WEB APPENDIX

W1 Evolution of DTCA Policy on ED Drug Advertising

Until recently, the United States government effectively prohibited the airing of television advertisements for pharmaceutical products. However, in 1997, the U.S. Food and Drug Administration (FDA) relaxed this restriction with the stipulation that the broadcast also disclose any significant side effects of the drug, thereby ushering in a new era for direct-to-consumer advertising (DTCA) of pharmaceuticals. In particular, ED drug manufacturers have consistently been top spenders in this relatively new advertising format.

ED drug ads have also generated controversy due to its content of sexual nature. For instance, a 2004 Viagra ad showed a recently married couple with background narration that poses and answers the question, "The guy who wanted to spend the entire honeymoon indoors? He's back." Then blue horns (representing the iconic "little blue pill") emerge from the man's head. The most recognizable Cialis ads feature a man and a woman side by side, relaxing in identical bathtubs on a romantic beach. In fact, many have deemed ED drug ads inappropriate for family viewing, which prompted US Representative Jim Moran to introduce a bill in 2009 to ban erectile dysfunction (ED) drug ads on TV between 6 a.m. and 10 p.m.

W2 Balance Tests

W2.1 Comparing centers of the focal DMAs

One of the identifying assumptions of the border identification strategy is that advertisers target their advertisement toward the population centers of DMAs, and disparities across the centers of DMAs drive some of the variation in advertising. We can easily check to see if the population centers of our DMAs are indeed different in terms of observed demographics. Table W1 shows that the centers are different in many dimensions. For instance, racial composition and family structure vary across the 4 DMA centers. The median household income also varies substantially (e.g., \$50,753 in Springfield, MA vs. \$69,971 in Boston, MA), implying that advertising levels would be different across DMAs

W2.2 Balance test #1: observable characteristics of border zip codes

Here we conduct the first set of balance tests to check whether the demographics of each pair of zip codes across each border are similar in terms of observed demographics. Table W2 shows that the demographics of border zip codes are similar on either side of each DMA border. Note that the zip codes in Berkshire county have slightly more African-American population than their counterparts on the other side of the border (1.3% vs. .5%) and larger population per zip code. Such differences are captured by zip code fixed effects in our estimation.

W2.3 Balance test #2: observables vs. advertising

Another way to check the randomness of border assignment is to test where the level of advertising predicts observable characteristics of markets across the border. Following Shapiro (2018), we ran regressions with advertising on the right hand side and different observables on the left hand side with border fixed effects. The results in Table W3 indicate that no variable is statistically significant.

W3 Robustness Checks for MA Data

In this section, we check our main model with other omitted variables and functions forms, and conduct two falsification tests to further strengthen our empirical results with 2001-2010 MA hospital birth data.

Table W1: Centers of DMAs

Metro Area (center of DMA only)	%Male	%White	%Black	%Asian	%Households - married families	%Households- families with kids	%Households- non-familes	%House Owned	Income ($)	Population	# households (center) / # TV homes (DMA)
Boston-Cambridge-Quincy, MA-NH	48.3	79.2	9.1	7.7	46.0	20.5	37.9	60.3	69,971	4,134,036	66.3
Providence-New Bedford-Fall River, RI-MA	48.4	90.4	4.6	2.3	47.5	19.4	33.6	62.3	54,955	548,285	34.4
Albany-Schenectady-Troy, NY	48.8	87.0	9.1	3.8	45.2	17.8	38.7	64.4	57,781	870,716	64.1
Springfield, MA	48.4	82.5	6.4	2.4	42.8	16.3	37.3	63.8	50,753	691,119	102.3

Note: The last column is calculated by dividing the number of households at the center of each DMA by the total number of TV homes in the entire DMA. For Springfield DMA, the ratio greater than 100 suggests that not all households in the DMA have televisions. Boston is located approximately 70 (20) miles from the Boston/Springfield (Boston/Providence) DMA border. Albany, NY is about 50 miles to the Albany/Springfield DMA border, and Springfield, MA is 30 miles from either side of the DMA border.

