The Impact of Uber on Drunk Driving in New Zealand

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In May 2014, the global ridesharing service, Uber, began operations in Auckland, New Zealand and by March 2019, Uber was available in seven cities across the country. As in other countries, Uber New Zealand's press releases claim that the presence of Uber reduces the incidence of drunk driving. Using monthly data on drunk driving crashes and alcohol-related driving offences in the various regions of New Zealand, we find that the presence of Uber in a city is often associated with small decreases in these indicators of drunk driving, but these results consistently lack statistical significance.

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I. Introduction

Drunk driving has long been a major issue in New Zealand society. In 2010/11, 17% of all traffic fatalities and 18% of all serious traffic injuries in New Zealand were considered "alcohol-induced" (White, et al., 2014).[1] Moreover, 31% of New Zealand traffic fatalities in 2013 involved some level of alcohol intoxication, the third-highest rate among twenty-four "high-income" countries (World Health Organisation, 2015). The annual social cost of alcohol-related crashes between 2011 and 2014 was estimated to be $495 million (Ministry of Transport, 2015). This estimate consisted of factors such as medical bills, legal fees, vehicle and property damage, and loss of life; all of which are directly incurred by drunk driving.

There have been several attempts to treat this problem in New Zealand. Some treatment strategies focus on raising awareness of the consequences of drunk driving through educational programmes, or advertising campaigns such as "Dilemmas" and "Legends" (NZ Transport Agency, 2019). Another strategy is random police checkpoints that give roadside breath tests, which serve to increase the likelihood of being caught. National policy has also been used to curb drunk driving; in May 2011, Parliament passed the "zero tolerance" law, which states that drivers under 20 years of age cannot drive if their blood alcohol concentration (BAC) is non-zero. This was followed in August 2014 by a lowering of the BAC limit for over-20 drivers from 80mg/100ml to 50mg/100ml, bringing New Zealand more in line with international best practice.

While the above interventions were aimed at solving the drunk driving problem, this paper focuses on a less intentional treatment strategy: the introduction of ridesharing. A ridesharing service is one that matches customers seeking transportation with private drivers in their area, usually through a smartphone application that supports credit-card transactions. Taking a rideshare is generally cheaper and more convenient for customers than taking a taxi. Ridesharing thus could act as a drunk driving treatment if a certain proportion of drivers drive drunk because their primary alternative, taking a taxi, is too costly and/or difficult to arrange, especially when intoxicated.

[1] "Alcohol-induced" traffic accidents were responsible for 43 out of 259 fatalities, and 614 out of 3,366 serious injuries.

Uber first entered New Zealand in May 2014, and expanded operations to a total of seven cities within five years of its entry[2]. Uber's entry into a city could thus act as a region-specific drunk driving "treatment", the effects of which can be separated from nationwide treatments such as advertising campaigns and law changes. Since Uber's entry into the country has been staggered across the last five years, we can use monthly data to isolate the treatment effect and observe any Uber-driven changes to the drunk driving rate of each city.

When launching their service in Christchurch, Uber themselves implied this result by claiming to be "having a positive impact on issues…such as drink-driving" (Bruce, 2016). The strongest verification of this so far is a 2016 study carried out on Uber's behalf, which found that 70% of Uber users in New Zealand had used the service after drinking; 41% of users who drink said that Uber had helped them avoid drunk driving; and 75% believed that Uber helped to reduce drunk driving in their community (NZ Herald, 2016). This paper provides a more comprehensive investigation of this claim.

Similar studies have been conducted overseas, specifically in the United States of America. These studies have tended to use a difference-in-differences approach to compare drunk driving rates in U.S. cities before and after the entry of Uber. Many have found some level of decrease in drunk driving rates that can be attributed to Uber, although the size and significance of the decrease varies across studies. In this study for New Zealand, we observe a weak negative effect, but never find this effect to be statistically distinguishable from zero.

The remainder of this paper is structured as follows: In the next section, we provide a short overview of the literature that links Uber and drunk driving. In section 3, we discuss the data sources and methods used in this paper. Section 4 presents the results of our analysis, while section 5 concludes.

II. The presence of Uber and drunk driving

Why might people who previously elected to drive drunk view Uber as a preferable option? One possible explanation is that Uber simply offers more convenience. There is a growing literature concerning the sharing economy and platform economics, both of which Uber utilises. Parker and Van Alstyne (2005) explain that a "platform intermediary" such as the Uber app

[2] Competitors like Zoomy, Ola, and DriveHer have entered the New Zealand market but remain small.

reduces transaction costs and maximises consumer surplus. Uber's app asks the passenger to select a destination and a pickup point; assigns a driver almost instantly; provides the passenger with information about the driver and their car; and handles payment electronically through previously entered payment details. This process bypasses transaction costs that are incurred by taking a taxi, such as arranging/locating a driver; articulating the destination; waiting for the taxi to arrive; identifying the taxi once it has arrived; and organising payment, sometimes with cash. These transaction costs can also be significantly exacerbated by intoxication. Therefore, it is reasonable to expect that intoxicated individuals would receive significantly more utility from a taxi service if able to bypass these transaction costs.

The other key reason is the financial cost of taking an Uber. Uber has been able to undercut taxi prices in New Zealand, with research from GO Rentals (2017) showing that taking a taxi to the airport in New Zealand cities is roughly twice as expensive as taking an Uber.[3] It is clear that, if a similar price disparity existed when travelling from the city to the suburbs, drunk drivers who previously considered taxis to be prohibitively expensive might now be incentivised to take an Uber instead.

It is important to note, though, that it is difficult to establish exactly how large the price disparity is in this situation. Firstly, it appears that there are additional regulations involved in being an "airport taxi" that may not be enforced for Uber (Chu, 2015), which could result in taxi prices being particularly high for airport trips. This may mean the results from the above study are exaggerated. Secondly, it is likely that late at night on Friday and Saturday (i.e. popular drinking times) will be a period of high demand and low supply for rideshare services; therefore, it is likely that Uber's surge pricing would be employed. Surge pricing results in a multiplier being applied to the standard Uber fares in order to equilibrate supply and demand (Hall, Kendrick, & Nosko, 2015). This could result in Uber prices being substantially higher than normal during peak drinking hours, which may reduce the incentive for consumers to switch away from taxis—or, indeed, from drunk driving.

