UBERING UNDER THE INFLUENCE

The Impact of Ridesharing on Drunk Driving

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Abstract

This essay uses a unique dataset detailing the number of hourly UberX rides since Uber market entry in fifteen counties throughout Illinois, employing a difference-in-differences design to estimate the impact of Uber on drunk driving, as represented by total DUIs and DUIs per capita. I find that Uber market entry has a moderately significant impact on reducing drunk driving, preventing approximately 3-11 DUIs in absolute terms, and preventing about 3 DUIs per 100,000 county residents in per capita terms. This negative effect is observed across age demographics, as each age cohort examined experiences approximately 2-3 fewer DUIs in total due to Uber market entry.

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1. INTRODUCTION

Given the option of taking an Uber[1], will fewer people decide to drive drunk? Intuition seems to strongly suggest so; the ridesharing platform, which pinpoints the geographic location of the rider and displays the fare in advance for payment through a mobile device, is a convenient and risk-free bet for would-be impaired drivers. With the explosion of ridesharing services like Uber and Lyft throughout the United States, anecdotal evidence abounds supporting this hypothesis[2]—but a clear understanding of the association between ridesharing and drunk driving remains elusive.

Using a unique dataset provided in agreement by Jonathan Hall, the Chief Economist and Director of Public Policy at Uber, I observe the total hourly number of UberX trips in fifteen counties throughout Illinois since Uber market entry. I use a difference-in-differences specification, the primary methodology used in the literature thus far, to exploit variation in both when Uber enters a county and the intensity of Uber activity in that county.

I find that Uber entry has a moderately significant impact on reducing drunk driving, examined both through total DUIs and DUIs per capita[3]. I estimate that about 3-11 DUIs[4] are prevented as a result of Uber market entry in absolute terms, and approximately 3 DUIs per 100,000 county residents are prevented in per capita terms. This negative effect is shared across age demographics, as each age cohort examined experiences 2-3 fewer DUIs in total. These results are supported by estimates that incorporate trips per capita, a more precise measure of Uber market penetration.

There are a number of ridesharing companies on the market, but I limit my analysis to the entry of Uber, the most dominant player by all indicators. Uber's valuation of $68 billion surpasses the $11.5 billion of its largest competitor Lyft,[5] Uber is more active by number of trips completed and number of

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[1] This essay uses the terms 'Uber' and 'UberX' interchangeably. UberX is Uber's most utilized service, as UberBlack, a premium ridesharing option, only accounted for 6% of Uber rides in 2016 (Covert 2016).
[2] Verbila (2015)
[3] DUI is the abbreviation for Driving Under the Influence.
[4] I make estimates with and without linear time trends, as I discuss in Sections 4 and 5. Models with linear time trends report a reduction of 3-4 DUIs, while those without report a reduction of 7-11 DUIs. For clarity, I only report a range of 3-11 here, explaining later how this range is segmented.
[5] Saiidi (2018)

cities served,[6] and Google search trends reveal that Uber generated 9 times as much interest as Lyft from March 2017 to March 2018.

Understanding the association between ridesharing and drunk driving has important public policy implications. Despite a decrease in drunk driving fatalities over the past 30 years[7], alcohol-impaired-driving caused 1 death every 53 minutes in 2014. The economic cost of these crashes, factoring in lost productivity, legal and court expenses, property damage and other elements, was estimated to be $44 billion in 2010—a number that does not begin to describe the trauma and disruption in quality of life experienced. Moreover, the individuals disproportionately involved in alcohol-related fatal traffic crashes are teenagers and young adults.[8] Identifying what role, if any, ridesharing can play in mitigating this economic cost and poignant loss of life is a key concern.

This study contributes to the existing literature on the association between ridesharing and drunk driving in three ways.

First, research thus far has established a timeline for rideshare market entry based on announcements from the Uber website that publicize the introduction of service in new locations,[9] supplementing this information with citations in local newspapers. The imprecise data on Uber treatment has led researchers to come to a range of conclusions, from Uber having no effect on alcohol-related crashes (Brazil and Kirk 2016), to reducing alcohol-related crashes by 10-11.4% (Martin-Buck 2017). The dataset provided allows me to precisely identify when Uber treatment begins, as well as the intensity of treatment— specifically, UberX trips per capita.

Second, this study expands upon research investigating the impact of Uber outside of areas with high population density. Brazil and Kirk (2016) investigate the 100 largest US metropolises, and Martin-Buck (2017) extends this analysis to all US cities with populations greater than 100,000. This study examines counties below these population thresholds to investigate whether the limited transit options of

[6] Korosec (2017)
[7] https://www.nhtsa.gov/risky-driving/drunk-driving
[8] NHTSA (2015)
[9] https://www.uber.com/newsroom/

these lower population density regions will impact the effect of ridesharing (as hypothesized in Morrison 2016).

Third, I focus on drunk driving arrests, distinguishing this study from the majority of past research that has employed traffic fatalities as an outcome variable. This study uses a unique dataset specifically provided by the State's Attorney of Champaign County, in combination with DUI arrest information manually aggregated from public records, in order to observe the number of DUI arrests in fifteen Illinois counties from 2010 to 2017. The robustness of the DUI data allows investigation of whether Uber has a heterogeneous impact across age cohorts, speculated in past literature, given that mobile usage rates differ across generations. I find a fairly significant decrease in DUIs across all age cohorts, suggesting that the impact of ridesharing extends beyond the youngest riders.

The succeeding analysis is structured as follows. Section 2 reviews the existing literature on ridesharing and drunk driving. Section 3 describes the Uber data and arrest data. Section 4 discusses the models used. Section 5 presents results. Section 6 discusses and concludes.