Table W2: Balance Test #1: Observed Characteristics of Border Zip Codes

DMA border	Counties where border zip codes belong to	Stat.	% Male	% White	% Black	% Asian	%Households - married families	%Households- families with kids	%Households- non-familes	%House Owned	Income ($)	Pop.
Albany/ Springfield	Berkshire	Mean	51.0	97.9	1.3	1.1	54.3	16.5	33.5	84.0	57,781	3,942
		SD	2.0	1.1	1.0	.5	8.4	2.6	4.9	13.0	12,520	6,011
	Frankline, Hampden, Hampshire (West)	Mean	50.5	98.7	.5	.9	54.4	17.8	33.3	85.0	63,162	1,357
		SD	.9	.4	.3	.4	6.2	4.1	5.7	5.7	10,754	372
Springfield/ Boston	Frankline, Hampden, Hampshire (East)	Mean	50.1	97.8	1.1	1.0	53.8	18.4	33.0	82.9	61,567	4,030
		SD	1.1	.7	.6	.3	5.5	2.6	3.0	10.6	11,940	3,416
	Worcester	Mean	49.9	97.8	1.1	1.0	55.0	20.8	30.6	78.0	68,869	3,370
		SD	1.1	1.0	.4	.7	8.0	3.4	3.8	10.2	21,527	3,532
Boston/ Providence	Norfolk, Plymouth	Mean	49.1	88.9	6.7	3.1	57.3	24.7	27.7	77.6	84,271	18,998
		SD	1.1	15.3	11.2	3.1	9.8	5.4	5.6	12.0	19,138	16,137
	Bristol	Mean	49.0	94.9	2.6	2.1	58.6	25.7	26.9	80.8	82,050	12,695
		SD	.8	2.3	1.4	1.4	6.2	4.8	5.4	6.8	13,383	7,522

Note: There are 6-12 border zip codes in each group of counties in the table. These zip codes account for .4 - 3.4% of county population in which they belong. For instance, the border zip codes in Worcester county include .4% of the county population, whereas those in Norfolk, Plymouth counties account for 3.4%.

Table W3: Balance Tests

	%Male	%White	%Black	%Asian	%Households - married families	%Households-families with kids	%Households-non-familes	%House Owned	Income ($)	Population
Ads	.2859	.7218	-.3990	-.0766	.2321	-.7647	.3503	1.2771	-2.57e+03	-190.1351
	(.1911)	(1.2401)	(.9049)	(.2740)	(1.2807)	(.7188)	(.8093)	(1.6708)	(2765.3321)	(1494.7143)
N	53	53	53	53	53	53	53	53	53	53
R^2	.2776	.1909	.1457	.2233	.0341	.3437	.1927	.0306	.2480	.3279

Note: All models include border fixed effects. None are statistically significant at 5%.

W3.1 Functional forms

We first check the robustness of our results against different assumptions with respect to functional forms. Model (1) of Table W4 replicates the results of weighted least squares with advertising, zip code fixed effects, and monthly fixed effects. In model (2), we obtain similar results with a log function of advertising in that advertising appears to have a significant and positive effect on birth rate. In model (3), we test a log-log regression and obtain similar results. We also fit the model using a quadratic function to represent advertising expenditures, but the parameters are found not statistically significant due to collinearity in weight least squares. However, we obtain robust results with other functional forms when we employ ordinary least squares.

