIP-code. This measure is merged with birth rates by ZIP-code, and, using a within-estimator, we estimate the impact of a relative change in driving distance on the relative birth rate. We find that an increase in driving distance to the nearest clinic leads to a statistically significant increase in birth rates.

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 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 these findings by suggesting that decreases in these programs lead to overall increases in fertility. More specifically, our results are consistent with Coleman and Joyce (2011) and Grossman et al. (2014), who find that new stringent abortion requirements and restrictions in 2004 and 2013-2014, respectively, reduced abortions in Texas, and with Girma and Paton (2013), who find that the 2003 parental consent law had no effect on underage pregnancies.

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, as well as work by Packham (2016) on teen birth rates. While our results are consistent with their findings of reduced contraceptive use and increased fertility, our empirical approach is different. For instance, Stevenson et al. (2016) focus on the extensive margin by defining 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. Our approach, on the other hand, is more concerned with the intensive margin, and is substantially more granular because we look at the relative changes in driving distance to the nearest clinic at the ZIP-code level.

Clinic closures could affect birth rates through two primary mechanisms. First, lack of access to women's health and family planning clinics could increase the birth rate due to lack of access to abortion. Some women who otherwise would have sought out abortion services now are unable to do so, and then deliver children who are recorded in the vital statistics records.

The other mechanism is that lack of access to contraception could also have increased the birth rate, with more women having unplanned pregnancies, due to using a less effective or no method of contraception. For our policy environment of interest, we expect these two mechanisms to push birth rates in the same direction, i.e., simultaneous decreased access to contraception and abortion lead to higher birth rates, and the lack of contraception mechanism is more likely to have an effect on fertility when interacted with the lack of abortion mechanism.

While we cannot separate these two mechanisms in this paper, the results will still be informative about the combined effect of clinic closures on fertility. Given that the funding cuts were implemented in part as a way to reduce state spending, our finding of increases in birth rates suggests that medium-term spending could in fact increase (e.g., due to the public expense of educating additional children).

Given a change in fertility, we also determine which demographic subgroups are driving this change. Jerman et al. from the Guttmacher Institute (2016) report that 85% of abortion patients nationwide are unmarried, 37% are white, 25% are Hispanic, 39% have a high school diploma or less, 59% have had at least one previous birth, and 58% are in their 20s. From this, we would expect decreased access to abortion to affect the unmarried birth rate, affect both white and Hispanic women, affect women of both low and high educational attainment, have some effect on births beyond the first child, and lower average mother's age at birth. On the contraceptive side, unfortunately, a clear hypothesis about demographic subgroups does not emerge since use is exceptionally widespread (Guttmacher 2015).

These increases in fertility from lack of access to contraception and abortion are also consistent with the overall mechanisms underlying changes in education, career, and fertility trends among women (see Goldin 2014 and Goldin 2015) and specifically increased maternal age (Matthews and Hamilton 2016). However, they potentially represent backtracking from the general progress to women's empowerment that results 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 a handful of 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 from 2007-2013 from a network of women's health and family planning clinics. This network was one of the largest recipients of funding from both the DSHS's Family Planning Program and the Women's Health Program. 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. These driving distances are then assigned to the period of time 9 to 12 months before each birth to approximate a mother's access to care before and in the early phases of her pregnancy.

The primary outcome variables—the crude birth rate[4] in each quarter in each ZIP-code—are calculated from a restricted version of all administrative birth certificates from the DSHS's Vital Statistics office for 2007-2013. 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 birth rate in each ZIP-code in each quarter for population, we first map the mother's ZIP-code to a ZCTA[5] using the crosswalk for 2011 (i.e., the midpoint of our data

[4] The World Bank defines crude birth rate as the number of live births occurring during the year, per 1,000 population estimated at midyear (see: http://data.worldbank.org/indicator/SP.DYN.CBRT.IN). Note that our birth rate is currently calculated at the quarterly rather than yearly level, and so on average has one quarter the magnitude.

[5] Because some ZIP-codes such as post office boxes have official populations of 0.

set) from UDS Mapper,[6] and then match each ZCTA with its five-year average population (entire and subgroups) from 2008-2013 from the U.S. Census.

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 (Currie and Schwandt 2014). Analogous to how we assign driving distance to each ZCTA-quarter, we average the monthly unemployment rate for nine and twelve months before the last month of each quarter.

III. Methodology

The methodology in this paper is analogous to that of Lu and Slusky (2016), which studies the relationship between relative changes in the driving distance to the nearest clinic and the incidence of preventive care.

We calculate the geodesic (i.e., crow-flies) distance from each Texas ZIP-code centroid to each clinic in each quarter in our primary clinic location data set using the Haversine formula. Then, for the clinic that has the shortest crow-fly distance, we calculate the driving distance, using the "traveltime3" program which uses Google Maps.[7]

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, and merge in the 5-year average population count to calculate the quarterly crude birth rate and birth rate for each ZCTA. Our measures are generally consistent with the literature, and using the 5-year average population count is a reasonable proxy for mid-period population since the population remains relatively stable between 2008-2013. Additionally, our results are robust using other relative, count-based specifications that do not incorporate population counts.