2. LITERATURE

To identify the association between ridesharing and drunk driving, studies have primarily employed difference-in-differences models (Brazil and Kirk 2016; Greenwood and Wattal 2017; Dills and Mulholland 2017; Martin-Buck 2017; Peck 2017).[10] Studies differentiate themselves through the outcome variables they use to define drunk driving, and the geographic regions they analyze. Despite often sharing datasets and methodology, the literature has yet to reach a consensus.

Greenwood and Wattal (2017) investigate Uber's launch in cities throughout California, the first market that Uber entered, from 2009-2014. They estimate that UberX entry reduces alcohol-related motor vehicle homicides significantly, by 3.6-5.6%. Dills and Mulholland (2017), carry out a similar study with a larger geographic scope, analyzing US counties nationwide from 2007-2015. In contrast, they estimate

[10] Studies have also used difference-in-differences design to estimate the impact of Uber on transit usage (Palsson 2017) and ambulance volume (Moskatel and Slusky 2017).

that Uber causes a moderately significant 0.2% decline in overall vehicle fatalities for each additional quarter that Uber is present, but has no impact on alcohol-related vehicle fatalities. Dills and Mulholland also include analysis of changes in DUI arrests and related crime rates, finding weak evidence that DUIs decline for the first three years that Uber is available.

Brazil and Kirk (2016), using the same vehicle fatality database as Dills and Mulholland (2017), examine changes in total, drunk driving-related, and weekend- and holiday-specific traffic. They find that Uber market entry has no impact on fatalities of any kind in the 100 most populated metropolitan areas in the US.

Martin-Buck (2017), however, reverses the findings of Brazil and Kirk (2016), estimating that rideshare entry reduces fatal alcohol-related auto accidents by 10-11.4%. Martin-Buck (2017) uses the same fatal crash dataset and examines every US city with a population greater than 100,000—a total of 273 cities from 2000-2014. Martin-Buck (2017) also examines changes in DUI arrests, and estimates that rates fall by 8.7-9.2% as a result of rideshare entry in cities with low to moderate transit usage, but observes no effect in cities where transit usage is high. Supporting Martin-Buck's results, Peck (2017) estimates that the New York City boroughs of Manhattan, Bronx, Brooklyn, and Queens experienced a 25-35% decrease in alcohol-related collisions[11] as a result of Uber introduction, a reduction of roughly 40 crashes a month across the boroughs.

In order to establish which populations are being treated, the studies discussed above rely on announcements from the Uber website that publicize the introduction of service in new locations.[12] Citations in local newspapers are used to supplement timelines. A shortcoming of this method is that the full radius of Uber treatment, meaning the extent to which Uber activity may extend beyond the publicized city into the surrounding geography, is unobserved. As a result, while Greenwood and Wattal (2017) and Dills and Mulholland (2017) interpret Uber's announcements to indicate treatment at the

[11] Fatal crashes are a subset of alcohol-related collisions.
[12] https://www.uber.com/newsroom/

county level, Martin-Buck (2017), like Brazil and Kirk (2016), argue that the impact of ridesharing service is more likely to be concentrated at the city level, and interpret treatment to occur as such.

Summarizing this uncertainty, Dills and Mulholland (2017) explain that most UberX expansions, from 2010 to 2014, were announced on Uber's blog, accompanied with a city-specific web page that included a map of the geographic region of service. Some entries were noted in local newspapers or websites. However, as the number of service areas grew, Uber updated their website and combined many service areas into one, eventually providing maps indicating service areas that were more widespread than initially displayed. Uber also stopped formally announcing every time it expanded coverage of an existing service location, and many expansions no longer received local news coverage.[13] Discussion with Jonathan Hall, Uber's Chief Economist, supports the understanding that the radius of Uber treatment has varied dynamically over time.

In addition, the existing literature does not observe the intensity of rideshare market penetration, likely to be distinct and dependent on each city's unique environment. Dills and Mulholland (2017) propose that it takes time for potential users to become aware of Uber market entry and for current users to grow more familiar with the process, assuming that Uber activity increases over time and in a linear fashion. This need not be the case—Uber usage might spike upwards abruptly and then level off. The dataset provided allows me to observe when Uber treatment begins, as well as changes over time in per capita Uber activity.

This study expands upon research investigating the impact of Uber outside of the nation's largest metropolises (Dills and Mulholland 2017). In cities, Uber often becomes a cheaper alternative to a taxi. For example, in Chicago, the Tribune observed in October 2017: "Cabs charge $2.25 per mile, compared to 95 cents per mile for Uber and Lyft, according to city data. And cabs charge 33 cents per minute of the

[13] Figures 1 and 2 of the Appendix illustrate the ambiguity in treatment region that Dills and Mulholland (2017) describe. When Uber launched in Champaign-Urbana, in February 2015, the city name 'Champaign-Urbana' is publicized, alongside a point representing the location. Currently accessing the site, however, only the city name 'Champaign' is displayed, with Urbana missing. The image now represents a service region identifying all of Champaign County.

trip versus 20 cents for the ride-share companies."[14] Yet, in the nation's small to medium-sized cities, with fewer taxis and limited public transportation options, the introduction of ridesharing may not just be an attractive substitute, but a whole new mode of transportation.[15] Martin-Buck (2017) finds support of this, as he observes that DUIs decrease more in cities with low to moderate transit usage. The counties sampled in this study include cities below Martin-Buck's population threshold.