Despite this uncertainty, and despite the inherent difficultly in predicting the behaviour of poor decision-makers, it seems plausible that the marginal drunk driver, i.e. one who only slightly

[3] Specifically, taxi rides were 1.86 times more expensive in Auckland; 2.11 times more expensive in Christchurch; and 1.70 times more expensive in Wellington.

prefers drunk driving to taking a taxi, may have switched to Uber when it became an option. Theory therefore supports the hypothesis that the introduction of Uber could have caused a decrease in drunk driving in New Zealand cities.

As modern ridesharing is a relatively recent phenomenon, the academic literature surrounding its impact is still emerging. However, we have identified thirteen studies that consider the impact of ridesharing on drunk driving, ten of which use data from the United States of America. This study thus extends the small literature that looks at the impact of ridesharing beyond North America.

Table 1: An Overview of the Literature on Ridesharing and Drunk Driving

Study	Dependent Variable	Pos. or Neg.	Size	Stat. Signif.	Where
Martin-Buck (2016)	fatal alcohol-related auto accidents	-	-10% to -11.4%	yes	U.S.
Brazil & Kirk (2016)	traffic fatalities	+	1%	no	U.S.
Greenwood & Wattal (2017)	alcohol-related motor vehicle fatalities	-	-3.6% to -5.6%	yes	U.S.
Peck (2017)	alcohol-related collision rate	-	-25% to -30%	yes	U.S.
Dills & Mulholland (2018)	fatal accidents	-	-0.20%	yes	U.S.
Downie (2018)	drunk driving	-	-5.4% to -7.3%	yes	U.S.
Morrison, Jacoby, Dong, Delgado, & Wiebe (2018)	crashes	-	depends on the city	unclear	U.S.
Barrios, Hochberg, & Yi (2020)	fatalities and fatal accidents	+	3%	yes	U.S.
Zhou (2020)	drunk driving	-	-4%	no	U.S.
Brazil & Kirk (2020)	traffic fatalities	+	1%	no	U.S.
Huang, Majid, & Daku (2020)	weekly road traffic-related deaths	-	< 2 deaths per province per year	yes	South Africa
Kirk, Cavalli, & Brazil (2020)	number of fatal accidents	+	3%	no	Great Britain
Lagos, Munoz, & Zulehner (2020)	drunk-driving fatal accidents and fatalities	-	about -50%	yes	Chile

Table 1 not only shows that most studies use U.S. data, it also suggests there is a very large variation in results. For example, using U.S. data, Peck (2017) finds a sizeable and significant negative effect on the alcohol-related collision rate, while Brazil and Kirk (2020) find no significant effect and Barrios, Hochberg and Yi (2020) find a positive effect on fatal accidents. A similar variation can be seen across countries. Finally, Morrison et al. (2018) show that results even can vary across cities. This geographical variation suggests it is important to analyse the impact of ridesharing in a wide range of settings, hence the importance of a study focusing on New Zealand.

III. Data and Methods

The New Zealand Transport Agency (NZTA) granted us access to their Crash Analysis System (CAS), which records detailed information about every vehicle crash that occurs in New Zealand (NZ Transport Agency, 2018). Using this data, we examine the monthly drunk driving crashes in each territorial authority of New Zealand. We also have data on the monthly number of alcohol-specific driving offences by police area, as provided by the New Zealand Police (2019). These datasets provide a good approximation of the frequency of drunk driving in each location. Using regional data allows us to separate the locations with Uber from those without, and using monthly data allows us to identify Uber's exact point of entry in each location.

We use data from January 2012 until March 2019.[4] Starting in January 2012 helps to avoid any confounding effects from the 2011 law changes, while still providing enough data about pre-Uber drunk driving trends in each city. The confounding factor of the December 2014 decrease in the adult legal BAC limit cannot be avoided, and it is important to note that, while this was a nationwide law change, it may have affected different locations in different ways.

Unfortunately, the geographical units used in the crash data are different from those used in the offence data. This forces us to keep the two datasets separate, as there is no easy way to compare the two types of geographical unit. For the sake of clarity, we will describe each type of geographical unit and use consistent terminology throughout this article:

- The crash data allow us to separate alcohol-related crashes by **territorial authority**. There are 67 territorial authorities in New Zealand; these consist of 13 city councils, 53 district councils, and the Chatham Islands Council. The population of territorial authorities varies a lot, from less than a thousand to over a million people, with the median population being about thirty thousand. Territorial authorities can be grouped into 16 **regions**, except for the Chatham Islands Council which does not belong to a region.

[4] The crash data was taken from the CAS website on August 24th, 2019. The offence data was published on the NZ Police website in May 2019.

- The offence data allow us to separate alcohol-related crashes by **police area**. There are 38 police areas in New Zealand, and they can be grouped into 12 **police districts**.

Table 2 lists the seven New Zealand cities which Uber has entered, along with the month of entry and corresponding geographical units. These units are what we are referring to when we report data for the number of crashes/offences in a given city. Although in some cases it may be possible to call an Uber outside of these geographical units, we have selected those that would see the vast majority of Uber traffic for each city.