Table W4: Different Functional Forms

	(1)	(2)	(3)
DV	Birth rate	Birth rate	Log(1+birth rate)
Zip code FEs	Y	Y	Y
Monthly FEs	Y	Y	Y
Ads	.008***		
	(.003)		
log(1+*Ads*)		.080***	.047***
		(.029)	(.017)
N	5,130	5,130	5,130
R^2	.362	.362	.371

Note: Birth rate is the number of births per 1,000 population per month at the zip code level. Robust errors are clustered at the zip code level. FEs stands for fixed effects. * $p<$ .1; ** $p<$ .05; *** $p<$.01

W3.2 More controls

Weather data are obtained from the National Oceanic and Atmospheric Administration (NOAA). The National Oceanic and Atmospheric Administration (NOAA) has weather stations around the US and provides station coordinates that can be matched to zip codes; however, not all zip codes in Massachusetts have NOAA weather stations during the time period of our study. Therefore, we aggregate weather data at the county level for each month. The average temperature is approximately 48 degrees Fahrenheit, with the mean precipitation of 4.26 inches and snow accumulation of 4.60 inches.

In model (2) in the table below, we add the weather data to our main model and find that weather parameter estimates are not significant. The ad parameters are not statistically different with and without weather variables. Therefore, we rule out the weather as a source of bias. We also include men's age distribution as additional controls in model (3) and do not find them significant. The US Census data show that the proportions of men aged 20-29, 30-44, and 45-59 to be 6%, 10%, and 11% of the total population, respectively.

Table W5: More Controls

	(1)	(2)	(3)
DV	Birth rate	Birth rate	Birth rate
Zip code FEs	Y	Y	Y
Monthly FEs	Y	Y	Y
Ads	.008***	.009***	.008***
	(.003)	(.003)	(.002)
Precipitation		-.003	-.003
		(.005)	(.005)
Snow		-.001	-.001
		(.002)	(.002)
Temperature		.001	.001
		(.004)	(.004)
Prop. men 20-29			3.887
			(11.269)
Prop. men 30-44			.546
			(7.498)
Prop. men 45-59			6.122
			(7.822)
N	5,130	5,130	5,130
R^2	.362	.362	.363

Note: Birth rate is the number of births per 1,000 population per month at the zip code level. Robust errors are clustered at the zip code level. FEs stands for fixed effects. * $p<.1$; ** $p<.05$; *** $p<.01$

W3.3 Other Potential Threats to Border Strategy

One source of concern is that condom advertisements can potentially confound the analysis, though how these can bias our estimates directionally is not clear, even if they are correlated with ED drug ads. On one hand, seeing a sensual condom ad can perhaps spur intercourse, possibly leading to more births. On the other hand, condom advertisements can also encourage more protected sexual intercourse and hence, fewer births.

Nevertheless, to see if there is a statistically significant relationship between the two types of ads, we collect data on condom advertisements and find that condom brands advertised very little in the MA local spot markets. Durex and Trojan, the duopolists in the US condom market, spent less than .01% of their television advertising budget for local spot ads. Therefore, condom advertisements were almost uniform across the entire state during 2001-2010, and any temporal changes in condom advertisements were absorbed by our monthly dummy variables. In other words, condom advertising can not explain the variation in birth rates across border zip codes, allowing us to rule this out as a potential confounder.

One additional threat is the lack of clear discontinuity at DMA borders. While AC Nielsen claims that it can track advertising by DMAs, it is unclear how precisely it can divide two regions across a border. Suppose a road constitutes a DMA border between two zip codes. Will a household on one side of the road receive different advertising than a household on the other side? If the two households are connected on the same cable line, would they not receive the exact same advertising? While such technical details of cable signal distribution are outside the scope of this study, these can undermine the identification of a border strategy. In our research, we narrow the border regions to the zip code, as opposed to the county level. If a DMA border does not clearly divide two DMAs, however, the identification is weakened as we focus on smaller geographic units contiguous to the border. Hence, it was important to check the preciseness of DMA border delineation. According to AC Nielsen's television market estimates, the precision of the number of homes in each DMA is in tens of houses.[1]

[1] http://www.nielsen.com/content/dam/corporate/us/en/public%20factsheets/tv/2012-2013%20DMA%20Ranks.pdf

For instance, the number of homes in the Springfield-Holyoke DMA in 2012 was 257,080 and that in the Boston DMA for this year was 2,379,690. Based on this report, we assume that the DMA border delineation is precise enough to not impact our use of border zip codes.

