Food Delivery Apps and Traffic Safety: Causal Inference Using Google Trends Data

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Abstract

In this paper, I examine one of the sharing economy's most recent additions to enhance the topic's emerging literature. I study the impact of Food Delivery App (Postmates, DoorDash, Uber Eats, etc.) implementation on traffic fatalities and alcohol related traffic fatalities in the US using data from the NHTSA FARS, the ACS, and Google trends. First, I frame reasonable expectations for the result based on a conceptual model rooted in the literature. I then estimate the causal effect using two difference-in-difference model specifications exploiting variation in implementation timing across Designated Market Areas. I also replicate methods used in the existing ridesharing papers using my panel to estimate the effect of Uber and Lyft entry on traffic fatalities. Ridesharing analysis finds a negative impact on traffic fatalities similar to other papers in the ridesharing literature. Main results show that Food Delivery App market penetration has a small positive effect on alcohol related traffic fatalities and a larger positive effect on general traffic fatalities.

1 Introduction

Food delivery apps (FDA) such as Doordash, UberEats, and Postmates have exploded in popularity in the past decade in similar fashion to their sharing economy counterparts Uber and Lyft. These apps have changed the way individuals across the US get food, drinks and plan their daily life in the past decade. This project aims to shed some light on potential externalities of the FDA market yet to be studied broadly in academic literature. Simultaneously, the United States is witnessing a large number of preventable deaths due to vehicular accidents. Additionally, with alcohol related fatalities making up 28% of all traffic-related deaths in the US in 2016 and 29% in 2018 (NHTSA 2017, 2019), it is prudent to question the impact of FDA use on traffic accident fatalities. Therefore, I work to answer the question: does FDA use impact yearly traffic fatalities in the US at the designated market area (DMA) level? Additionally, I digress to examine ridesharing's impact on traffic fatalities to replicate papers in this vein of literature using my own panel data. These are questions of interest not only for academics interested in the sharing economy and its consequences, but also for the general public concerned with traffic safety.

While there has been extensive research on the matter of ridesharing and its impact on traffic safety outcomes, there has yet to be a paper published examining FDA's effect in this regard. In this paper, I intend to cover this gap in the literature by utilizing difference-in-difference models demonstrated in the ridesharing-focused literature. Before answering this question, I use my panel data to explore ridesharing's impact on traffic accidents to replicate papers already answering this question and test the validity of my data in testing my FDA hypothesis. I then estimate two different difference-in-differences specifications to explore my estimate's sensitivity. These models will test my hypotheses that FDA market penetration will decrease alcohol related and general traffic fatalities. Due to limited access to implementation data from the FDA companies themselves, I also provide methodology to use Google trends data as a proxy for FDA and ridesharing market penetration. I find evidence of an increase in the amount of traffic fatalities, alcohol related and otherwise, in response to FDA introduction.

I begin the study with a review of the relevant literature to the question at hand in section

1.1. I then turn to my conceptual model that incorporates the findings of that literature into a framework to ground my hypothesis for the effect of FDA implementation on traffic fatalities. Section 3 describes the sources and characteristics of the panel data used for analysis. Next, I break down the empirical analysis used to identify and estimate the causal effects in Section 4. Section 5 outlines the main and additional results. The discussion and conclusion explore once again my results, their implications, and their limitations.

1.1 Literature Review

As more consumers turn toward apps like Doordash, Postmates, and Uber Eats to get their meals, it's surprising that academic journals have yet to publish literature regarding the impact of food delivery apps (FDA's) on alcohol related traffic crimes. In light of the nascent state of the FDA literature, I examine studies on consumer behavior related to food delivery and studies on ridesharing's traffic safety implications. Having a better understanding of the factors that influence individuals to utilize FDA's will be critical when considering their impact on traffic safety outcomes. Additionally, looking at ridesharing's impact on traffic safety may reveal some key insights as such a close relative within the sharing economy family.

First, I examine the nature of FDA consumer behavior to ground my research in the context of the food delivery industry. It appears some of the strongest motivations for the use of online food delivery services are related to time-saving, convenience, and prior online purchase experience (Yeo et al., 2017). Ray et al. (2019) builds upon these motivations to examine factors contributing to an individual's intent to use FDA's in particular rather than the general online food delivery case. Utilizing uses and gratification theory, they find that convenience has no significant relationship to usage intent contrary to the findings of Yeo et al. (2017). On the other hand, they find significant positive correlations between customer experience, ease-of-use, and restaurant search and intent to use FDA's.