Table 2: New Zealand Cities with Uber as of March 31st, 2019

City	Month of entry	Territorial authority/authorities	Region	Police area(s)	Police district(s)
Auckland	May 2014	Auckland	Auckland	*several*[5]	Auckland City, Counties/Manukau, Waitematā
Wellington[6]	Oct 2014	Lower Hutt City, Porirua City, Upper Hutt City, Wellington City	Wellington	Hutt Valley, Kapiti-Mana, Wellington	Wellington
Christchurch	Mar 2016	Christchurch City	Canterbury	Canterbury Metro	Canterbury
Hamilton	Jan 2018	Hamilton City	Waikato	Hamilton City	Waikato
Tauranga	Jan 2018	Tauranga City	Bay of Plenty	Western Bay of Plenty	Bay of Plenty
Dunedin	May 2018	Dunedin City	Otago	Otago Coastal	Southern
Queenstown	Jun 2018	Queenstown-Lakes District	Otago	Otago Lakes Central	Southern

There are a wide range of econometric tools available with which to conduct this analysis. Following the precedent set by similar studies, we primarily use a difference-in-differences framework, always accounting for both time and location fixed effects. The main dependent variable is the number of monthly drunk driving crashes/offences by location. Uber's influence on this will be measured using an independent dummy variable, which will be set to 1 when Uber is present in a given month and location, and 0 otherwise. We include other explanatory variables,

[5]Auckland City: Auckland Central, Auckland East, Auckland West;

Counties/Manukau: CM Central, CM East, CM South, CM West;

Waitematā: Auckland Motorways, Waitematā East, Waitematā North, Waitematā West

[6] Note that we are considering the Wellington metropolitan area, or "Greater Wellington".

including local population and time-specific dummy variables accounting for other policy changes. Additionally, we experiment with more specific dependent variables, as alcohol-related crashes can be stratified by severity and timing.

It is important to note that, when retrieving data from the Crash Analysis System, there are multiple ways to filter the data for crashes involving alcohol. Given we are primarily interested in crashes involving an intoxicated driver who is over the legal BAC limit, we define "drunk driving" crashes as those where the following contributory factor code (Hewitt, 2016) is associated with the crash: 103 — alcohol test above limit or test refused.

We are therefore omitting the following alcohol-related codes, as they do not confirm that alcohol was a contributory or causal factor in a crash:

- 101 — alcohol suspected;
- 102 — alcohol test below limit;
- 105 — impaired non-driver (pedestrian/cyclist/passenger, etc.);
- 100 — other alcohol.

Although some previous studies have chosen to include drug-related crashes and offences as part of their analysis, we have chosen to omit this and focus only on alcohol. This is because the data contains relatively low numbers of drug-related crashes and offences, suggesting fairly infrequent testing. For example, the first crash reported as drug-related in the dataset occurred in May 2016, at which point three Uber entries had already taken place. Therefore, it seems unlikely that including these in the analysis would help to draw meaningful conclusions.

To control for different locations having different population growth rates, we include local population data in the analysis where possible. However, it is important to note that population data is only available for territorial authorities, and not for police areas. Therefore, local population data can only be included in the regressions involving the crash data. Moreover, the available population data is annual rather than monthly, and therefore only gives the population of each territorial authority in June of each year. To obtain local population data for all months, we have used a linear logarithmic interpolation procedure. We believe this is a suitable solution, as the costs of the extra assumptions required for interpolation are outweighed by the benefits of being able to include local population in the regressions without drastically reducing the number of observations. To capture any changes in the number of cars on the road that are not related to population, we also include the number of other (i.e. non-drunk driving) crashes.

Another important control variable we consider is the presence of local alcohol policies (LAPs) (Tyler-Harwood & Kutinova Menclova, 2021), (Alcohol Healthwatch, 2018). These are localised extensions of the Sale and Supply of Alcohol Act 2012, which allows territorial authorities to develop their own set of rules regarding the location, density and opening hours of licensed alcohol-providing premises. LAPs have been adopted in 34 out of 67 territorial authorities on a staggered basis from August 2014 to September 2018. We include a dummy variable to denote the presence of LAPs in a territorial authority, as their introduction could potentially affect drunk driving rates and would not be captured in time or location fixed effects. Similarly to population, it is difficult to determine whether an LAP is present in a police area due to the different boundaries, so we omit this variable from the analysis of the offence data.

IV. Regression Analysis

A. Crash data

First, we analyse the data describing the number of drunk driving crashes in each territorial authority. For an overview of this data, see Table 3 and Figures A1 and A2 in the appendix. Table 3 contains the yearly number of drunk driving crashes in each region of New Zealand from 2012 to 2018, while Figures A1 and A2 graphically depict the monthly crash trend in each of the New Zealand cities where Uber has entered over the period of interest.

In our regression analysis, we use the following model:

$$y_{it} = \alpha + \beta Uber_{it} + \gamma \mathrm{X}_{\mathrm{it}} + \delta_i + \omega_t + \varepsilon_{it}$$

where y_{it} is the dependent variable in question, usually the number of drunk driving crashes in location i in month t. $Uber_{it}$ is the dummy variable that is set to 1 if Uber is present in location i in month t, and 0 otherwise. X_{it} is a vector including the other control variables: local population, other crashes, and LAPs. δ_i and ω_t represent location and time fixed effects respectively, which are always included due to the panel structure of the data.

The first set of regressions (Table 4) simply considers the effect of Uber on all drunk driving crashes. We include regressions with and without the extra control variables. Because the dependent variable contains discrete count data, a Poisson regression is the more appropriate estimation method. However, for context we also include the results of an OLS regression for each model. For both types of regression, we include robust standard errors clustered at the location level.

Table 3: Yearly Number of Drunk Driving Crashes in New Zealand by Region

Region	2012	2013	2014	2015	2016	2017	2018
Auckland	881	795	730	826	930	1,287	1,354
Bay of Plenty	147	123	100	139	187	181	245
Canterbury	285	248	279	243	305	340	374
Chatham Islands[7]	0	1	2	0	0	0	0
Gisborne	32	34	26	26	36	50	59
Hawke's Bay	93	66	56	72	99	125	136
Manawatu-Wanganui	125	110	103	108	142	160	212
Marlborough	23	17	12	16	21	31	35
Nelson	20	28	15	19	23	33	33
Northland	115	120	115	114	147	169	210
Otago	112	107	102	87	159	153	196
Southland	62	44	48	66	60	60	58
Taranaki	60	41	44	48	69	72	96
Tasman	19	26	13	13	23	31	28
Waikato	236	221	175	196	246	309	376
Wellington	210	164	152	196	186	262	287
West Coast	25	14	18	24	17	30	32
Total	2,445	2,159	1,990	2,193	2,650	3,293	3,731

Note that blue text denotes the presence of Uber in the corresponding region and year. Dunedin and Queenstown are both located in the Otago region.