Television advertising via over-the-air signals is also a possible source of concern. However, Shapiro (2018) noted that less than 7% of households depend on over-the-air signals. This figure is likely lower at DMA borders where there is less unreliability of TV signals over the air due to increased transmission distance. In addition, the Federal Communications Commission takes steps to manage over-the-air signal transmission localized to a given DMA. We also note that simultaneous reception of multiple broadcast feeds, whether by over-the-air signals or cable system, would lead to overly conservative treatment effects, as controls would potentially be exposed to treatment.[2]

Another relevant threat is due to couples moving across DMAs during pregnancy. Our data include the zip code of childbirth, but not necessarily the zip code in which the couple watches the ED drug television advertising. If a significant proportion of couples watch ED drug advertisements in one DMA and give birth in another DMA, our estimates can be biased. We assume that moving to another DMA during pregnancy is infrequent and hence, does not significantly affect our estimates.

W3.4 Other drug category

We construct a falsification test using data related to advertising for other drugs. Increased advertising for drugs that are irrelevant to erectile dysfunction should have no impact on birth rates. To conduct this test, we collect additional data on television advertising of major over-the-counter allergy drugs (*Benadryl*, *Claritin*, and *Zyrtec*) and re-run the analyses. In other words, we replace the total advertising expenditure of ED drugs with that of allergy drugs. Note that another major allergy drug, *Allegra*, was approved for over-the-counter sales in 2011 and so did not advertise during this period. The allergy television advertising

[2] We thank an anonymous reviewer for this point.

during our data period was \$4.91 per 100 population per month, with a standard deviation of \$3.64. Results are presented in Table W6, and unlike ED drug ads, we do not find a significant relationship between allergy drug ads and birth rates.

Table W6: Falsification Test #1: Allergy Drug Advertising

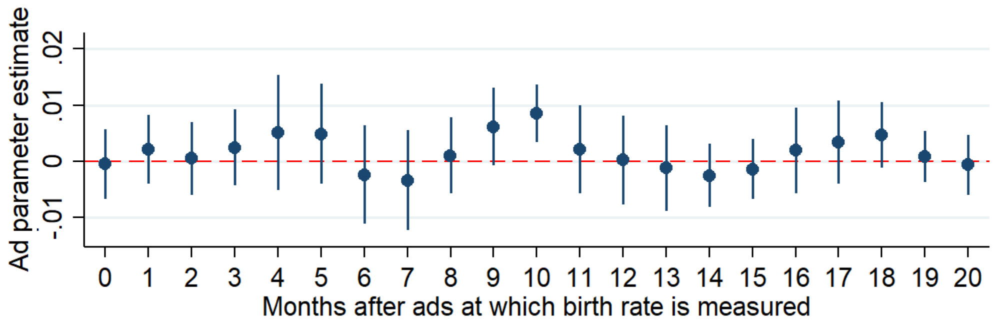
	(1)	(2)	(5)
	WLS	Border 1	School
ED drug ads	-.003	-.003	.001
	(.008)	(.010)	(.011)
Zip code and monthly FEs	Y	Y	Y
Border-quarterly FEs		Y	
School-year FEs			Y
N	5,130	5,130	4,940
R^2	.361	.382	.413

Note: Birth rate (DV) is the number of births per 1,000 population per month at the zip code level. The ads regressor is allergy ad dollars spent per 100 capita. Robust errors are clustered at the zip code level. FEs stands for fixed effects. * $p<.1$; ** $p<.05$; *** $p<.01$

W3.5 Gestation period

In matching the birth rate with the month of advertising exposure, we run regressions the birth rate at time t+10 on ED drug advertising at time t, allowing 10 months for obtaining ED drugs (including doctor and pharmacy visits) if necessary, attempting conception, and accounting for gestation period. We additionally run regressions matching the advertising with the hospital birth rates (dependent variable) at varying time intervals, plotted in Figure W1. Given the gestation period, we would not expect any significant change in birth rate soon after advertisement, and we do not find evidence that more advertising leads to higher birth rates for 7 or 8 months following the advertisement. However, we find a positive and significant effect of ED drug advertising on childbirth 10 months later, corroborating a potential causal relationship between advertising and births. The effect, however, is short-lived: we do not find any significant effect after 10 months.