One study relates traffic conditions with FDA's. In this paper, Correa et al. (2019) find no significant correlation between google traffic estimations and transaction volume for FDA's. Thus, consumer intent to utilize an FDA is unphased by potential delivery delays.

Willingness to order food through an FDA during peak traffic hours may have important implications for traffic safety outcomes as a result of FDA implementation.

Shifting focus toward ridesharing's impact on traffic accidents, papers investigating Uber and traffic injuries found overwhelmingly conflicting results. Barrios et al. (2020) utilizes a difference-in-differences approach to find that the arrival of ridesharing services in US cities has led to a 3% increase in fatal accidents. On the other hand, Kirk et al. (2020) found no compelling evidence of correlation between Uber and fatal road injuries, while finding a negative correlation between Uber rollout and serious road injuries in Great Britain. Some possible explanations for these different findings could be differences in location and/or methodology. Kirk et al. employed a negative binomial regression in order to examine association while Barrios et al.'s difference-in-differences method with the potential to capture a causal relationship between ridesharing and road injuries.

The papers that looked into Uber and alcohol related traffic injuries specifically also contributed conflicting results. Brazil and Kirk (2020) find that the introduction of Uber has no association with alcohol related auto fatalities using their Poisson regression with data from the NHTSA. Conversely, Martin-Buck (2017) finds that ridesharing "significantly" reduces alcohol related fatalities and DUI arrests in a large subset of his observations of US cities using a difference-in-differences model with data from the FBI Uniform Crime Reporting Program. These conflicting results may be explained by differences in data sources and methodology.

Two studies focused more narrowly on ridesharing's impact on alcohol use. Burgdorf et al. (2019) considers whether access to ridesharing services lead to an increase in alcohol consumption in the US. They find that Uber does in fact correlate to an increase in average drinks per day in the United States using a difference-in-differences approach. More specifically, they find that Uber has the greatest effect on alcohol use for those between the ages 21 and 34 with a 7.4% increase in total drinks compared to a 3.6% increase for those aged 21-64. Additionally, Zhou (2020) also utilizes difference-in-differences to examine Uber's impact on alcohol related behaviors. He finds that while Uber's presence in a city increases binge drinking behavior, there is no evidence that it increases the number of drinking days per week for individuals. These findings imply that the social implications of ridesharing are far more convoluted than literature simply exploring Uber's effect on traffic fatalities may suggest.

Overall, a brief survey of literature relating to the advent of FDA's and ridesharing's effects on accidents and alcohol use revealed that more study is needed to better understand the true relationship between FDA's and traffic accidents in particular. It also begs the question of whether the FDA market's effects on alcohol related offenses will be as convoluted as that of ridesharing. This paper will be the first to consider this causal relationship. As Doordash, Postmates and their competitors continue to change the way Americans live their daily lives, it is crucial to add their study to the body of research on the sharing economy. The conflicting results within this area of study require a careful and methodical econometric approach to answer a question of such importance to public safety, especially as food delivery app access is considered as treatment.

2 Conceptual Model

In order to provide intuition for the expected effects of FDA technology on the traffic fatalities, I propose the following theoretical model relating the two phenomena. Since there is not yet a body of literature discussing food delivery apps in particular as they impact vehicular accidents, I consider studies examining ridesharing apps to motivate intuition for my research question. The model I implement to form my hypothesis is inspired by the conceptual framework of Barrios et al. (2020) in their paper investigating the effects of ridesharing on accident rates. I make adjustments to their model to account for intuitive differences in road effects between ridesharing services and FDA services.