Note that, for both the Uber and LAP dummy variables, we report the coefficient followed by the standard error and p-value respectively. All three are rounded to three decimal places. For the OLS regressions, the coefficients can be interpreted as the numerical change in the dependent variable in response to the presence of Uber/LAPs. For the Poisson regressions, the coefficients can be interpreted as the change in the mean of the natural log of the dependent variable in response to the presence of Uber/LAPs. Therefore, for these regressions, $\exp(coefficient) - 1$ represents the percentage change in the dependent variable in response to the presence of Uber/LAPs. For

[7] Chatham Islands is a territorial authority that is not part of any region.

clarity, the coefficient is followed by an asterisk if it is significant at the 10% level ($p < 0.10$), and two asterisks if it is significant at the 5% level ($p < 0.05$).

Table 4: The Impact of the Presence of Uber on Overall Drunk Driving Crashes

Regression number	**(1)**	**(2)**	**(3)**	**(4)**
Dependent variable	Number of drunk driving crashes	Number of drunk driving crashes	Number of drunk driving crashes	Number of drunk driving crashes
Uber	3.549* (2.018, 0.083)	-0.012 (0.030, 0.683)	-1.258 (1.340, 0.351)	-0.023 (0.038, 0.537)
LAPs	—	—	-0.440** (0.212, 0.041)	-0.078 (0.054, 0.151)
Local population	—	—	✓	✓
Other crashes	—	—	✓	✓
Location fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Estimator	OLS	Poisson	OLS	Poisson
N	5,829	5,829	5,829	5,829
R^2 / Pseudo R^2	0.9069	0.7199	0.9464	0.7203

Beneath each coefficient is the standard error and p-value, respectively.
Note that this is <u>not</u> a confidence interval.* denotes significance at the 10% level, and ** denotes significance at the 5% level.

Interestingly, regression (1) suggests that Uber is associated with an average monthly *increase* in drunk driving crashes of 3.549. While this is statistically significant at the 10% level, this regression does not include the control variables, so it is likely an under-specified model.

Once extra variables are included, the Uber coefficient in regression (3) actually flips its sign and suggests that Uber decreases drunk driving crashes by 1.149 crashes each month. The Poisson regressions, (2) and (4), suggest that Uber reduces drunk driving crashes by 1.22% and 2.35%, respectively. However, none of these coefficients are statistically significant, so one cannot infer with any reasonable level of confidence that the true value of the coefficient is non-zero. We would therefore interpret from regressions (2)-(4) that Uber may cause a small decrease in drunk driving crashes, but that there is not enough evidence to conclusively confirm this.

To further examine the effect of Uber, drunk driving crashes can be separated by severity (Table 5). We define "severe" drunk driving crashes as those that involved fatalities or serious injuries; and "non-severe" drunk driving crashes as those that only involved minor injuries, or no injuries at all. If Uber is to be considered an effective drunk driving treatment, it would need to reduce severe crashes as well as non-severe crashes, given that severe crashes incur most of the social costs of drunk driving. The next set of regressions examines the effect of Uber on both types of crashes, using both OLS and Poisson estimations with the full set of independent variables.

Table 5: The Impact of the Presence of Uber on Severe vs. Non-Severe Drunk Driving Crashes

Regression number	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable	Severe drunk driving crashes	Severe drunk driving crashes	Non-severe drunk driving crashes	Non-severe drunk driving crashes
Uber	0.055 (0.090, 0.542)	0.034 (0.102, 0.741)	-1.290 (1.369, 0.350)	-0.033 (0.040, 0.412)
LAPs	-0.010 (0.030, 0.743)	-0.000 (0.102, 1.000)	-0.433** (0.201, 0.035)	-0.084 (0.057, 0.135)
Local population	✓	✓	✓	✓
Other crashes	✓	✓	✓	✓
Location fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Estimator	OLS	Poisson	OLS	Poisson
N	5,829	5,829	5,829	5,829
R^2 / Pseudo R^2	0.6226	0.3297	0.9407	0.7195

Beneath each coefficient is the standard error and p-value, respectively. Note that this is not a confidence interval.* denotes significance at the 10% level, and ** denotes significance at the 5% level.

The Poisson regression (6) suggests Uber is associated with a 3.42% increase in severe drunk driving crashes, and regression (8) suggests Uber is associated with a 3.33% decrease in non-severe drunk driving crashes. The OLS regressions also carry the same sign (positive and negative, respectively). This implies that Uber is perhaps more likely to reduce non-severe crashes than severe crashes, and it is surprising to see a positive coefficient in the regressions for severe crashes. However, these coefficients are all statistically insignificant at both a 5% and 10% level, with especially high p-values in regressions (5) and (6), and the coefficient estimates are therefore not sufficiently different from zero to reliably infer a causal effect of Uber entry.

Table 6: The Impact of the Presence of Uber on Weekend vs. Weekday Drunk Driving Crashes

Regression number	**(9)**	**(10)**	**(11)**	**(12)**
Dependent variable	Weekend drunk driving crashes	Weekend drunk driving crashes	Weekday drunk driving crashes	Weekday drunk driving crashes
Uber	-0.732 (0.698, 0.298)	-0.015 (0.053, 0.774)	-0.479 (0.717, 0.506)	-0.034 (0.038, 0.371)
LAPs	-0.191* (0.107, 0.079)	-0.070 (0.065, 0.283)	-0.245* (0.124, 0.053)	-0.086 (0.058, 0.139)
Local population	✓	✓	✓	✓
Other crashes	✓	✓	✓	✓
Location fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Estimator	OLS	Poisson	OLS	Poisson
N	5,829	5,829	5,829	5,829
R^2 / Pseudo R^2	0.9315	0.6559	0.8971	0.6017

Beneath each coefficient is the standard error and p-value, respectively. Note that this is <u>not</u> a confidence interval.* denotes significance at the 10% level, and ** denotes significance at the 5% level.

Given that we also have data about the exact time of each crash, we can separate drunk driving crashes into those that occurred on a weekend and those that did not (Table 6). We follow the lead of the CAS and define the "weekend" as the time between 6:00pm on Friday and 6:00am on Monday. Although this time period only constitutes 35.7% of the week, 57.9% of drunk driving crashes in the dataset occurred during these hours. It has been established that Uber's surge pricing is more likely to be in effect during the weekend due to a spike in demand from intoxicated passengers. Greenwood & Wattal (2017) found that, while Uber did impact drunk driving in California overall, there was no effect when restricting the data to weekends only. Therefore, it is worth examining the New Zealand data to see if a similar distinction exists.