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

[7] Our previous work on this topic that looked at the impact of driving distance increases on preventive care rates also used several alternative measures of clinic proximity and found comparable results (Lu and Slusky 2016).

For each ZCTA, we then use the driving distance data from the ZIP-code of the same name.[8] We average the driving distance 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 average the driving distance three quarters before (e.g., June 30) and 4 quarters before (e.g., March 31). This provides a reasonable estimate of the average driving distance during the period shortly before (e.g., when a woman may be seeking contraceptives) and after conception (e.g., when a woman may be seeking an abortion).

The econometric specification is within-ZCTA, over-time:

$$y_{zt} = \beta_0 + \beta_1 dist_{zt} + \beta_2 UR_{zt} + \boldsymbol{\beta}_3 \boldsymbol{\zeta}_z + \boldsymbol{\beta}_4 \boldsymbol{\tau}_t + \varepsilon_{zt}$$

where the unit of analysis is ZCTA *z* in quarter-year *t*. *y* is a measure of the birth rate, and *dist* is the driving distance from a ZCTA the previous year, averaged as described above. *UR* refers to the county-level unemployment rate (BLS 2016), to control for the effects of the regional labor market on fertility. Like driving distance, this is the average of the rates for the month that is nine months before the end of the quarter and twelve months before the end of the quarter.

$\boldsymbol{\zeta}$ and $\boldsymbol{\tau}$ are ZCTA, quarter, and year fixed effects. We cluster standard errors by county, which is more conservative than clustering by ZCTA 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.

While our primary specification is ordinary least squares with fixed effects, there is some concern that the ZCTAs with non-zero population but zero births are censoring our data and therefore biasing our result. We therefore also use a fixed effect Poisson specification, still

[8] 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's never a case where X -> Y but Y->A. If X -> Y then Y->Y.

clustering our standard errors at the county level as above (see Simcoe 2008). We also use a more general fixed effect negative binomial specification (see Allison and Waterman 2002).

As an additional alternative measure of the birth rate, we look at the log of the count of births, and ignore population. This has the advantage of considering relative changes in the birth rate instead of absolute ones, but forces us to limit the sample to those ZCTAs that have at least 1 birth in each quarter.

This empirical approach is then applied to demographic subgroups, including age, marital status, ethnicity, and educational attainment.[9] As in our previous work (Slusky and Lu 2016) we do not look at income-based subgroups due to increased concerns over endogeneity.

Finally, we look at birth rates by birth parity and mother's age. This supplements the above analysis by providing a clearer picture as to who is most affected by clinic closures that lead to higher fertility.

IV. Results

Table 1 shows summary statistics at the ZCTA-quarter level.

[9] Hicks-Courant and Schwartz (2016)'s fascinating result that family planning clinics are associated with a lower high school dropout rate does not concern us here because we're looking at women over 18 here and so for the most part their education is finished.

Table 1: Summary Statistics (N = 41,822 ZCTA-Quarters)

	(1) mean	(2) sd	(3) min	(4) max
Panel A: Population that is…				
Everyone	13,220	16,379	2	115,538
Female	6,660	8,323	0	59,693
Female & Age 15-19	479	668	0	6,127
Female & Age 15-44	2,806	3,720	0	26,683
Female & Age 15-44 & Hispanic	1,145	2,163	0	23,605
Female & Age 15-44 & Non-Hispanic White	1,125	1,630	0	14,213
Female & Age 18+	4,905	6,022	0	42,627
Female & Age 18+ & <=HS diploma	2,395	2,855	0	21,730
Panel B: Births to mothers that are…				
All	51.00	71.08	0	634
Age 15-19	5.94	9.80	0	110
Age 15-44	50.84	70.86	0	632
Age 15-44 & Hispanic	24.90	49.41	0	628
Age 15-44 & Non-Hispanic White	17.44	25.38	0	287
Age 18+	48.95	68.09	0	596
Age 18+ & <= HS diploma	24.23	39.63	0	443
Having their 1st child	19.77	27.50	0	237
Having their 2nd Child	15.73	22.00	0	174
Married	29.32	42.42	0	374
Panel C: Other (weighted by population)				
Mother's age (years)	27.15	2.165	13	47
Unemployment rate (9-12 months ago)	6.9	1.9	1.8	19.5
Driving distance (miles, 9-12 months ago)	26.7	45.6	0.278	289.9
Change in driving distance (miles)	14.6	52.0	-17.3	276.9

Panel A has the breakdown of average population, with about half being male and half female. Among females, a little less than half are of reproductive age (15-44), and about one-third of that is Hispanic and one-third is non-Hispanic white. Of the female population, approximately two-thirds are adults (18+), and of that about two-fifths have a high school diploma or less.

Panel B then has analogous average counts of births. The overwhelming majority of births are to women ages 15-44, and more than half of those are to Hispanic women, with less than one-third to non-Hispanic White women. Most births are to adult women (18+) and about half of those are to mothers with a high school diploma or less. About 40% of births are first births, and about one-third second births. Lastly, more than half of births are to married women.