Letting *Fatal* represent traffic fatalities in DMA d and year t and σ represent food delivery app implementation level, I propose that traffic accidents can be considered as

$$Fatal_{d,t} = f(VMT_{d,t}(\sigma), Q_{d,t}(\sigma)), \tag{1}$$

where $VMT_{i,t}(\sigma)$ represents vehicle miles traveled as a function of FDA implementation and $Q_{i,t}(\sigma)$ represents driver quality as a function of FDA implementation. I also assume that

$$\frac{dVMT}{d\sigma} < 0 \quad and \quad \frac{dQ}{d\sigma} > 0, \tag{2}$$

based on the intuition that as FDA is implemented in a particular DMA, the total vehicle miles traveled decreases as fewer individual drivers are making trips to pick up food thanks to the consolidation of food delivery trips due to the apps. Also, as FDA is implemented, average driver quality in the particular DMA increases as consolidation of food delivery trips to paid drivers may shift riskier drivers away from going to pick up food.

Intuitively, and supported by the findings of Edlin (2003) and Edlin and Karaca-Mandic (2006), I impose that

$$\frac{\partial Fatal}{\partial VMT} > 0 \quad and \quad \frac{\partial Fatal}{\partial Q} < 0. \tag{3}$$

In words, the number of alcohol related accidents increase as total vehicle miles traveled increase and decrease as the quality of the average driver increases.

Therefore, using the chain rule on equation (1) to consider how our total alcohol related accidents should be expected to change with respect to FDT, I find that

$$\frac{\partial Fatal}{\partial \sigma} = \frac{\partial Fatal}{\partial VMT} \cdot \frac{dVMT}{d\sigma} + \frac{\partial Fatal}{\partial Q} \cdot \frac{dQ}{d\sigma} < 0, \tag{4}$$

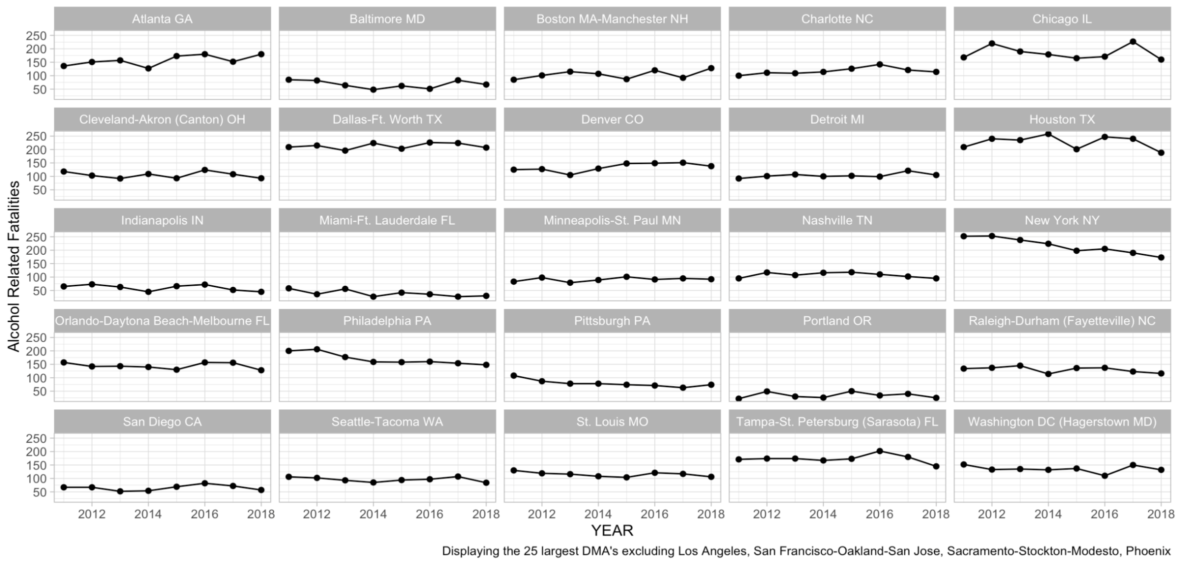
Thus, I expect the rollout of FDA in a particular region to result in a decrease of alcohol related fatal accidents.

3 Data

I pull my outcomes, treatment and covariates from various sources to create a panel with 1620 DMA-year observations of each variable for 2011 through 2018.

My *outcomes* of interest, the number of yearly traffic fatalities and alcohol related fatalities were retrieved from the NHTSA Fatality Analysis Reporting System, iterated over to obtain one data set with all years of interest, and aggregated from the individual accident level to DMA level. Figure 1 below displays the trend for alcohol related fatalities over the years of interest across the 25 largest DMA's[1] in the sample, and serves as a reference in my later discussion of of assumptions required for causal inference.