Third, I focus on drunk driving arrests, distinguishing this study from the majority of past research that has employed traffic fatalities as an outcome variable. I do this for two reasons. First, given my geographic region of interest, there are not enough traffic fatality observations to conduct a robust investigation. Second, in 2014, US Law enforcement made 1.1 million arrests for driving under the influence, but there were only 9,967 fatalities in alcohol-impaired vehicle crashes.[16] Traffic fatalities identify a severe, but relatively infrequent, consequence of drunk driving, while arrests may yield a broader picture of ridesharing's impact on drunk driving.

Studies examining Uber's association with DUI arrests have used the FBI Uniform Crime Reporting program (Dills and Mulholland 2017; Martin-Buck 2017). Despite being the most complete nationwide collection of DUI arrest data available, Martin-Buck (2017) reports that in a sample of all U.S. cities with populations above 100,000, only 45% of the cities report DUI arrests for every month between 2000 and 2014. In contrast, this study uses a unique dataset specifically provided for this essay from the State's Attorney of Champaign County, in combination with DUI arrest information that has been manually aggregated from public records, in order to observe the total number of DUI arrests in fifteen Illinois counties from 2010 to 2017. This robust set of more than 33,000 observations can be segmented by age of arrestee, extending previous work that speculates Uber may have a heterogeneous impact across age cohorts.

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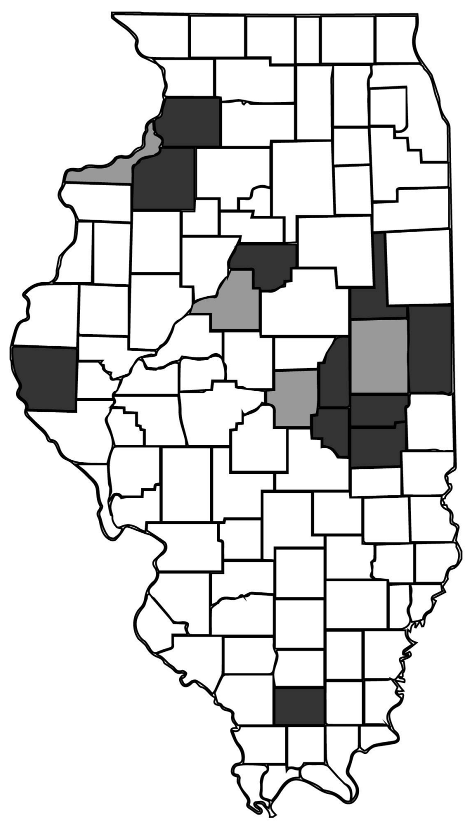
[14] Byrne (2017)
[15] To illustrate, in Champaign-Urbana, there were fewer than 7 taxis per 10,000 people operating between July 2011 and December 2011. In 2012, Washington, DC, reported that there were 120 taxis per 10,000 people, and NYC reported there were 26 taxis per 10,000 people in 2012. (Dempsey 2012; Mathis 2012).
[16] https://ucr.fbi.gov/

3. DATA

The map below illustrates the fifteen Illinois counties analyzed in this study. Counties shaded dark gray experience no significant Uber entry, while counties shaded light gray experience Uber entry. DUI Arrests from 2010-2017 are observed for all fifteen counties. While this study limits analysis to the fifteen colored counties, given time to collect additional data, the analysis could reasonably be extended to all counties in Illinois and other states as well, reinforcing the external validity of the findings. Table 1 (at the end of this document) lists the names of the fifteen counties that make up the observation sample.

Map of Illinois, illustrating counties sampled:
Dark Gray—No significant Uber activity observed. *Light Gray*—significant Uber activity observed.



3.1 INDEPENDENT VARIABLE - UBER TRIP DATA

Data on Uber activity was obtained specifically for this essay through an agreement with Jonathan Hall, the Chief Economist and Director of Public Policy at Uber. The dataset consists of the total number of UberX trips per hour since Uber market entry in fifteen counties throughout Illinois. The completion time of the trip is the hour assigned to the ride. In the event that the trip begins in one county and ends in another, the trip is attributed to the county where the trip was completed. I then sum trips by month for each county to create a longitudinal dataset of month-year observations. Figures 1 and 2 illustrate Uber trips over time on a per capita basis.[17]

[17] County population data is drawn from the US Census Bureau QuickFacts tool. Population is then divided by 10,000 to put per capita estimates on a 'per 10,000 residents basis', allowing for easier comparison between counties. I do not attempt to calculate per capita estimates limited to a 'drinking-age' population, but use total reported population for consistency and convenience.

Figure 1.