Finally, Panel C has a few other weighted averages of interest. The average maternal age at birth is 27, and the average unemployment rate around the time of conception is 6.9%, though there is wide variation in both variables. The average driving distance to the nearest clinic around the time of conception was 26.7 miles and the average change in driving distance over the course of the sample period was an increase of 14.6 miles. Again, as with many of the variables, this also has a wide range, with some ZIP-codes experiencing a distance *decrease* by up to 17.3 miles and some experiencing an increase by almost 300 miles. The average 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.[10]

Table 2 presents our main regression results, which restrict the sample to ZCTAs with a non-zero population.

[10] 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 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.

Table 2: Impact of Driving Distance on Crude Birth Rate

	(1) Crude birth rate	(2) Crude birth rate	(3) Births	(4) Births	(5) Births
	OLS	OLS	Poisson	Poisson	Negative Binomial
Driving Distance - 100 mi	0.0449***	0.0455***	0.0120***	0.0120***	0.0144***
	(0.0140)	(0.0133)	(0.00313)	(0.00281)	(0.00379)
Unemployment Rate		-0.0654***	-0.0165***	-0.0165***	-0.0163***
		(0.00951)	(0.00246)	(0.00123)	(0.00155)
Observations	41,822	41,822	41,822	41,822	41,822
R-squared	0.110	0.114			
Number of ZCTA	1,901	1,901	1,901	1,901	1,901
Birth Year FE	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES
SE Clustered By	County	County	County	ZCTA	ZCTA
Weight	Population	Population			
Mean	3.858	3.858			

Clustered robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first column shows that an increase in distance of 100 miles[11] to the nearest clinic leads to a statistically significant increase in the quarterly crude birth rate of 0.045 births per 1,000 individuals in the population. In relative terms, this is an increase of approximately 1.2 percent, off of a sample mean quarterly crude birth rate of 3.858 per 1,000 individuals. The second column 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

[11] This is the same unit used in our previous work on this topic. 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. Our previous work also tested multiple nonlinear functions of driving distance and found comparable results (Lu and Slusky 2016).

results below, we will always include the local unemployment rate as a control and omit the regression analogous to column (1).[12]

Columns (3)-(5) then re-estimate this regression using models other than OLS. This is to address two problems: 1) birth data is left censored, as a ZCTA cannot have negative births, and 2) births are discrete (i.e., integers), which means that especially low population ZCTAs have large percentage changes from the addition or subtraction of a single birth. Columns (3) and (4) use a fixed effect Poisson specification (with the count of births as the dependent variable), where column (3) shows the results of an analysis that clusters robust standard errors at the county level as in the OLS specification and column (4) clusters at the ZCTA level. Both are statistically significant at the 1 percent level and show the same 1.2 percent increase (as the coefficients here are in log points). These results are consistent despite the fact that neither makes any use of the ZCTA population data at all, nor any weighting. Finally, column (5) uses a more general fixed-effect negative binomial specification and finds a result that is comparable, though slightly larger in magnitude.[13]

Table 3 repeats the main regression of Table 2 with alternative outcome measures.

[12] Table A2 in the Appendix repeats this with the employment to population ratio from the BEA, which is administrative data as opposed to the imputed local unemployment rate, and finds comparable results.

[13] While there is a Stata function ("xtpqml") for a fixed effect Poisson regression (using quasi-maximum likelihood) that clusters robust standard errors at a less granular level than the fixed effect, the authors do not know of an analogous function for a fixed effect negative binomial regression (analogous to "xtnbreg"). Therefore, we cluster at the ZCTA level in column (5), and repeat the regression of column (3) clustering at the ZCTA level in column (4) for comparison. All show comparable results.

Table 3: Impact of Driving Distance on Alternative Outcome Measures

	(1) Crude birth rate	(2) Ln(births)	(3) Births / women 15-44	(4) Births to women 15-44
	OLS	OLS	OLS	Poisson
Driving Distance - 100 mi	0.0541***	0.0139***	0.221***	0.0122***
	(0.0134)	(0.00315)	(0.0607)	(0.00316)
Unemployment Rate	-0.0724***	-0.0180***	-0.332***	-0.0165***
	(0.0109)	(0.00244)	(0.0447)	(0.00247)
Observations	29,876	29,876	40,854	40,854
R-squared	0.162	0.977	0.104	
Number of ZCTA	1,358		1,857	1,857
Birth Year FE	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES
Weight	Population	Births	Female 15-44	
Mean	3.883		18.37	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column (1) replicates the OLS specification from above for the ZCTAs that have at least one birth in each quarter, and finds comparable results.[14] For this subsample, column (2) shows the result if the log of the count of births is used as the dependent variable, and weights each observation in the regression by the number of births (instead of the population). This semi-log approach produces a coefficient in log points, which at 0.0139 is comparable to the 1.2 percent increase found above.

[14] This restriction is necessary for using the log of birth rate (since the log of zero is negative infinity).