Figure 1: Alcohol Related Fatalities by Year



A proxy for Food Delivery App (FDA) implementation was retrieved from Google trends using the R package "gtrendsR". As shown in Hall et al. (2018), there is evidence of a strong correlation between Google trends search intensity for Uber and Lyft and the number of rideshare drivers in a given city. Other papers have used this evidence of correlation to better understand implementation intensity while using ridesharing market penetration as treatment (Berger et al., 2018; Barrios et al., 2020). Given the similar nature of FDA's and ridesharing apps, one could assume that a similar correlation exists between Google trends search intensity and FDA driver uptake. I scrape data on search intensity of the terms "Doordash", "Uber Eats" and "Postmates" for 200 DMA's in the US and create a *treatment* variable indicating whether a DMA had search interest greater than zero for any of the FDA terms in a given year. I exclude Utica, Syracuse, Odessa-Midland, Albuquerque-Santa Fe, Phoenix, Bakersfield, Los Angeles, Palm Springs, San Francisco-Oakland-San Jose, Reno, and Sacramento-Stockton-Modesto from the panel as these DMA's split counties making aggregation of covariate data from the county to DMA level imprecise.

[1] As measured by the number of TV homes in each given DMA.

Google trends search intensity data is reported as an index from 0 to 100 for each search term in question. I summed these indices across each search term for each DMA-year observation and consider the observation a treated unit if this sum exceeds zero. Thus, my treatment is a binary indicator of whether the given observation had any reported Google search interest for any of the FDA's in my data.

Covariates for each DMA's median household income, percentage of population within the ages 20 and 39, and percent of population with a college degree come from the American Community Survey. Selection of the aforementioned covariates were informed by previous papers in the ridesharing literature. I also include an index of ridesharing popularity aggregated from search intensity for each DMA-year from Google trends.

Table 1: Summary Statistics

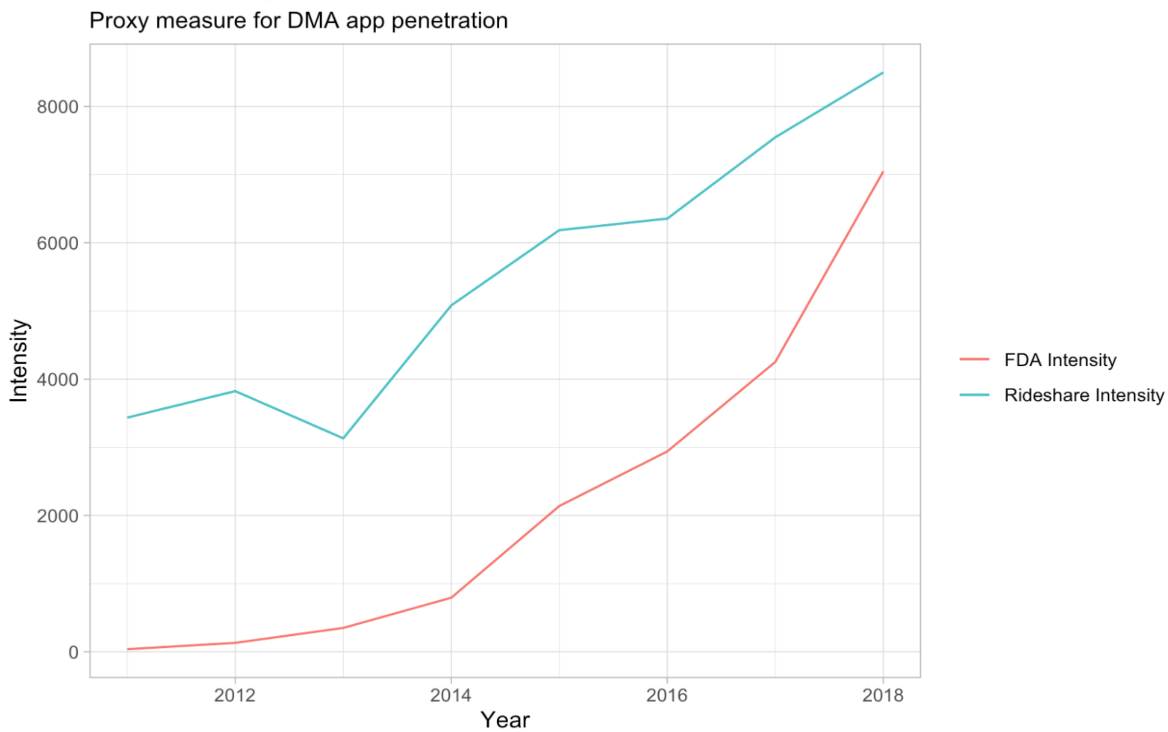
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Fatalities	1,620	152.156	157.693	1	52	211	1,102
FDA	1,620	0.365	0.482	0	0	1	1
Alcohol Fatalities	1,620	42.869	42.300	0	14.8	59	258
Year	1,620	2,014.501	2.294	2,011	2,012	2,017	2,018
Median Income	1,620	15,746.96	12,900.96	0	0	26,000	50,000
% with college degree	1,620	0.137	0.109	0.000	0.000	0.224	0.372
% between age 20 & 39	1,620	0.183	0.137	0.000	0.000	0.288	0.405
Ridesharing Intensity	1,620	26.533	29.962	0	0	39	200
RS	1,620	0.643	0.479	0	0	1	1