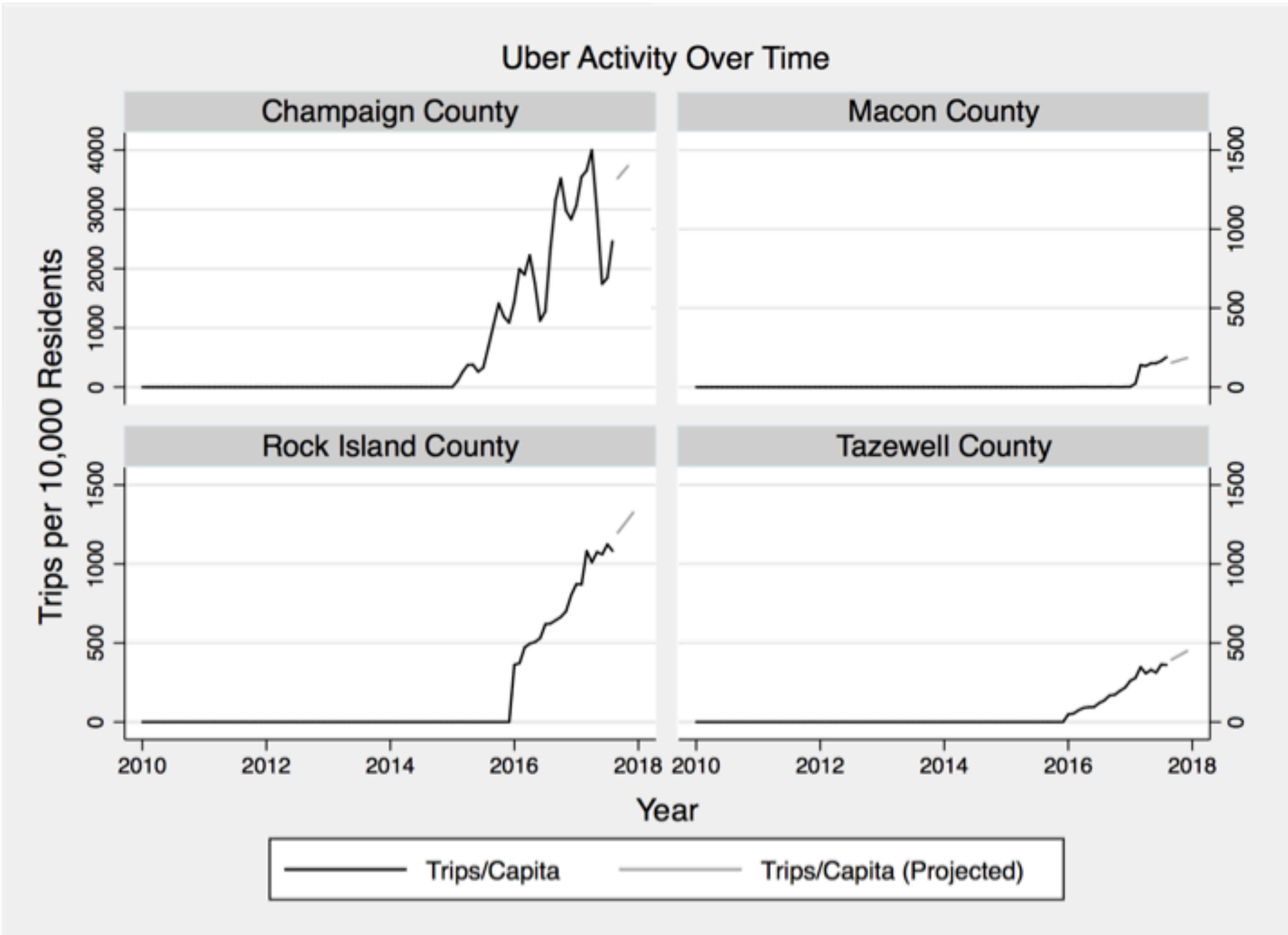


Figure 1 describes per capita UberX trips over time from 2010 to 2017 for the four counties that experience significant Uber activity. Trips per capita is on a per 10,000 residents basis. Observations are by month-year. The dark lines show data provided by Uber. The lighter grey lines show projections that I make based on linear estimate for trips/capita for the last three months of 2017 (as this data was not provided by Uber).

Figure 2.