Figure W1: Falsification Test #2: Gestation Period



Note: The graph plots estimated coefficients of the advertising parameter in model (1) of Table 3, matching advertising with birth rates (dependent variable) at varying time intervals.

W3.6 Ad stock/persistence

Figure W1 shows that ED drug advertising appears to have had a significant impact on birth rates following gestation periods (i.e., 10 months after). We also show that ED drug advertising does not appear to have any significant lingering effect in the months following the airing of the advertisements. Additionally, we construct the following advertising stock model, similar to that of Dubé, Hitsch and Manchanda (2005); Shapiro (2018); Tuchman (2019):

$$y_{z,t+10} = \beta_0 + \beta \sum_{k=0}^{K} \rho^k log(1 + a_{z,t-k}) + \mu_z + \tau_t + \epsilon_{zt}$$

ρ captures the retention rate of advertising carry-over; it accounts for the "persistence" of advertising from previous periods. We allow the carry-over effect to last four months (i.e., K=4 in the estimation, and we estimate it using nonlinear least squares. The coefficient for advertising stock is .01 ($p<$ .05), similar in magnitude with the model that excludes ad persistence. More importantly, the ad "persistence" ρ is found to be not statistically significant. A model with a non-negative constraint on ρ also results in an estimate very close to zero. Therefore, we conduct all our main analyses without ad persistence.

W4 More on the Expansion of Zip Codes

W4.1 Related Theory On The Expansion Around Borders

The economics and marketing literature has exploited discontinuities in a population's exposure to a treatment condition based on its members' locations relative to a geographic boundary. Examples include measuring the impact of minimum wages (Card and Krueger 1994), returns to education (Black 1999), industry location (Holmes 1998), and advertising (Shapiro 2018) along state and DMA boundaries. The key identifying assumption in the border strategy is the unconfoundedness assumption (Rosenbaum and Rubin 1983; see Imbens and Wooldridge 2009 for further discussions):

$$W_i \perp (Y_i(0), Y_i(1)) \mid X_i$$

where $W_i = 1$ if unit i receives the treatment, and $W_i = 0$ if unit i is in the control group. $Y_i(0)$ ($Y_i(1)$) denotes the outcome for the control (treatment) group, and X_i is a set of observed covariates. This assumption requires that, conditional on X_i, there is no unobserved factors that are correlated with both the assignment and the outcome. We can write an estimating equation in a regression setting such that $Y_i = \alpha + \tau W_i + \beta' X_i + \epsilon_i$. Unconfoundedness is then equivalent to the independence of the error term ϵ_i and W_i given X_i. In our setting, controlling for X_i, the identification of border strategy relies on the assumption that ED drug advertising amount W_i is uncorrelated with ϵ_i, unobserved factors that drive births. Therefore, for the same set of X_i, the unconfoundedness assumption is less likely to hold as we progressively add more regions away from the border that are more heterogeneous and subject to ad targeting (e.g., large cities at the center of DMAs), weakening the unconfoundedness assumption and potentially leading to a biased estimate. We employ the border identification strategy at the zip-code level, a much smaller geographic unit than previous literature has used (e.g., county or state). Using layers of zip codes, we further advance the identification strategy by empirically demonstrating that progressively adding non-border geographic units (e.g., incrementally adding zip codes distant far from the border) yields biased parameter estimates. Imbens and Wooldridge (2009, pg. 261) note that unconfoundedness is not directly testable, even with a large sample size. Therefore, researchers rely on balance tests of observables. We show that balance tests progressively fail as we add more heterogeneous zip codes of large cities at the center of DMAs, indicating that there may be more unobserved (to the researcher) factors (ϵ_i) correlated with the ad assignment and targeting (W_i).