All four regressions suggest that Uber is associated with a small reduction in drunk driving crashes on both weekends and weekdays. Regression (10) suggests a 1.52% decrease on weekends, while regression (12) suggests a 3.45% decrease on weekdays. Moreover, the coefficient in regression (10) carries a p-value of 0.774, so the effect on weekends is very likely to have a true value of zero. This is consistent with the hypothesis, and previous findings, that Uber has a bigger effect on drunk driving on weekdays when surge pricing is less likely to be in effect. However, once again it is important to note that all Uber coefficients in regressions (9) – (12) are small and statistically insignificant at a 10% level, so strong conclusions cannot be made about Uber's effect on weekends versus weekdays.

The effect of Uber on drunk driving in individual cities can also be examined by restricting the dataset to a city and its immediately surrounding territorial authorities, which might be expected to share strong similarities with the city and therefore act as a suitable control group. We look at the three most populated cities—Auckland,[8] Wellington,[9] and Christchurch[10]—as these would be expected to have the largest Uber user base and have had access to Uber for longest. The results of these regressions can be found in Table 7.

The Poisson regressions suggest Uber is associated with decreases in drunk driving crashes in Auckland and Christchurch of 14.20% and 3.13% respectively; and an increase in Wellington of 28.70%. Although none of these coefficients are statistically significant at the 10% level, the Uber coefficients in the Auckland and Wellington regressions are relatively large and consistent in sign with their OLS counterparts, which are statistically significant at the 5% level. Therefore,

[8] Using a control group of Hauraki, Kaipara, Thames-Coromandel, Waikato, and Whangarei.

[9] Using a control group of Carterton, Kapiti Coast, Masterton, and South Wairarapa.

[10] Using a control group of Ashburton, Hurunui, Selwyn, and Waimakariri.

there is some evidence pointing to an Uber-driven decrease in drunk driving crashes in Auckland, and an Uber-driven increase in drunk driving crashes in Wellington. Given the high p-value in regression (18) and the changing sign on the Uber coefficient between regressions (17) and (18), Uber does not appear to have had a meaningful impact on drunk driving crashes in Christchurch.

Table 7: The Impact of the Presence of Uber on Crash Data for Each of the Three Major Cities and Their Surrounding Areas

Regression number	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
Dependent variable	Drunk driving crashes in Auckland	Drunk driving crashes in Auckland	Drunk driving crashes in Wellington	Drunk driving crashes in Wellington	Drunk driving crashes in Christchurch	Drunk driving crashes in Christchurch
Uber	-24.508** (0.628, 0.000)	-0.133 (0.142, 0.349)	0.599** (0.215, 0.027)	0.252 (0.160, 0.115)	3.558** (0.559, 0.003)	-0.031 (0.154, 0.842)
LAPs	-0.583 (1.340, 0.682)	-0.009 (0.163, 0.954)	0.629 (0.393, 0.153)	0.062 (0.064, 0.327)	-0.595 (1.181, 0.641)	-0.109 (0.295, 0.710)
Local population	✓	✓	✓	✓	✓	✓
Other crashes	✓	✓	✓	✓	✓	✓
Location fixed effects	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓
Estimator	OLS	Poisson	OLS	Poisson	OLS	Poisson
N	522	522	696	696	435	435
R^2 / Pseudo R^2	0.9701	0.9063	0.7047	0.3803	0.8827	0.6627

Beneath each coefficient is the standard error and p-value, respectively. Note that this is not a confidence interval.* denotes significance at the 10% level, and ** denotes significance at the 5% level.

B. Offence Data

Next, we analyse the data describing the number of alcohol-specific driving offences in each police area. For an overview of this data, see Table 8 and Figures A3 and A4 in the appendix. Table 8 contains the yearly number of alcohol-specific driving offences in each police district of

New Zealand from 2012 to 2018, while Figures A3 and A4 graphically depict the monthly offence trend in each of the New Zealand cities where Uber has entered over our period of interest.

In our regression analysis, we use the following model:

$$y_{it} = \alpha + \beta Uber_{it} + \delta_i + \omega_t + \varepsilon_{it}$$

where y_{it} is the number of drunk driving offences in location i in month t. Again, $Uber_{it}$ is the dummy variable that is set to 1 if Uber is present in location i in month t, and 0 otherwise. In this model, we do not include the vector of control variables, $\mathrm{X_{it}}$, due to a lack of data that is organised into police areas. The location and time fixed effects, δ_i and ω_t, are still always included.

Table 8: Yearly Number of Alcohol-Specific Driving Offences in New Zealand by Police District

Region	2012	2013	2014	2015	2016	2017	2018
Auckland	2,434	2,175	1,662	2,163	2,321	2,251	2,346
Bay of Plenty	2,896	2,478	2,082	2,659	2,761	2,893	3,039
Canterbury	3,353	2,734	2,707	3,140	2,878	2,555	2,434
Central	2,319	1,820	1,607	2,019	2,005	1,857	1,947
Counties/Manukau	3,038	2,816	2,335	2,994	2,401	2,892	2,955
Eastern	1,906	1,808	1,539	1,504	1,425	1,665	1,973
Northland	1,472	1,273	1,175	1,783	1,601	1,268	1,305
Southern	1,650	1,350	1,230	1,577	1,754	1,694	1,854
Tasman	976	929	759	881	971	1,172	1,122
Waikato	2,337	2,127	1,842	2,473	2,776	2,673	2,422
Waitemata	3,147	3,045	2,370	2,807	2,521	2,629	2,622
Wellington	2,115	1,985	1,661	2,139	2,065	1,994	1,888
Total	27,643	24,540	20,969	26,139	25,479	25,543	25,907

Note that blue text denotes the presence of Uber in the corresponding region and year. Dunedin and Queenstown are both located in the Otago region.

Once again, the first set of regressions with the offence data considers the effect of Uber on all alcohol-specific driving offences (Table 9), and we use both OLS and Poisson regressions, with robust standard errors clustered at the location level.