Column (3) shows the result from a broad age-specific birth rate (births to women aged 15-44 divided by the female population aged 15-44) instead of the crude birth rate used above. Not surprisingly, the coefficient on "driving distance" is statistically significant, positive, but much larger in magnitude than our main result presented above. The relative impact, however, of increased driving distance is comparable between our main specification and this specification; in relative terms, this increase of 0.221 births per 1,000 women of reproductive age is also 1.2 percent, off of a sample mean birth rate of 18.37. The primary reason that the magnitude is roughly five times larger is that while the numerator of the age-specific birth rate is very close to that of the crude birth rate (as the vast majority of births are to mothers aged 15-44), the denominator is roughly one-fifth the size because it excludes men, women under 15, and women over 44. Column (4) confirms this, using a fixed effect Poisson specification as above. And as in Table 2, the coefficient on the local unemployment rate is negative and statistically significant.

Table 4 begins a series of tables that unpack the 1.2 percent rise in the crude birth rate and the age-specific birth rate shown above. Here, we look at the teen (or adolescent) birth rate, which is defined as births to mothers ages 15-19 divided by the population of women ages 15-19.[15]

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

Table 4: Impact of Driving Distance on Teen Birth Rate

	(1) Crude birth rate	(2) Teen birth rate	(3) Teen births	(4) Teen birth rate	(5) Ln(Teen Births)
	OLS	OLS	Poisson	OLS	OLS
Driving Distance - 100 mi	0.0455*** (0.0135)	-0.147* (0.0831)	0.0148* (0.00781)	-0.0107 (0.0860)	0.0154** (0.00663)
Unemployment Rate	-0.0653*** (0.00956)	-0.156** (0.0642)	-0.000340 (0.00617)	-0.139** (0.0672)	-0.00373 (0.00507)
Observations	37,114	37,114	37,114	15,884	15,884
R-squared	0.133	0.096		0.190	0.880
Number of ZCTA	1,687	1,687	1,687	722	
Birth Year FE	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES
Weight	Population	Female 15-19		Female 15-19	Teen births
Mean	3.863	13.20		14.28	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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 birth rate in OLS, while column (3) uses a fixed effect Poisson approach. These results are much noisier than the ones above, with the two results having different signs and only being statistically significant at the 10% level. Just looking at the subset with at least one birth in each quarter (Column 4) shows no statistical significance. The log specification in column (5) gives a result that is more in line with the main results, and is consistent with the Poisson result but still substantially noisier[16] than the main results.

Table 5 shows results from an investigation into whether the fertility increase reported in

[16] Table A3 in the Appendix attempts additional heroics with the teen birth rate and still only finds middling results.

Table 2 is driven by changes for married or unmarried mothers.

Table 5: Impact of Driving Distance on Birth Rate by Marital Status

	(1) Crude birth rate	(2) Married births/pop	(3) Married births	(4) Unmarried births/pop	(5) Unmarried births
	OLS	OLS	Poisson	OLS	Poisson
Driving Distance - 100 mi	0.0456***	0.00498	0.00313	0.0406***	0.0232***
	(0.0133)	(0.0111)	(0.00492)	(0.0115)	(0.00606)
Unemployment Rate	-0.0654***	-0.0493***	-0.0236***	-0.0161**	-0.00753*
	(0.00952)	(0.00780)	(0.00304)	(0.00700)	(0.00439)
Observations	41,118	41,118	41,118	41,118	41,118
R-squared	0.114	0.066		0.069	
Number of ZCTA	1,869	1,869	1,869	1,869	1,869
Birth Year FE	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES
Weight	Population	Population		Population	
Mean	3.859	2.218		1.640	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Unlike the previous table where we use the corresponding female population, here we use the total population of the ZCTA as the denominator of the birth rate. This is because we are concerned that marital status is more endogenous to birth than education (and certainly race, ethnicity, or age). Our results are again consistent using the Poisson specification, which does not use population at all, and so again our choice of a denominator does not appear to be a concern.[17]

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. Since this

[17] 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.

restriction only applies to a few low-population ZCTAs, the results are almost identical to our main specification. Columns (2) and (3) then look at births to only married women. Here, while the mean rate is larger (2.2 births to married women per 1,000 people), the coefficient is miniscule and statistically insignificant in both specifications. Columns (4) and (5) then look at births to unmarried women, and find that while the mean rate is smaller (1.6 per 1,000 women), the coefficient is larger and statistically significant, representing a 2.5 percent increase in the OLS specification, comparable to the 2.3 percent increase in the Poisson specification.

Table 6 repeats the same process but now stratifying by educational attainment.

Table 6: Impact of Driving Distance on Birth Rate by Educational Attainment

	(1) Births/Female Pop 18+	(2) Births/Female Pop 18+ <HS	(3) Births to Female 18+ <=HS	(4) Births/Female Pop 18+ >HS	(5) Births to Female 18+ >HS
	OLS	OLS	Poisson	OLS	Poisson
Driving Distance - 100 mi	0.141***	0.167	0.0119	0.237**	0.0153**
	(0.0347)	(0.128)	(0.0118)	(0.102)	(0.00780)
Unemployment Rate	-0.168***	-0.124***	-0.0123**	-0.122***	-0.0125***
	(0.0260)	(0.0464)	(0.00511)	(0.0263)	(0.00277)
Observations	37,664	37,664	37,664	37,664	37,664
R-squared	0.119	0.173		0.065	
Number of ZCTA	1,712	1,712	1,712	1,712	1,712
Birth Year FE	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES
Weight	Female Pop 18+	Female Pop 18+ <HS		Female Pop 18+ >HS	
Mean	10.15	10.56		9.386	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Given that the census's population variables for educational attainment are for women age 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 birth to a woman age 18+ with a high school diploma or less and one to a woman age 18+ with more than a high school diploma. While the magnitude of this coefficient is larger than above (since we are excluding men and children from the denominator), the relative magnitude is the same percentage increase that we showed above.