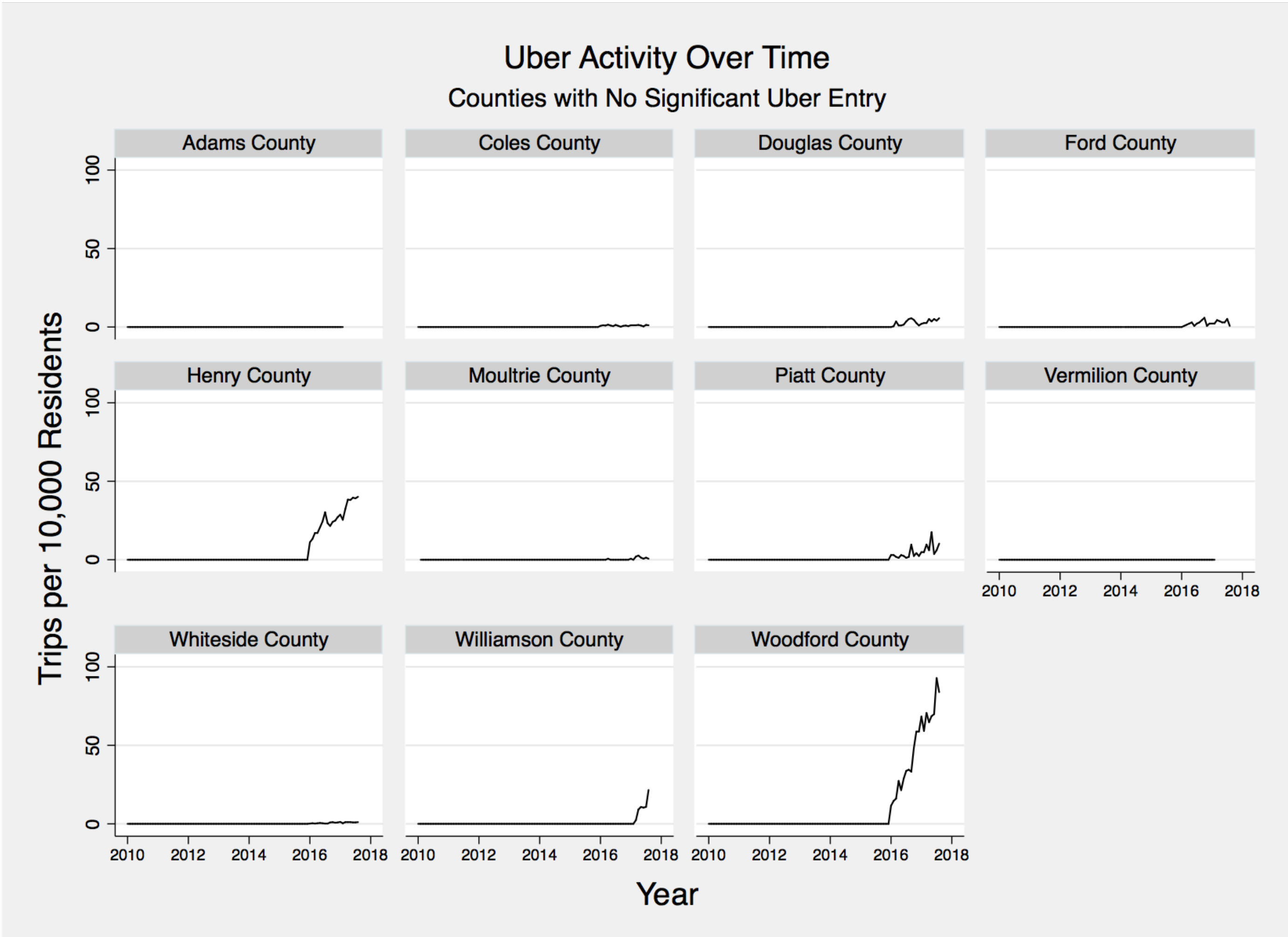


Figure 2 describes per capita UberX trips over time from 2010 to 2017 for the 11 counties that do not experience significant Uber activity. Trips per capita is on a per 10,000 residents basis. Observations are by month-year. The dark lines show data provided by Uber.

3.2 OUTCOME VARIABLE – DRIVING UNDER THE INFLUENCE (DUI) ARREST DATA

The dataset on DUI arrests from Champaign County was obtained specifically for this essay through an agreement with Julia Reitz, the State's Attorney of Champaign County. DUI arrest information from all other counties was manually aggregated from public records, accessed through online case lookup tools.[18]

The dataset provided by the State's Attorney contains complete information on each DUI arrest, such as time of arrest, gender, and offense location. I retain the offender's date of birth, and combine the Champaign County records with compiled records of the remaining counties, which include offense date and offender date of birth. For each DUI observation, I calculate the offender's age at time of arrest, and indicate the corresponding age cohort: <24, 24-29, 30-40, or 41< . This age segmentation is selected for both qualitative and quantitative reasons. Qualitatively, I attempt to capture age segments that are likely to exhibit differences in going out behavior. This segmentation identifies teen and college years, young adulthood, early middle age, and middle age and beyond. Figure 3 shows that the proclivity to drive drunk among these age cohorts is distinct, illustrated by differences in the age distribution of DUIs. Quantitatively, the age cohorts selected correspond to segments observed by the US Census Bureau, allowing per capita estimates of DUIs by age to be made.

All observations that indicate driving under the influence due to substances other than alcohol (marijuana, for example) are dropped.[19] This drops 2,816 observations, leaving a total of 33,367 DUI arrests across all counties from 2010-2017. Table 1 describes the breakdown of total DUI arrests by county. Table 2 describes the breakdown of total DUI arrests by age cohort. Like Uber trips, I sum DUIs by month for each county to create a longitudinal dataset of month-year observations. I maintain counts of the DUI age segmentation for each county month-year observation.

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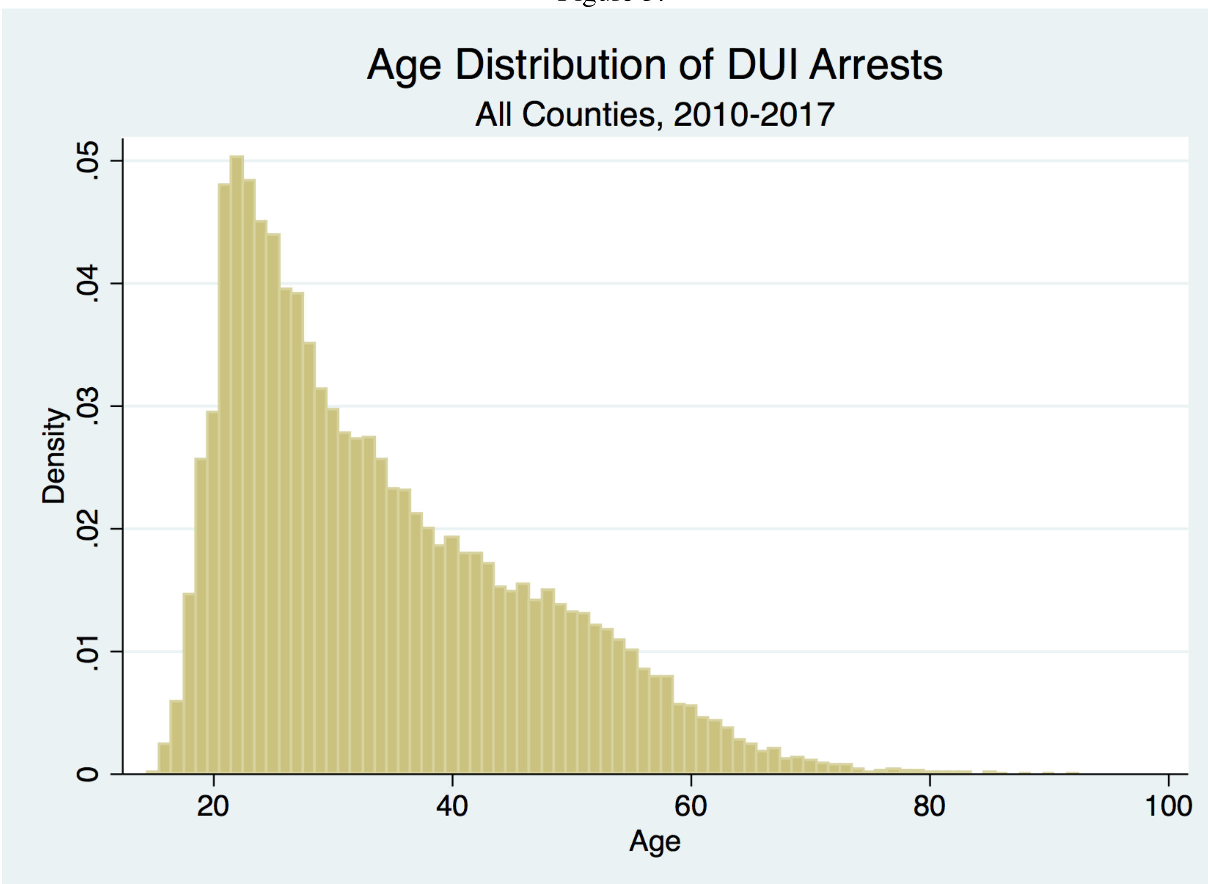
[18] Cases are accessed both through county circuit clerk websites, as well as http://www.judici.com/, which centralizes many counties' court records.