Regression (19) suggests that the presence of Uber is associated with a decrease in alcohol-specific driving offences by 5.74 crashes per month on average, while regression (20) suggests that it is associated with a 9.64% reduction on average. The p-values for these regressions are both relatively low, but not low enough to conclude significance at a 90% or 95% confidence level.

Although the data does not allow separation of alcohol-specific driving offences by severity or date, it is still possible to look at the impact of Uber on offences in individual cities. Once again, we restrict the dataset to a city and consider its immediately surrounding police areas as a control group. Again, we choose the three most populated cities—Auckland,[11] Wellington,[12] and Christchurch[13]— the results for which can be found in Table 10.

Table 9: The Impact of the Presence of Uber on Overall Alcohol-Specific Driving Offences

Regression number	**(19)**	**(20)**
Dependent variable	Alcohol-specific driving offences	Alcohol-specific driving offences
Uber	-5.744 (5.452, 0.299)	-0.092 (0.070, 0.192)
Location fixed effects	✓	✓
Time fixed effects	✓	✓
Estimator	OLS	Poisson
N	3,306	3,306
R^2 / Pseudo R^2	0.7708	0.5517

Beneath each coefficient is the standard error and p-value, respectively. Note that this is not a confidence interval.* denotes significance at the 10% level, and ** denotes significance at the 5% level.

Regression (22) suggests Uber has caused a 10.60% decrease in alcohol-specific driving offences in Auckland. On the other hand, regressions (23) – (26) yield statistically significant coefficients and higher R^2/pseudo-R^2 values. Regression (24) suggests Uber is associated with a 4.06% increase in alcohol-specific driving offences in Wellington, while regression (26) suggests Uber is associated with a 27.92% decrease in alcohol-specific driving offences in Christchurch. Each of these results is also reasonably consistent with the respective OLS regression. It is

[11] Using a control group of Far North, Waikato East, Waikato West, and Whangarei.

[12] Using a control group of Manawatu, Wairarapa and Whanganui.

[13] Using a control group of Canterbury Rural and Mid-South Canterbury.

especially noteworthy that Uber appears to have had such a large impact on alcohol-specific driving offences in Christchurch, especially given that we did not find a similar impact on drunk driving crashes. However, it is important to note that the regressions involving Christchurch used quite a low number of observations due to the relatively small number of police areas constituting Christchurch and its surrounding areas. This could potentially impact the robustness of any conclusions.

Table 10: The Impact of the Presence of Uber on Offence Data for Each of the Three Major Cities and Their Surrounding Areas

Regression number	**(21)**	**(22)**	**(23)**	**(24)**	**(25)**	**(26)**
Dependent variable	Alcohol-specific driving offences in Auckland	Alcohol-specific driving offences in Auckland	Alcohol-specific driving offences in Wellington	Alcohol-specific driving offences in Wellington	Alcohol-specific driving offences in Christchurch	Alcohol-specific driving offences in Christchurch
Uber	-5.870 (7.726, 0.460)	-0.101 (0.128, 0.431)	2.212** (0.854, 0.049)	0.040** (0.015, 0.006)	-36.432** (0.862, 0.001)	-0.246** (0.021, 0.000)
Location fixed effects	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓
Estimator	OLS	Poisson	OLS	Poisson	OLS	Poisson
N	1,305	1,305	522	522	261	261
R^2 / Pseudo R^2	0.4290	0.2453	0.7442	0.4325	0.9498	0.8675

Beneath each coefficient is the standard error and p-value, respectively. Note that this is <u>not</u> a confidence interval.
* denotes significance at the 10% level, and ** denotes significance at the 5% level.

V. Discussion

Overall, these findings indicate that Uber is mostly associated with small but statistically insignificant decreases in both drunk driving crashes and alcohol-specific driving offences. While a Poisson regression suggests that Uber is associated with a 2.35% decrease in drunk driving crashes, a 95% confidence interval indicates the true value of this relationship could be anywhere between a 10.20% decrease and a 5.19% increase. A similar confidence interval suggests that Uber's apparent 9.64% decrease in alcohol-specific driving offences could actually be anywhere between a 25.83% decrease and a 4.71% increase. In both cases, while it is perhaps more likely that there has been a decrease, there is not enough evidence to make any strong conclusion regarding causality between Uber and the drunk driving indicators.

A similar situation exists when comparing Uber's relationship with severe vs. non-severe drunk driving crashes, or weekend vs. weekday drunk driving crashes; ultimately, we cannot confirm that any distinction exists between each of the two groups. When looking only at each of New Zealand's three major cities, we find a small amount of evidence suggesting that Uber is associated with drunk driving crashes decreasing in Auckland and increasing in Wellington relative to their respective surrounding areas. The findings also indicate that Uber is associated with alcohol-specific driving offences increasing in Wellington and decreasing in Christchurch relative to their respective surrounding areas.

The lack of a consistent and sizeable effect can be related back to the economic theory behind the relationship between Uber and drunk driving. We established that there may have been a subset of the population, described as "marginal drunk drivers", who viewed drunk driving as marginally preferable to taking a taxi, but might now view Uber as preferable to drunk driving. Although the existence of this group cannot be ruled out, it seems like it is not a large enough subset of the New Zealand population to cause a noticeable difference in drunk driving crashes and alcohol-specific driving offences.

There are many reasons why drunk drivers with this specific preference order might only constitute a very small proportion of all drunk drivers. Many individuals who drive drunk, and especially those who are likely to cause crashes, may be beyond the threshold of rational decision-making and are not in a suitable frame of mind to weigh up the costs and benefits of alternate transportation options. They may also possess an innate belief in their own driving ability while drunk, and hence the low likelihood of crashing or getting caught. It is also possible that using Uber does not provide substantially more utility than taking a taxi for most users, and therefore the number of people who consider drunk driving as a middle ground between those two options may be quite low. Additionally, Uber's advantage of being easier to use when intoxicated may not always be relevant, as people often make transport arrangements when they make the initial decision, while sober, to leave home with or without their car.