Columns (2)-(5) then look at the change in the birth rate for women age 18 and above with and without a high school diploma, both in OLS and Poisson specifications. While all four columns show increases in fertility of comparable orders of magnitude, the percentage change for women of lower educational attainment in column (2)—1.6 percent—is smaller than the one for women of higher educational attainment (2.5 percent) in column (4) and not statistically significant. The Poisson results in columns (3) and (5) also show this disparity of a greater relative effect on more educated women, even though their birth rate is lower.

Table 7 stratifies our regression by ethnicity, focusing on women ages 15-44 to be consistent with how the census population data by ethnicity is reported.

Table 7: Impact of Driving Distance on Birth Rate by Ethnicity

	(1) Births/Female Pop 15-44	(2) Births/Female 15-44 Hispanic or Non-Hispanic White	(3) Births/Female 15-44 Hispanic	(4) Births to Female 15-44 Hispanic	(5) Births/Female 15-44 Non-Hispanic White Hispanic	(6) Births to Female 15-44 Non-Hispanic White
	OLS	OLS	OLS	Poisson	OLS	Poisson
Driving Distance - 100 mi	0.213***	0.238***	0.274**	0.0107*	1.089*	0.0597**
	(0.0618)	(0.0782)	(0.124)	(0.00573)	(0.592)	(0.0300)
Unemployment Rate	-0.336***	-0.308***	-0.250***	-0.0105**	-0.277***	-0.0173***
	(0.0447)	(0.0503)	(0.0910)	(0.00443)	(0.0490)	(0.00302)
Observations	35,288	35,288	35,288	35,288	35,288	35,288
R-squared	0.127	0.124	0.110		0.027	
Number of ZCTA	1,604	1,604	1,604	1,604	1,604	1,604
Birth Year FE	YES	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES	YES
Weight	Female Pop 15-44	Female Pop 15-44 Hispanic or Non-Hispanic White	Female Pop 15-44 Hispanic		Female Pop 15-44 Non-Hispanic White	
Mean	18.31	18.90	22.20		17.05	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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) repeats this but excludes women who are neither Hispanic nor non-Hispanic White. The results in both are comparable in percentage terms to our main results above.

Columns (3)-(6) then look at the effects of an increase in driving distance on the birth rates for Hispanic and non-Hispanic White women, both in OLS and Poisson specifications. As with the education results, all of the coefficients are positive, but there is a large difference in magnitude, with a 1.2 percent increase for Hispanic women in column (3) but a 6.4 percent increase for non-Hispanic White women in column (5). The Poisson results in columns (4) and (6) are consistent with this disparity. While the results are not as statistically significant as the main results, and the difference between them is not statistically significant,[18] they are still suggestive of the fertility increase being larger for non-Hispanic White women when compared to Hispanic women.

Table 8 breaks down the impact of the fertility increase shown above by order of birth. One could imagine that this fertility increase results from women having additional children beyond their planned number of children. Alternatively, it could result from women having the same number of children as they had planned, but earlier.

[18] For example, the difference in the coefficients in columns (4) and (6) is 0.049, but the square root of the squared sum of the standard errors is 0.031, giving a t-statistic of only 1.604 and a p-value of 0.11.

Table 8: Impact of Driving Distance on Birth Rate by Parity

	(1) Crude birth rate	(2) Crude birth rate (1^{st} kid)	(3) Births (1^{st} kid)	(4) Crude birth rate (2^{nd} kid)	(5) Births (2^{nd} kid)	(6) Crude birth rate (3^{rd}+ kid)	(7) Births (3^{rd}+ kid)
	OLS	OLS	Poisson	OLS	Poisson	OLS	Poisson
Driving Distance - 100 mi	0.0455***	0.0276***	0.0188***	0.0264***	0.0214***	-0.00841	-0.00625
	(0.0133)	(0.00443)	(0.00288)	(0.00601)	(0.00478)	(0.00751)	(0.00586)
Unemployment Rate	-0.0653***	-0.0246***	-0.0174***	-0.0215***	-0.0181***	-0.0188***	-0.0142***
	(0.00953)	(0.00550)	(0.00369)	(0.00426)	(0.00373)	(0.00421)	(0.00297)
Observations	40,634	40,634	40,634	40,634	40,634	40,634	40,634
R-squared	0.117	0.066		0.036		0.052	
Number of ZCTA	1,847	1,847	1,847	1,847	1,847	1,847	1,847
Birth Year FE	YES	YES	YES	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES	YES	YES	YES
Weight	Population	Population		Population		Population	
Mean	3.859	1.496		1.190		1.172	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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) to (7) then repeat the OLS / Poisson 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 in columns (2), (4), and (6) sum to the mean in column (1)). We see here a substantial increase in the number of first and second children (1.8 percent and 2.2 percent, respectively) but an insubstantial and statistically insignificant change for third children.