Note: Data retrieved from Sample contains DMA-year observations from the period of interest (2011-2018). Percent with college degree refers to individuals with at least a bachelor's degree. Variables from ACS are aggregated to the DMA level using the survey's provided weighting system.

Figure 2 below compares the Google search intensity for both FDA's and ridesharing apps over the years in our panel. Unsurprisingly, the newer category of FDA's starts with a very low intensity in 2011 as it is just being introduced to the market. Confirming the explosive growth of FDA's, their intensity is growing rapidly toward the end of our sample.

The data also show how positively correlated[2] FDA and Ridesharing intensities are.

Figure 2: Google Search Intensity by Year



Some of the methodology used in the creation of my panel may have introduced biases and limitations in the data. Using the continuous Google trends search intensity measure as a proxy for binary FDA implementation treatment could create ambiguity as I selected an arguably arbitrary cutoff to create the treatment dummy. Constrained by the availability of more granular Google trends data, I had to aggregate my outcomes and covariates from the county to DMA level. This reduced my sample size and subsequent statistical power.

4 Empirical Analysis

I use a differences-in-differences (DiD) strategy to estimate the causal effect of FDA implementation on alcohol-related traffic fatalities. As papers examining the traffic implications of FDA implementation have little precedent, I looked to strategies utilized by papers examining traffic outcomes due to ridesharing apps. My choice to use DiD is inspired by papers that

[2] cor(FDA intensity, Ridesharing intensity) = 0.76

aim to identify the causal effect between ridesharing and traffic safety outcomes. Examples include Martin-Buck (2017), Burgdorf et al. (2019), Barrios et al. (2020), and Zhou (2020).

Given the variation in treatment timing and numerous sites used for analysis, I use a two-way fixed effects regression specification to estimate the DiD model. This strategy requires that the following assumptions hold to estimate a causal effect:

1. *Treatment is independent of potential outcomes:* allocation of FDA implementation was not determined by a DMA's amount of traffic fatalities. While FDA rollout likely is not random, it is unlikely that FDA's are selecting locations to serve based on traffic fatalities rates. The same argument is tested regarding ridesharing implementation using a multinomial logit model in Barrios et al. (2020).

2. *Stable Unit Treatment Value Assumption:* each DMA's number of traffic fatalities depends only on its own treatment and not that of surrounding DMA's. This assumption could be one source of uncertainty as DMA's near each other may have driver spillover and subsequent traffic fatality spillover.

3. *Parallel Trends:* treatment and control groups would have maintained a constant difference in traffic fatalities in the absence of treatment. Figure 1 demonstrates how this is a feasible assumption given the alcohol related fatalities trends for the 25 larges DMA's in my panel.