W4.2 Balance Test

In the DMA-border identification strategy originally employed in Shapiro (2018), the unit of analysis was the border county. In our analysis, we focus on border zip codes in Massachusetts. Intuitively, zip codes are much smaller geographic units than counties, and so border zip codes allow for a more precise regression discontinuity setting. Moreover, there are only eight border counties in Massachusetts (Figure 1). Therefore, aggregating our zip code data to the county level would not give us sufficient data variation to perform county-level analyses. In addition, we would lose information through data aggregation. Therefore, given the high granularity of our data, the appropriate unit of analysis is the zip code around a DMA.

Although our unit of analysis is finer, the general intuition underlying a border identification strategy remains the same: one side of the DMA border is similar to the other side after controls, except for the intensity of television advertising. In this section, we carefully assess our zip code-level border identification strategy visually as well as statistically. We show that our border zip codes are mostly rural areas and that their observables are statistically balanced with respect to advertising levels. We then consider the inclusion of incremental layers of non-border zip codes and investigate whether the balance tests of the two sides of the border hold. We find that the balance tests fail quickly and that the estimate parameters on advertising decrease as we progressively add more non-border zip codes.

To assess whether the two sides of borders are comparable, we follow Shapiro (2018) and fit regressions including various demographic variables on advertising to see if higher advertising on one side of a border predicts different demographic variables that can be relevant with respect to birth rates. Since the US Census collects zip code-level demographics every decade, we use 2010 demographics data and collect 10 variables (% male, % White, % Black, % Asian, % household of married families, % households of families with kids, % households of non-families, % houses owned, income, and population size) that are potentially related to childbearing decisions. We then regress them on the average level of ED drug advertisements in 2009 to see if there is a sign of imbalance. For brevity, we summarize the significance of balance tests in Table W7. As expected, advertising does not predict demographic variables in border zip codes immediately adjacent to DMA borders (layer 1), thus bolstering our claim that zip codes on either side of DMA borders comprise comparable control/treatment groups for identification.

As we add layer 2, however, three variables (percentage of households with families with kids, percentage of non-family households, and income) are significantly predicted by advertising. Once we include all border and non-border zip codes that belong to border counties (layers 1-4), half of the demographic variables (percentages of ethnicity, percentage of households of married families with kids, and income) are predicted at a statistically significant level by advertising level. Note that we can include zip code fixed effects to absorb time-consistent differences of zip codes. The essence of the balance tests is, however, to assuage concerns that the two sides of borders are comparable in the hope that unobservables evolved similarly around the border. The strength of this parallel trend of unobservables assumption becomes more fragile if a study involves longer panel data, such as a decade as in this study. Also, border-time fixed effects in a border identification strategy do not solve the problem of the two sides around the border being incomparable groups. Since the observables are not balanced with zip codes that are far from the border (layers 2, 3, and 4), we suspect that it would bias our estimates: The differing evolution of the unobservables on either side of the border can be correlated with advertising level in the 10-year period that we study.

Table W7: Summary of Balance Tests

DV	Layer 1	Layers 1-2	Layers 1-3	Layers 1-4
%Male				
%White				***
%Black				**
%Asian				**
%Households - married families		*	*	
%Households - families with kids		***	***	***
%Households - non-families		***	***	*
%House owned				
Income($)		***	***	***
Population				

Note: The regressor for each regression is the amount of ED drug advertisement. The full results with parameter estimates are shown in Web Appendix W2. * $p< .1$; ** $p< .05$; *** $p<.01$

W5 Different Functional Forms for the US Data

In this section, we check the robustness of our results against different assumptions with respect to functional forms. Model (1) of Table W8 replicate the results of weighted least squares with advertising, county and monthly fixed effects, as well as DMA x LevitraEntry fixed effects. Model (2) and (3) show significant and positive effects of the imputed conception rates and linear and quadratic forms of advertising. In model (4), we test a log-log regression and obtained similar results.