[19] The legal definition of driving under the influence can be found in Illinois Compiled Statutes: (625 ILCS 5/11-501). http://www.ilga.gov/legislation/ilcs/fulltext.asp?DocName=062500050K11-501. The description of charges that accompanies each DUI arrest observation is used to decide whether the arrest is alcohol or drug induced.

The age distribution of DUIs for all counties from 2010-017 is illustrated in Figure 3.[20] DUI Arrests per capita, on a per 10,000 residents basis, are illustrated by county from 2010-2017 in Figure 4. Appendix 3 illustrates the same relationship, but shows total DUI arrests instead of DUIs per capita.

Figure 3.



Age Distribution of DUI Arrests from 2010-2017 for all counties in sample.

[20] Although the sample is limited to Illinois, the age distribution strongly resembles nationwide estimates made by the Bureau of Justice Statistics. https://www.bjs.gov/index.cfm?ty=datool&surl=/arrests/index.cfm#

Figure 4.

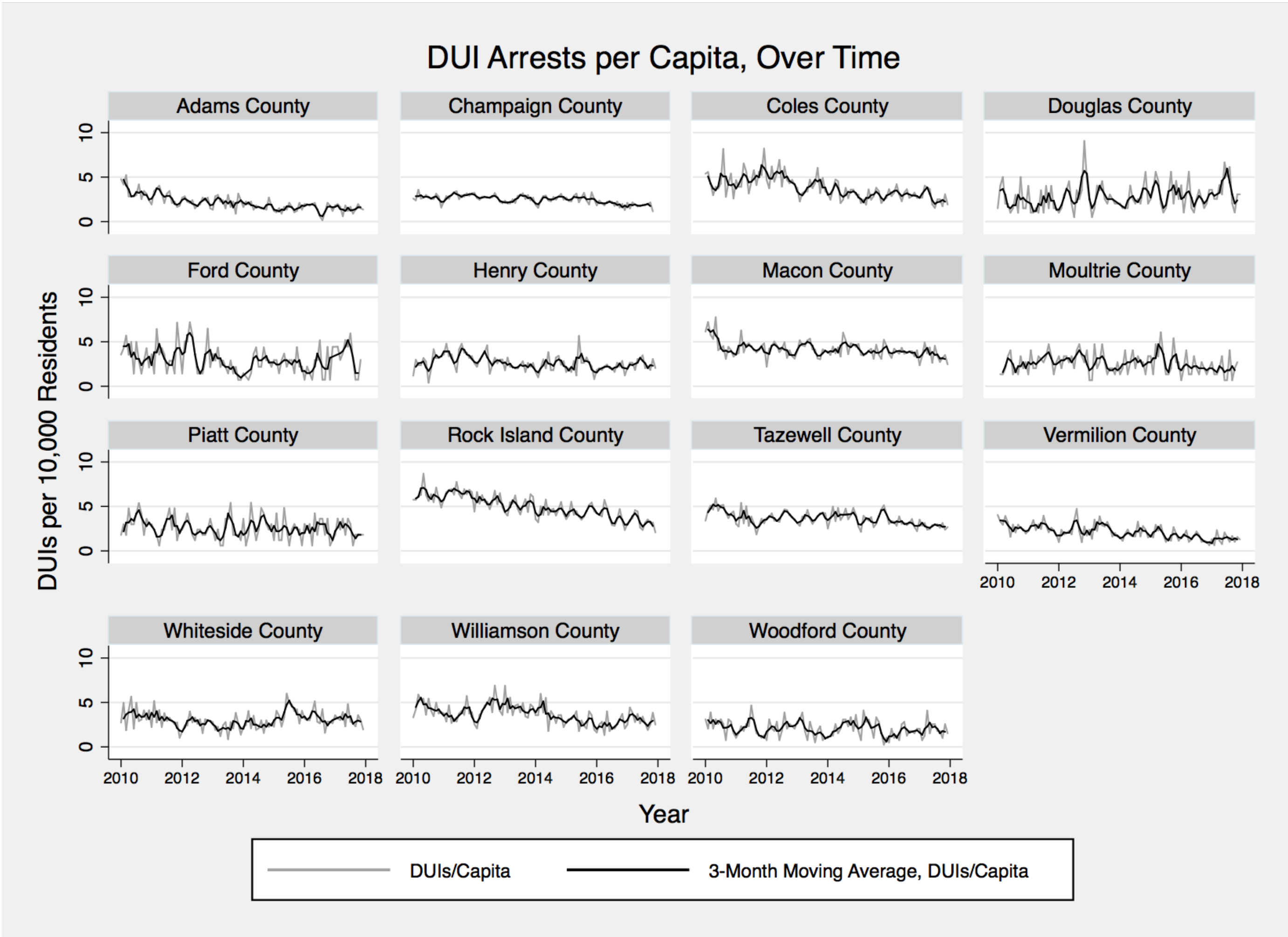


Figure 4 shows per capita DUI Arrests from 2010-2017 for all counties sampled. DUIs per capita is on a per 10,000 residents basis. Observations are by month-year. The light lines show DUIs/capita, while the dark lines show the 3-month moving average of DUIs/capita.

4. METHOD

This study uses a difference-in-differences design that takes advantage of variation in when Uber enters a county as well as variation in the intensity of Uber penetration in that county, as measured by trips per capita. Estimates are based on the following specifications:

1. Impact of Uber Entry (0/1) on Total DUI Arrests

$$\Upsilon_{cmt} = \beta D_{c,mt} + \eta_c + \theta_{mt} + \delta_c \cdot t + \epsilon_{cmt}$$

$\boldsymbol{\Upsilon_{ct}}$ is total DUI arrests in county *c* in month *m* and year *t*. $\boldsymbol{D}$ is 1 if UberX is active in county *c* in month *m* and year *t* and 0 otherwise. $\boldsymbol{\eta_c}$ is a county specific fixed effect and $\boldsymbol{\theta_{mt}}$ is a month-year specific fixed effect. This specification includes county-specific linear, monthly time trends, $\boldsymbol{\delta_c \cdot t}$, but results are presented with and without this variable.

2. Impact of Uber Entry (0/1) on DUI Arrests per Capita

$$\gamma_{cmt} = \beta D_{c,mt} + \eta_c + \theta_{mt} + \delta_c \cdot t + \epsilon_{cmt}$$

$\boldsymbol{\gamma_{cmt}}$ is defined to be DUIs per capita. The per capita output is reported on a per 10,000 residents basis. $\boldsymbol{D}$ is 1 if UberX is active in county *c* in month *m* and year *t* and 0 otherwise. The regression is run with and without the county-specific linear, monthly time trends.

3. Impact of Uber Trips per Capita on DUI Arrests per Capita

$$\gamma_{cmt} = \beta T_{c,mt} + \eta_c + \theta_{mt} + \delta_c \cdot t + \epsilon_{cmt}$$

$\boldsymbol{\gamma_{cmt}}$ is defined to be DUIs per capita. $\boldsymbol{T}$ is defined to be trips per capita. Again, the per capita variables are reported on a per 10,000 residents basis. The regression is run with and without the county-specific linear, monthly time trends