4. *Linear and Additive Effects:* the effect of treatment and covariates on fatalities are linear and unaffected by changes in other predictors. (Imai and Kim, 2020)

I first run the following two-way fixed effects regressions to perform a DiD model with variation in treatment timing (Goodman-Bacon, 2018):

$$AF_{d,t} = \beta FDA_{d,t} + \lambda FDA_{d,t} * RS_{d,t} + X_{d,t} + \gamma_d + \delta_t + \epsilon_{d,t} \tag{5}$$

$$F_{d,t} = \beta FDA_{d,t} + \lambda FDA_{d,t} * RS_{d,t} + X_{d,t} + \gamma_d + \delta_t + \epsilon_{d,t} \tag{6}$$

Where $AA_{(d,t)}$ and $F_{(d,t)}$ represent our outcomes of interest, the number of alcohol related traffic fatalities in a DMA-year, and $FDA_{(d,t)}$ is the treatment indicator for whether the DMA has an FDA presence in year t. $RS_{d,t}$ represents the Google search intensity for ridesharing services in a given DMA-year. I include an interaction term between $FDA_{d,t}$ and $RS_{d,t}$ to account for the highly correlated relationship between their implementations as shown in figure 2. My parameter of interest, therefore, depends on ridesharing intensity. β , is the average treatment effect on the treated (ATT) of FDA implementation on the outcome of interest when ridesharing intensity is 0. Otherwise, I will use $\beta + \lambda * RS_{d,t}$ as my treatment effect where $RS_{d,t}$ is evaluated as its mean value[3] for the entire panel. $X_{d,t}$ is a vector of DMA-specific and time varying covariates, and γ_d and δ_t represent DMA and year fixed effects.

To test my initial specification's sensitivity, I also run a weighted two-way fixed effects models in the spirit of (Imai and Kim, 2020). They argue, contrary to traditional belief among researchers, that the two-way fixed effects model does not translate to the classic 2x2 DiD framework to the modern setup with multiple time periods and units. They propose the weighted two-way fixed effects model allowing for negative weights as equivalent to the multi-period DiD estimator. This specification is intended to reduce estimation bias and relax the linearity assumption imposed by the traditional two-way fixed effects model.

4.1 Ridesharing Analysis

I use my unique panel to run supplemental DiD models estimating the effect of ridesharing (Uber and Lyft) implmentation as represented by Google trends data on traffic fatalities. This digression serves to replicate existing papers in the literature studying the traffic safety outcomes of ridesharing. The following two regressions implement the two-way fixed effects DiD model to measure the causal effect,

$$AF_{d,t} = \beta RS_{d,t} + X_{d,t} + \gamma_d + \delta_t + \epsilon_{d,t} \tag{7}$$

[3]The *mean* value of RS as a continuous measure of Google trends intensity for keywords "Uber" and "Lyft" across my panel is 26.53 (labeled Ridesharing Intensity in table 1).

$$F_{d,t} = \beta RS_{d,t} + X_{d,t} + \gamma_d + \delta_t + \epsilon_{d,t} \tag{8}$$

where $RS_{d,t}$ now represents an indicator for ridesharing entry[4], $X_{d,t}$ is a vctor of DMA-specific and time varying covariates, and γ_d and δ_t represent DMA and year fixed effects.

5 Results

5.1 Ridesharing Model

Table 2 displays the DiD regressions to estimate the effect of Uber and Lyft on traffic fatalities. I find a small insignificant negative impact on alcohol related traffic fatalities and a larger negative impact on general traffic fatalities (-17.825, $p<0.05$). This effect is approximately 12% of the average value of yearly traffic fatalities in my panel, 152.2.

5.2 Main Results

My results in Table 3 display FDA's impact on alcohol related traffic. My initial specification with just FDA indicator and two-way fixed effects finds a very imprecise estimate of 0.745 with a standard error of 0.756. Column 2 shows that FDA implementation has a small significant (1.401, $p<0.1$) positive impact on alcohol related traffic fatalities when controlling for ridesharing intensity and demographic covariates. My full specification with all covariates and interaction term shows that FDA implementation causes a statistically insignificant increase of 1.3674 alcohol related traffic fatalities for DMA's when evaluated at the mean value of ridesharing intensity.