Even if the group of marginal drunk drivers is a reasonable proportion of all drunk drivers, they may not have made a noticeable impact on drunk driving rates if the overall user base of Uber in each city is relatively low. It is possible that Uber has not "caught on" to the same extent in New Zealand cities as, for example, in New York City, where Peck (2017) found a substantial effect of Uber on the alcohol-related collision rate.

In summary, we have found no strong indication of a causal relationship between the entry of Uber and the incidence of drunk driving in New Zealand. While the coefficients in the regressions frequently reflect small Uber-related decreases in the drunk driving indicators, they are generally not statistically significant at any reasonable confidence level. Therefore, our findings do not support Uber's claim that they are having a beneficial impact on drunk driving, but also do not conclusively disprove this claim.

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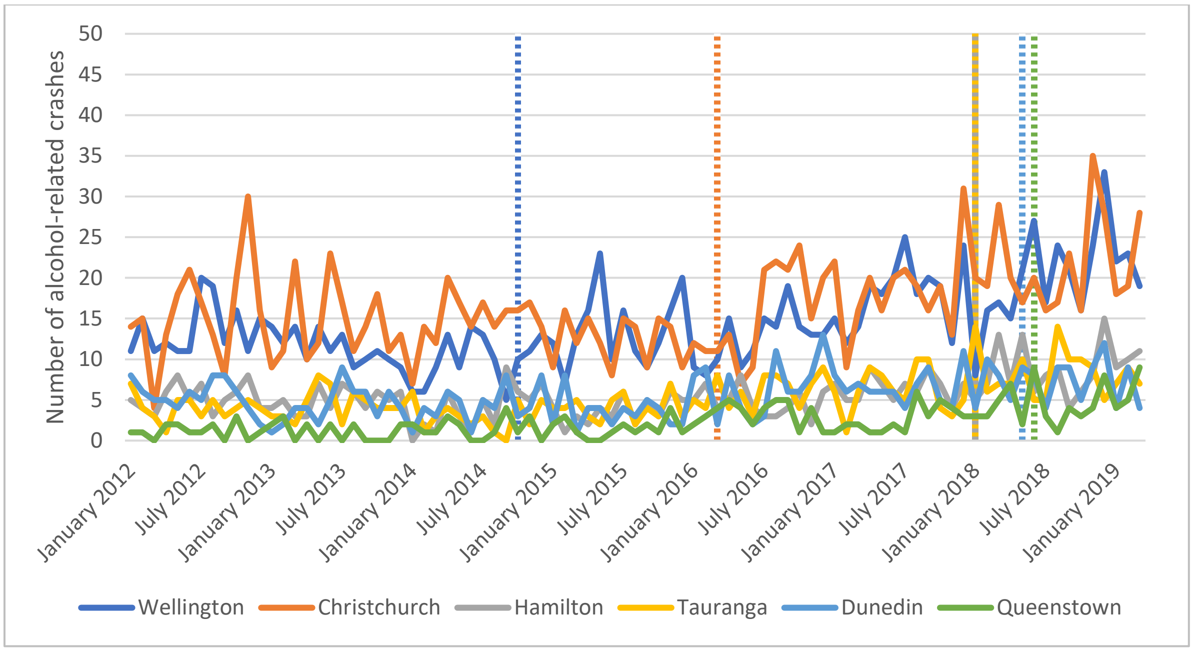
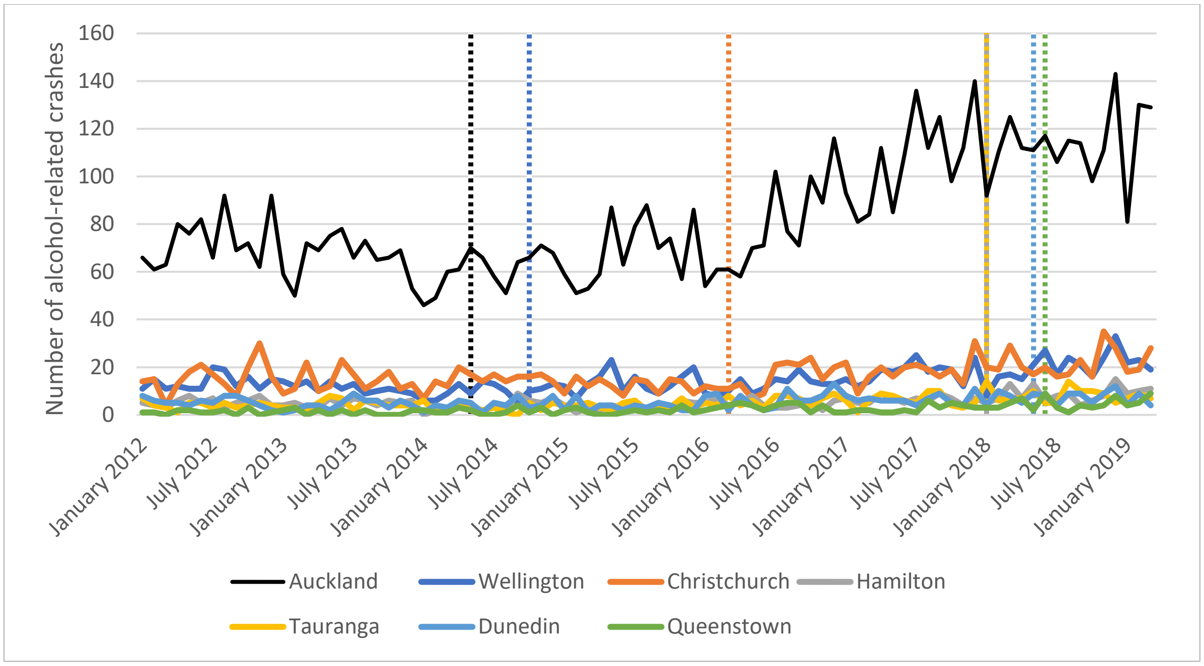
Appendix

Figure A1: Monthly Number of Drunk Driving Crashes in Cities with Uber, not Including Auckland (January 2012 – March 2019)