Standard errors are clustered at the county level. Month-year fixed effects are included to control for common variation over time across all counties, such as an increase in DUIs during the holiday season, or the impact of a statewide recession. County-specific linear, monthly time trends are included as well, following the example of Dills and Mulholland. These time trends control for the possibility of differing trends in drunk driving specific to each county. To illustrate, suppose the overall trend in DUI arrests for treated counties is flat, but DUIs trend upward in some counties that Uber enters early, and downward in some counties that Uber enters late. It will appear that there are many periods where DUIs are high following entry, and a smaller number of periods where DUIs look low, following later entry. In this example, regression without these county-specific time trends would find that Uber increases DUIs, even if in reality Uber has no effect.

It is important to emphasize the relative strengths of the specifications, as discussed by Palsson (2017): employing Uber market entry dates (using an indicator of 0/1 to identify treatment) is easy to interpret, but using penetration rates (trips per capita) is more precise. When the 0/1 indicator is used, DUI arrests change by amount β as a result of Uber market entry. But, because take-up rates can vary between locations, this may be imprecise. In Figure 1, for example, we observe that trips per capita in Champaign County vary over time at a different rate than trips per capita in Macon County. Using penetration rates allows for differing levels of Uber activity, but as Palsson (2017) notes, this variable communicates an equilibrium outcome for the county, not a measure of exogenous difference in supply. Neither identification method is ideal, but taken together, reasonable estimates should result.

4.1 THREATS TO IDENTIFICATION

Factors influencing drunk driving that vary over time at the county level may threaten identification. Previous studies that examine a broad geographic scope utilize a number of controls in order to ensure comparability in fatal accident and DUI rates across treated and untreated geographies prior to Uber entry. These controls have included population, income, age, education levels, and unemployment rates. These controls are pertinent, given that a number of policy factors are understood to impact drunk driving rates, such as alcohol taxes and graduated licensing laws. I attempt to control for these factors by limiting the geographic scope of my analysis to Illinois and select my sample to ensure that treated and untreated counties demonstrate a parallel decrease in DUIs prior to Uber entry.

Figure 5 illustrates the parallel trends assumption, plotting DUIs per capita over time, segmented by counties that Uber never enters and counties that Uber eventually enters. All county descriptive statistics are reported in Table 3, and a comparison of descriptive statistics for counties that Uber never enters against counties that Uber eventually enters is presented in Table 4. Table 5 compares DUI arrests rates between counties that Uber never enters with counties that Uber eventually enters.

Regarding the outcome variable employed, using arrest data may reflect both changes in criminal activity and police behavior, as Jackson and Owens (2011) note. If police choose to shift resources away from DUI enforcement, results will overestimate the impact of ridesharing, but if police crack down on DUIs, results will underestimate the effect. I cannot empirically rule out that police behavior is not captured as well, but through discussions with the State's Attorney of Champaign County, I have been assured that no significant strategic shifts in DUI enforcement occurred during the observation period.