Table W8: Different Functional Forms

	(1)	(2)	(3)	(4)
DV	Conception rate	Conception rate	Conception rate	Log(1+Conception rate)
log(1+Ads)	72.103***			135.309***
	(21.617)			(40.781)
Ads		18.378**	41.609***	
		(7.176)	(11.693)	
Ads^2			-3.983***	
			(1.170)	
R^2	.907	.907	.907	.996

Note: The conception rate (DV) is the number of imputed conceptions per 1M population per month at the county level. The unit of ads is ED drug ad dollars spent per 100 capita. The sample size is 22,645 county x months, and robust errors are clustered at the DMA level. All specifications include county, monthly fixed effects, as well as DMA x LevitraEntry fixed effects. * $p<$ .1; ** $p<$ .05; *** $p<$.01

W6 Regressions for Google Searches

To test the association between the ads and the searches, we fit linear regressions to our data. We first regress different search keywords on the amount of ED drug ads (models 1, 3, and 5 in Table W9) and then included year and month fixed effects to account for the general time trend and seasonality (models 2, 4, and 6).

Table W9: ED Drug Advertising vs. Google Keyword Searches

Keywords	ED drug names		"Erectile dysfunction"		"Get pregnant"	
Model	(1)	(2)	(3)	(4)	(5)	(6)
ED drug ads	2.540***	3.169***	.265	.399	7.441***	1.934***
	(.441)	(.388)	(.359)	(.309)	(.756)	(.498)
DMA, year, month FEs	N	Y	N	Y	N	Y
N	2,654	2,654	490	490	840	840
R^2	.013	.648	.001	.581	.082	.825

Note: ED drug brands include Viagra, Levitra, and Cialis. ED drug advertising is the log of one plus the previous month's advertising dollars per 100 capita. Heteroskedasticity robust errors are reported. WLS models are used with the DMA population as the weight. FEs stands for fixed effects. * $p<$ .1; ** $p<$ .05; *** $p<$.01

W7 Summary Statistics of the Census Data for Heterogeneity

Table W10: Summary Statistics of 2000 US Census

Variable	Mean	SD	p25	Median	p75
1999 median household income ($)	54,250.63	11,559.47	46,523.00	52,111.50	60,571.00
% families with children under 18 years	30.52	5.56	26.57	30.08	34.20
% men 30 to 44 years	9.71	1.12	9.10	9.60	10.20
% employment over 16 years	65.65	5.76	62.80	66.00	69.40

Note: Families defined here are families with a husband and a wife. The percentages of families is relative to the total families in a given county in 2000. The other percentages are with respect to the total population in the county.

W8 Birth Order Analyses

Table W11: Effect of ED Drug Ads on Birth Order

	(1)	(2)
ED drug ads	.035**	.043***
	(.017)	(.016)
County and monthly FEs	Y	Y
DMA x Levitra FEs		Y
N	22,645	22,645
R^2	.805	.809

Note: The dependent variable is the average birth order at the county x month level. The ads regressor is the log of one plus ED drug ad dollars spent per 100 capita. Robust errors are clustered at the DMA level. FEs stands for fixed effects. * $p<.1$; ** $p<.05$; *** $p<.01$

WEB APPENDIX REFERENCES

Black, Sandra E (1999), 'Do better schools matter? parental valuation of elementary education', *The Quarterly Journal of Economics* **114**(2), 577–599.

Card, David and Alan B Krueger (1994), 'Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania', *The American Economic Review* **84**(4), 772–793.

Dubé, Jean-Pierre, Günter J Hitsch and Puneet Manchanda (2005), 'An empirical model of advertising dynamics', *Quantitative marketing and economics* **3**(2), 107–144.

Holmes, Thomas J (1998), 'The effect of state policies on the location of manufacturing: Evidence from state borders', *Journal of political Economy* **106**(4), 667–705.

Shapiro, Bradley T (2018), 'Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants', *Journal of political economy* **126**(1), 000–000.