Table 9 then continues this part of the analysis by looking at 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.

Table 9: Impact of Driving on Mother's Age

	(1) Crude birth rate	(2) Mother's Age (Years)	(3) Mother's Age (Years)
	OLS	OLS	OLS
Driving Distance - 100 mi	0.0482***	-0.0918***	-0.0918***
	(0.0135)	(0.0164)	(0.0162)
Unemployment Rate	-0.0656***		-0.00575
	(0.00961)		(0.0124)
Observations	37,555	37,555	37,555
R-squared	0.134	0.075	0.075
Number of ZCTA	1,901	1,901	1,901
Birth Year FE	YES	YES	YES
Birth Quarter FE	YES	YES	YES
ZCTA FE	YES	YES	YES
Weight	Population	Population	Population
Mean	3.870	27.15	27.15

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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). Columns (2) and (3) then estimate our regression using OLS, with and without the unemployment rate control, which makes no difference to the coefficient of interest. We find that an increase of 100 miles in driving distance to the nearest clinic leads to a decrease in the age of the mother by 0.0918 years, or approximately one month.

V. Robustness checks

The appendix contains results and discussion of several robustness checks. They are discussed here briefly. In Table A1, we add the driving distance to the nearest clinic funded by the Texas Department of State Health Services (DSHS)'s Family Planning Program (as in Lu and Slusky 2016) to allay the concern that clinics from the network we study are closing and then reopening as part of a different network. We find, however, that adding this control makes no difference in the results. Table A2 uses the local employment to population ratio instead of the unemployment rate and finds comparable results. Finally, Table A3 looks at the teen birth rate in only the most populous ZCTAs and finds comparably ambiguous results to those presented in Table 4.

VI. Discussion

Our results show that increases in driving distance to the nearest clinic lead to statistically significant increases in the birth rate on the order of 1 to 2 percent, and that this increase is robust to a variety of specifications and sample restrictions. Stratified analysis shows that this result is driven by adult women (not teenagers) who are unmarried, have higher educational attainment, are non-Hispanic White, and are having their first or second child.

This result is consistent with Bailey (2012)'s work though from the opposite direction, showing that removing access to family planning and abortion raises the birth rate. It is also consistent with previous findings that stringent abortion requirements reduced the abortion rate (Coleman and Joyce 2011; Grossman et al. 2014) and raised the rate of childbirth (Stevenson et al. 2016), but did not affect underage pregnancies (Girma and Patton 2013). Our results are not quite in agreement with Packham (2016) who found a more consistent increase in the teen birth rate, but this could potentially be explained by our substantially different methodologies, where ours focuses more on the intensive margin and hers on the extensive margin. It is also possible that any effect on the teen birth rate is being overwhelmed by the enormous decline in the teen birth rate over the past few decades (Lindo and Packham 2015).

The results of the stratified analysis are also broadly consistent with the literature, which shows that the overwhelming majority of women having abortions are unmarried (Jerman et al. 2016). Reduced access leading to lower maternal age is also a counterpoint to the overall trend of rising maternal age (Matthews and Hamilton, 2016), in this case coming from reductions in access to care.

The most puzzling results are those of educational attainment and ethnicity, both showing that more affluent (i.e., better educated or white) women are more affected. One potential explanation is that our paper is measuring an intensive margin, and more affluent women are affected by that. A small distance increase may already put care out of the reach of a less affluent individual (i.e., more sentitivity to the extensive margin), whereas a more affluent one can adapt to a moderate increase but not a large one (i.e., more sensitivity to the intensive margin).

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. Our analysis shows that these clinic closures lead to higher birth 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 cover all ZIP-codes in Texas during 2007-2013, and by focusing on a direct consequence of family planning clinic closures, namely birth rates. An increase in birth rates resulting from decreased access to contraception and abortion 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.

References

Alison, Paul D. and Richard P. Waterman. “Fixed-Effects Negative Binomial Regression Models.” Sociological Methodology, 32: 247-265.

Anderson, Michael L. and David A. Matsa. 2011. “Are Restaurants Really Supersizing America?” American Economic Journal: Applied Economics, 3(1): 152-188.

Bailey, Martha. 2012. “Reexamining the Impact of U.S. Family Planning Programs on U.S. Fertility: Evidence from the War on Poverty and Early Years of Title X.” American Economic Journal: Applied Economics, 4(2): 62-97.

Buchmueller, Thomas C., Mireille Jacobson, and Cheryl Wold. 2006. “How Far to the Hospital?: The Effect of Hospital Closures on Access to Care.” Journal of Health Economics, 25(4): 740-761.

Bureau of Economic Analysis. 2006-2014. Regional Data. http://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1 (accessed June 24, 2016).

Bureau of Labor Statistics. 2006–2014. Local Area Unemployment Statistics. United States Department of Labor. http://www.bls.gov/lau/ (accessed June 24, 2016).

Coleman, Silvie and Ted Joyce. 2011. “Regulating Abortion: Impact on Patients and Providers in Texas.” Journal of Policy Analysis and Management, 30(4): 775–797.