Table 4 demonstrates FDA implementation's effect on general traffic fatalities. I find that the large significant positive ($p<0.01$) effect of 9.179 traffic fatalities in column 1 is diminished as we add ridesharing and demographic controls. In my final specification controling

[4]Created using the same method as the FDA variable: RS = 1 if the sum of intensity for all ridesharing keywords is greater than 0 and RS = 0 otherwise.

for FDA and ridesharing's implementation interaction, I find a smaller significant positive effect of FDA on traffic fatalities (0.4728, $p<0.01$) when evaluated at ridesharing intensity's mean. Due to the specification, this positive effect diminishes to a negative effect for DMA's with lower ridesharing intensity. In locations where there is no ridesharing intensity, FDA implementation has a large significant ($p<0.01$) negative effect of -17.278 traffic fatalities.

5.3 Weighted Two-way Fixed Effects

Table 5 illustrates how the weighted two-way fixed effects DiD specification tells a similar story as the traditional two-way fixed effects model in table 3. I find the same positively signed effect, yet my estimates become smaller in magnitude and more imprecise due to larger standard errors. Focusing on my full specifications, we find a small insignificant effect of FDA on alcohol related fatalities of 1.897. Table 6 shows that my full specification also estimates a statistically insignificant effect of 1.827 for general traffic fatalities.

Table 2: Effect of Ridesharing on Traffic Safety Outcomes

	Dependent variable:	
	Alcohol Traffic Fatalities	Traffic Fatalities
	(1)	(2)
Ridesharing Implementation	-0.461	-17.825^{**}
	(2.728)	(7.178)
Percent College Degree	14.648	208.757^{***}
	(18.340)	(48.262)
Percent between age 20 & 39	1.756	-148.017^{***}
	(15.845)	(41.695)
Median Income	-0.0002	0.001^{***}
	(0.0001)	(0.0003)
Observations	1,620	1,620
R^2	0.001	0.027
Fixed Effects	Yes	Yes
F Statistic (df = 4; 1406)	0.435	9.877^{***}
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01	

Table 3: Effect of FDA on Alcohol Related Traffic Fatalities

	Dependent variable:		
	Alcohol Fatalities		
	(1)	(2)	(3)
FDA	0.745	1.401^{*}	0.253
	(0.756)	(0.834)	(1.275)
Ridesharing Intensity		-0.035^{**}	-0.071^{**}
		(0.017)	(0.035)
Percent College Degree		13.652	9.858
		(18.839)	(19.104)
Percent between age 20 & 39		3.014	7.802
		(14.775)	(15.310)
Median Income		−0.0002	−0.0001
		(0.0001)	(0.0001)
FDA*Ridesharing			0.042
			(0.036)
Observations	1,620	1,620	1,620
R^2	0.001	0.005	0.006
Fixed Effects	Yes	Yes	Yes
F Statistic	0.972	1.482	1.472

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Effect of FDA on all Traffic Fatalities

	Dependent variable:		
	Traffic Fatalities		
	(1)	(2)	(3)
FDA	9.179^{***}	0.818	-17.278^{***}
	(2.001)	(2.130)	(3.195)
Ridesharing Intensity		0.412^{***}	-0.155^{*}
		(0.044)	(0.087)
Percent College Degree		124.842^{***}	65.077
		(48.127)	(47.882)
Percent between age 20 & 39		-140.117^{***}	-64.696^{*}
		(37.744)	(38.372)
Median Income		0.0003	0.0004
		(0.0003)	(0.0003)
FDA*Ridesharing			0.669^{***}
			(0.089)
Observations	1,620	1,620	1,620
R^2	0.015	0.087	0.122
Fixed Effects	Yes	Yes	Yes
F Statistic	21.046^{***}	26.788^{***}	32.536^{***}

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 5: Effect of FDA on Alcohol Related Traffic Fatalities

	Dependent variable:		
	Alcohol Traffic Fatalities		
	(1)	(2)	(3)
FDA	1.558	2.019	−0.298
	(1.410)	(1.792)	(5.298)
Ridesharing Intensity		−0.064	−0.153
		(0.159)	(0.275)
% College Degree		−0.012	−0.003
		(0.011)	(0.054)
% between age 20 & 39		−0.027	−0.003
		(0.024)	(0.052)
Median Income		0.0001	0.0003
		(0.0006)	(0.0007)
FDA*Ridesharing			0.083
			(0.188)
DF	1,620	1,620	1,620
Residual S.E.	14.29	14.61	14.59
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