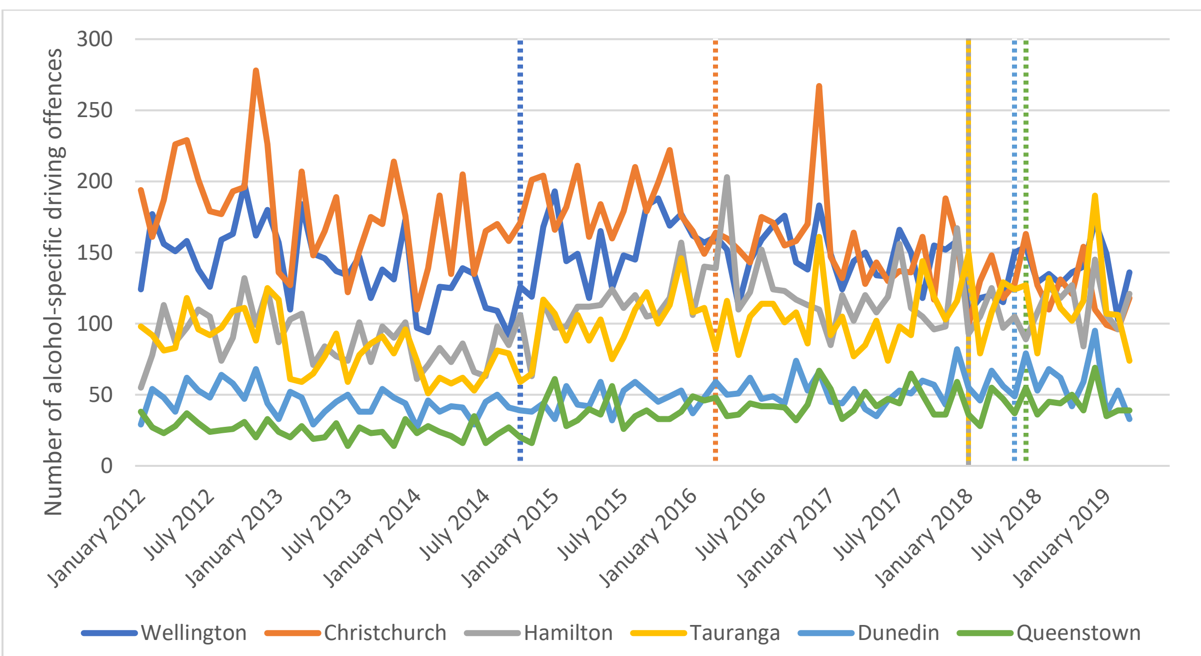
The vertical dashed lines represent Uber's month of entry into the city of the corresponding colour. Note that Uber entered into both Hamilton and Tauranga in January 2018, hence the yellow and grey vertical line.

Figure A2: Monthly Number of Drunk Driving Crashes in Cities with Uber, Including Auckland (January 2012 – March 2019)



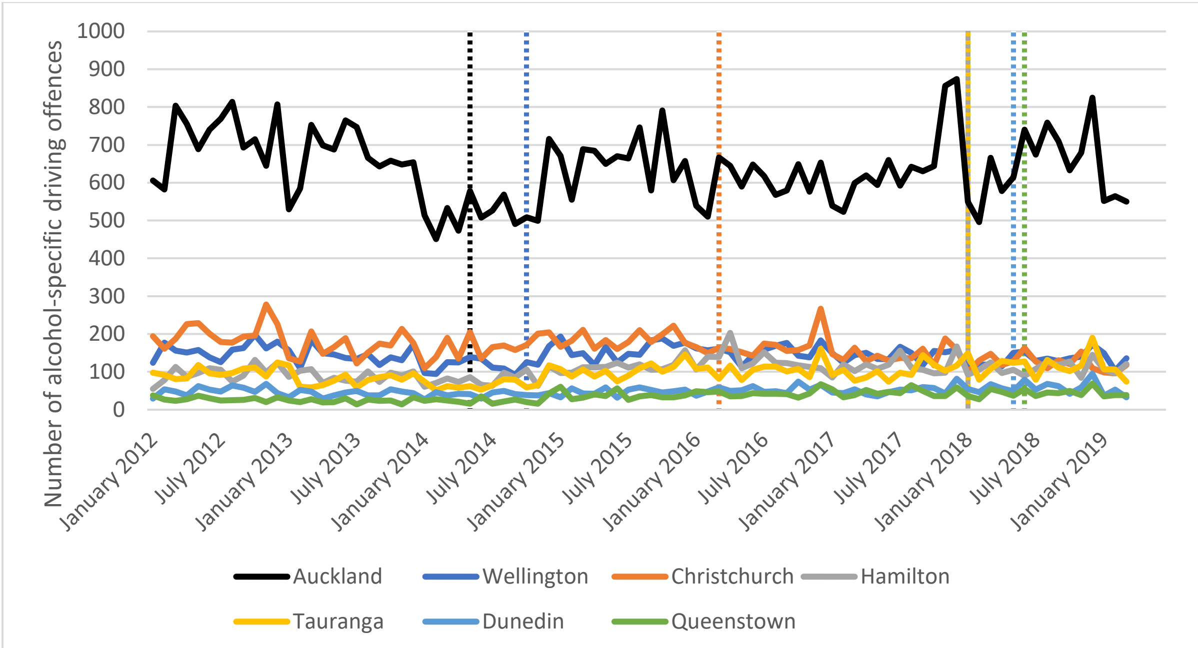
The vertical dashed lines represent Uber's month of entry into the city of the corresponding colour. Note that Uber entered into both Hamilton and Tauranga in January 2018, hence the yellow and grey vertical line.

Figure A3: Monthly Number of Alcohol-Specific Driving Offences in Cities with Uber, not Including Auckland (January 2012 – March 2019)



The vertical dashed lines represent Uber's month of entry into the city of the corresponding colour. Note that Uber entered into both Hamilton and Tauranga in January 2018, hence the yellow and grey vertical line.

Figure A4: Monthly Number of Alcohol-Specific Driving Offences in Cities with Uber, Including Auckland (January 2012 – March 2019)



The vertical dashed lines represent Uber's month of entry into the city of the corresponding colour. Note that Uber entered into both Hamilton and Tauranga in January 2018, hence the yellow and grey vertical line.