Currie, Janet, Stefano DellaVigna, Enrico Moretti, and Vikram Pathania. 2010. “The Effect of Fast Food Restaurants on Obesity and Weight Gain.” American Economic Journal: Economic Policy, 2(3): 32-63.

Currie, Janet, Michael Greenstone, and Enrico Moretti. 2011. “Superfund Cleanups and Infant Health.” American Economic Review, 101(3): 435-441.

Currie, Janet and Reed Walker. 2011. “Traffic Congestion and Infant Health: Evidence from E-ZPass.” American Economic Journal: Applied Economics, 3(1): 65-90.

Currie, Janet and Hannes Schwandt. 2014. “Short- and long-term effects of unemployment on fertility.” PNAS, 111(41): 14734-14739.

Frost, Jennifer J., Rachel Benson Gold, and Amelia Bucek. 2012. “Specialized Family Planning Clinics in the United States: Why Women Choose Them and Their Role in Meeting Women’s Health Care Needs.” *Women’s Health Issues*, 22(6): e519-e525.

Gerdts, Caitlin, et al. 2016. “Impact of Clinic Closures on Women Obtaining Abortion Services After Implementation of a Restrictive Law in Texas.” American Journal of Public Health, 106(5): 857-864.

Girma, Sourafel and David Paton. 2013. “Does Parental Consent for Birth Control Affect Underage Pregnancy Rates? The Case of Texas.” Demography 50: 2105–2128.

Goldin, Claudia. 2014. “A Grand Gender Convergence: Its Last Chapter.” American Economic Review, 104(4): 1091–1119.

Goldin, Claudia. 2015. “Career and Family: Collision or Confluence.” *Mimeo* available at http://www.bc.edu/content/dam/files/schools/cas_sites/economics/pdf/Seminars/SemS2016/ColumbiaArrowPaper_CG.pdf (accessed June 24, 2016).

Goodman, David C., Elliott S. Fisher, Therese A. Stukel, and Chiang-Hua Chang. 1997. “The Distance to Community Medical Care and the Likelihood of Hospitalization: Is Closer Always Better?” American Journal of Public Health, 87(7): 1144-1150.

Grossman, Daniel et al. 2014. “Change in abortion services after implementation of a restrictive law in Texas.” Contraception 90: 496–501.

Guttmacher Institute. 2015. “Contraceptive Use in the United States.”

Hicks-Courant, Katherine, and Aaron L. Schwartz. 2016. “Local Access to Family Planning Services and Female High School Dropout Rates.” Obstetrics & Gynecology, 127(4): 699-705.

Hill, Elaine L. 2013. “Shale Gas Development and Infant Health: Evidence from Pennsylvania.” Charles H. Dyson School of Applied Economics and Management, Cornell University, Working Paper.

Hill, Elaine L. 2014. “The Impact of Oil and Gas Extraction on Infant Health in Colorado.” Mimeo from author. See http://www.elainelhill.com/research (last accessed 4/14/2014).

Jerman, Jenna, Rachel K. Jones, and Tsuyoshi Onda. 2016. “Characteristics of U.S. Abortion Patients in 2014 and Changes Since 2008.” Guttmacher Institute.

Lindo, Jason M. and Analisa Packham. 2015. “How Much Can Expanding Access to Long-Acting Reversible Contraceptives Reduce Teen Birth Rates?” NBER Working Paper No. 21275.

Lu, Yao and David J. G. Slusky. 2016. “The Impact of Women's Health Clinic Closures on Preventive Care.” American Economic Journal: Applied Economics, 8(3): 100-124.

Matthews, T.J., and Brady E. Hamilton. 2016. “Mean Age of Mothers is on the Rise: United States, 2000–2014.” NCHS Data Brief No. 232.

Packham, Analisa. 2016. “Family Planning Funding Cuts and Teen Childbearing.” *Mimeo* available from author at https://sites.google.com/site/analisapackham/research (last accessed June 24, 2016).

Rossin-Slater, Maya. 2013. "WIC In Your Neighborhood: New Evidence on the Impacts of Geographic Access to Clinics." Journal of Public Economics, 102: 51-69.

SAS. 2013. ZIP-code Data Set containing centroid coordinates. SAS documentation at http://support.sas.com/community/newsletters/news/feature/2q2007/zipcode.html (accessed February 12, 2016); instructions at http://www.ats.ucla.edu/stat/sas/faq/SASZIPcode.htm (accessed February 12, 2016).

Simcoe, T. 2008. "Xtpqml: Stata module to estimate fixed-effects poisson (quasi-ml) regression with robust standard errors." Statistical Software Components.

Stevenson, Amanda J., Imelda M. Flores-Vazquez, Richard L. Allgeyer, Pete Schenkkan, and Joseph E. Potter. 2016. "Effect of Removal of Planned Parenthood from the Texas Women's Health Program." New England Journal of Medicine, 374: 853-860.

Texas Department of State Health Services (DSHS). Fiscal years 2007–2014 (September 1, 2006–August 31, 2014). DSHS Family Planning Program funded family planning agencies and clinic sites. Contact information at https://www.dshs.state.tx.us/famplan/default.shtm#contact x (accessed February 12, 2016).