Table 6: Effect of FDA on Alcohol Related Traffic Fatalities

	Dependent variable:		
	Traffic Fatalities		
	(1)	(2)	(3)
FDA	5.849	2.035	−1.868
	(2.351)	(3.201)	(8.537)
Ridesharing Intensity		0.484	.336
		(0.384)	(0.624)
% College Degree		−0.012	−0.019
		(0.019)	(0.087)
% between age 20 & 39		−0.027	−0.018
		(0.042)	(0.084)
Median Income		−0.0003	0.000
		(0.002)	(.002)
FDA*Ridesharing			0.139
			(0.1341)
DF	1,620	1,620	1,620
Residual S.E.	40.65	39.52	39.44
Note:	Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01		

6 Discussion

The ridesharing analysis displayed in table 2 confirms the results of several other papers examining the impact of ridesharing on traffic safety outcomes. Martin-Buck (2017) and Greenwood and Wattal (2017) both find evidence of ridesharing's negative effect on traffic fatalities using DiD models. Martin-Buck (2017) gets outcome data from the FBI's Uniform Crime Reporting Program, Greenwood and Wattal (2017) retrieve their outcome from the California Highway Patrol's Statewide Integrated Traffic Report System and both papers get ridesharing entry data directly from Uber. These similar findings provide evidence of my panel's robustness and validity in providing reliable estimates of causal effects using treatment from Google trends.

Contrary to the hypothesis proposed by the conceptual model in equations (1) through (4), my main analysis finds some evidence that FDA implementation has a positive effect on traffic fatalities and alcohol related traffic fatalities in the US when the specification is evaluated at the mean value of ridesharing intensity. The intuition provided by my simple conceptual model may not accurately represent reality. One particularly rigid assumption was that the implementation of FDA's would lead to an increase in the proportion of higher quality drivers on the road. Individuals that decide to drive for FDA's may not necessarily substitute worse drivers off the road. Additionally, the introduction of FDA's may not prevent individuals from driving, but rather encourage them to order food for delivery more often when they may have cooked at home instead. In this case, FDA's would increase the drivers and vehicle miles traveled in a given DMA, increasing the likelihood of accidents.

Limitations to my data and model specification may have created some bias in these results. As discussed in section 3, the lack of an objectively precise treatment indicator and more granular data likely reduced the accuracy of my estimates. Ideally, I would have access to precise FDA implementation data at the county or city level. Not only would this reduce the ambiguity of treatment, but having data at the county level would allow for more observations and a more precise estimate. Additionally, my estimates of the impact on alcohol related fatalities may suffer from a lack of power as there are fewer DMA-year observations experiencing alcohol related fatalities. My weighted fixed effects models confirm the positive sign of main model's estimated effects, however their estimates are insignificant. This raises some concerns for the specification of my main model.

Future research of FDA's impact on traffic safety outcomes would benefit from granular data on FDA implementation directly from the companies at the city or county level. Additional areas of research that may be of interest to policy makers could explore the possibility of an FDA substitution effect causing fewer drivers to be on the road at any given time, or the possibility of the opposite case.

7 Conclusion

In this paper, I studied the effect of Food Delivery Apps (FDA's) on traffic fatalities. I began my analysis with a conceptual model to provide intuition for my hypothesis of a negative effect. I then turned to the impact of ridesharing services (Uber and Lyft) on traffic fatalities as there is existing literature in this vein to test the validity of my unique data set for causal inference using a DiD model. My main DiD results estimating FDA's impact on traffic fatalities find a positive effect. In other words, I find evidence that FDA implementation increases both general and alcohol related traffic fatalities at the DMA level.

As FDA's become increasingly prevalent, it is important to explore any unintended impacts they may have on traffic safety. In this study, I am able to produce two estimates of the impact of FDA implementation on all traffic fatalities and alcohol related traffic fatalities using both traditional and more novel estimators. Both pairs of estimates provide evidence contrary to my hypothesis that FDA implementation increases both general and alcohol related traffic fatalities at the DMA level. I also provide analysis of ridesharing's effect on traffic fatalities to replicate previous papers and verify the validity of the use of Google trends data as proxy for treatment. As more individuals rely on the sharing economy for income and services, policy makers may be concerned with these results as they draft legislation relating to FDA's and the sharing economy at large.

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