Texas Department of State Health Services (DSHS). Birth years 2007-2013. DSHS Birth Certificates. Application information at https://www.dshs.state.tx.us/irb/applirb.shtm (accessed February 12, 2016).

UDS Mapper. 2011. ZIP-code to ZCTA Crosswalk. Available at http://www.udsmapper.org/docs/Zip_to_ZCTA_Crosswalk_2011_JSI.xls (accessed February 24, 2016).

United States Census Bureau. 2012. Population Estimates. 2008–2012 5-Year American Community Survey. http://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml (accessed June 24, 2016).

White, Kari, Daniel Grossman, Kristine Hopkins, and Joseph E. Potter. 2012. "Cutting Family Planning in Texas." New England Journal of Medicine, 367: 1179-1181.

Appendix

In Table A1,we incorporate data on the locations of clinics funded by the DSHS Family Planning Program that were not affiliated with the network of clinics which provided our primary data source (we refer to clinics from this primary data source as being "in-network"). This addresses the potential concern that in-network clinics closed at the same time as (or were replaced by) clinics of other networks in the Family Planning Program, and ignoring the distance to those out-of-network clinics could bias our results.[19]

Table A1: Impact of Driving Distance on Crude Birth Rate with Distance to DSHS Clinics

	(1) Crude birth rate	(2) Crude birth rate	(3) Births
	OLS	OLS	Poisson
Driving Distance - 100 mi	0.0449***	0.0456***	0.0120***
	(0.0140)	(0.0133)	(0.00312)
Driving distance to DSHS – 100 mi	0.0120	0.0138	0.00625
	(0.0876)	(0.0980)	(0.0268)
Unemployment Rate		-0.0654***	-0.0166***
		(0.00952)	(0.00246)
Observations	41,822	41,822	41,822
R-squared	0.110	0.114	
Number of ZCTA	1,901	1,901	1,901
Birth Year FE	YES	YES	YES
Birth Quarter FE	YES	YES	YES
ZCTA FE	YES	YES	YES
Weight	Population	Population	
Mean	3.858	3.858	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[19] Note that the DSHS data indicate out-of-network clinic funding end and start dates, which are not necessarily the same as clinic closure/opening dates.

Our results in this table are entirely comparable to those in Table 2. One potential explanation for the different effects of in-network versus out-of-network clinics is the relative popularity of in-network clinics, which are specialized and more easily recognizable as women's health providers. This is consistent with Lu and Slusky (2016), which also finds minimal impact adding this control.

In Table A2, instead of using the county level unemployment rate from the Bureau of Labor Statistics Local Area Unemployment Statistics, we instead use the employment to population ratio from the Bureau of Economic Analysis. The advantage of this alternative approach is that while the LAUS unemployment rates are interpolated[20], the BEA data comes from administrative records.

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

Table A2: Impact of Driving Distance on Crude Birth Rate using Employment/Population

	(1) Crude birth rate	(2) Births	(3) Births	(4) Births
	OLS	Poisson	Poisson	Negative Binomial
Driving Distance - 100 mi	0.0357***	0.00971***	0.00971***	0.0123***
	(0.0126)	(0.00298)	(0.00283)	(0.00384)
Employment/Population	1.964**	0.472**	0.472***	0.479***
	(0.822)	(0.216)	(0.0692)	(0.0757)
Observations	41,822	41,822	41,822	41,822
R-squared	0.111			
Number of ZCTA	1,901	1,901	1,901	1,901
Birth Year FE	YES	YES	YES	YES
Birth Quarter FE	YES	YES	YES	YES
ZCTA FE	YES	YES	YES	YES
SE Clustered At	County	County	ZCTA	ZCTA
Weight	Population			
Mean	3.858			

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table corresponds to Table 2, and calculates the impact of an increase in driving distance on the crude birth rate (using OLS) and the count of births using a Poisson specification (clustering both at the county and ZCTA level) and a more flexible negative binomial specification. 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.

Table A3 re-estimates the results of Table 4 using only the most populous ZIP-codes, 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 main regressions.

Table A3: Impact of Driving Distance on Teen Birth Rate Using Only Populous ZIP-codes

	(1) Crude birth rate	(2) Teen birth rate	(3) Teen births
	OLS	OLS	Poisson
Driving Distance - 100 mi	0.0659***	0.179**	0.00726
	(0.0196)	(0.0824)	(0.00680)
Unemployment Rate	-0.0558***	0.0589	0.00292
	(0.0176)	(0.131)	(0.00864)
Observations	6,270	6,270	6,270
R-squared	0.340	0.270	
Number of ZCTA	285	285	285
Birth Year FE	YES	YES	YES
Birth Quarter FE	YES	YES	YES
ZCTA FE	YES	YES	YES
Weight	Population	Women 15-19	
Mean	4.500	17.20	

Robust standard errors clustered at the county level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The result in column (1) shows a 1.5 percent increase, comparable to our main result. While the OLS coefficient in column (2) is suggestive of an increase in teen fertility, the Poisson specification in column (3) is both insubstantial and statistically insignificant. This unfortunately means that limiting the sample to the most population ZCTAs does not improve the clarity of the results for teen fertility.