A third threat to identification arises if Uber enters a market based on factors correlated with drunk driving. Addressing this possibility while investigating the impact of ridesharing on transit usage, Palsson (2017) analyzes 386 metropolitan statistical areas in the United States, finding that Uber largely enters MSAs in population rank order. According to Palsson (2017), population is the strongest predictor of when Uber enters an MSA, and population and education levels are the best predictors of whether Uber enters an MSA. I observe this finding in my sample as well, given that both Uber entry and Uber activity are strongly correlated with county population. This population-entry relationship is presented in Table 6. To further account for endogeneity in Uber entry decisions, I also report specifications in Table 10 where I limit the sample to the counties that Uber eventually enters, exploiting differences in the timing of market entry.

Figure 5.

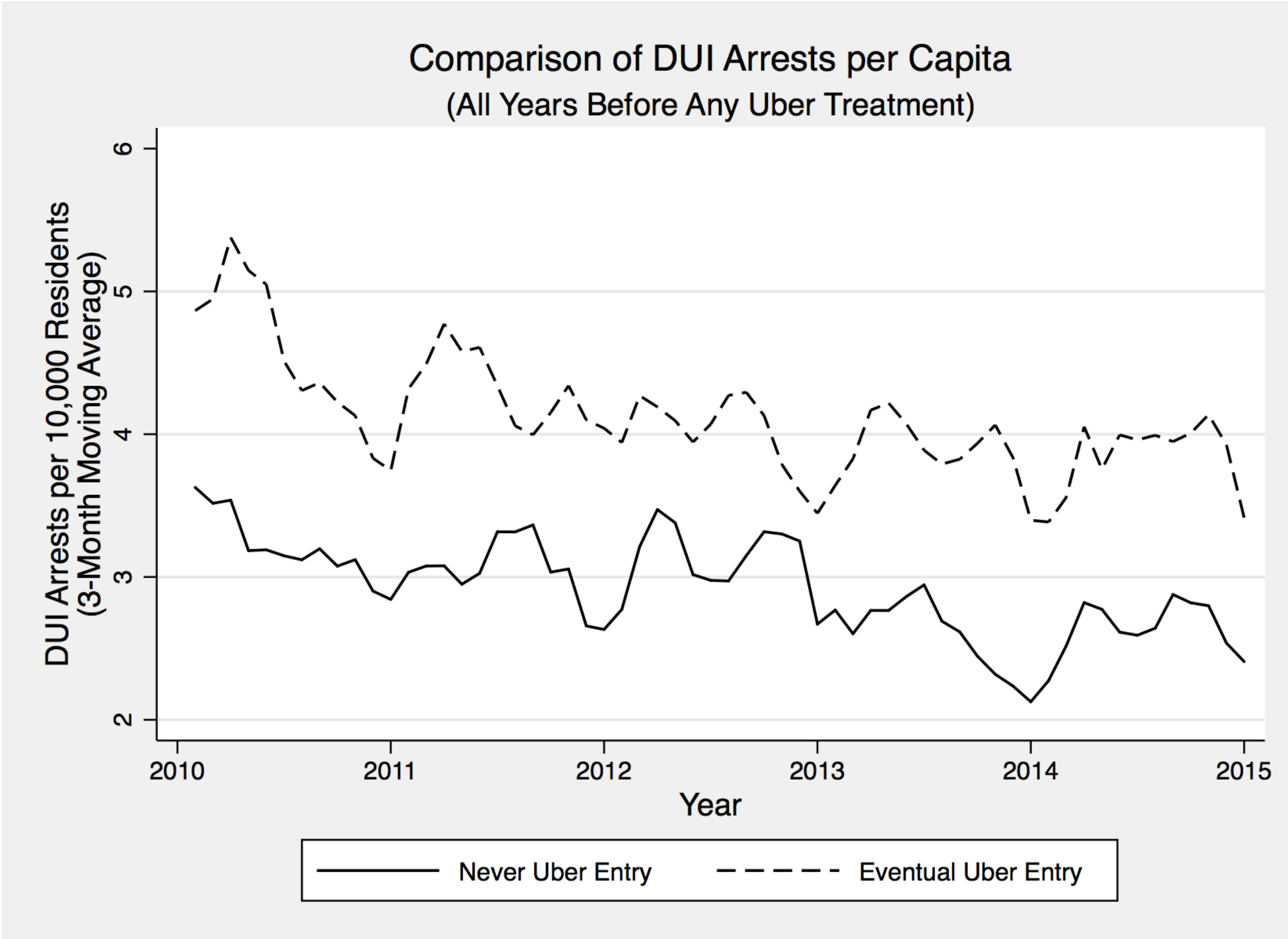


Figure 5 illustrates the parallel trends assumption, comparing the mean of DUIs per capita between counties that never experience Uber entry (solid line) and those that experience eventual Uber entry (dashed line). The 3-month moving average of DUIs per capita is shown. The pre-treatment comparison period shown here extends until February, 2015, when Uber enters Champaign County and treatment is first observed. DUIs per capita is on a per 10,000 residents basis. Observations are by month-year.

5. RESULTS

Figure 6 visually illustrates the association between Uber market entry and drunk driving, suggesting a moderately negative association between Uber and DUI arrests per capita in the four counties that experience significant Uber activity. The graphs show DUIs per capita in the months before and after Uber treatment, with the vertical lines indicating month of Uber entry. Overall, DUIs per capita appear lower in the treatment period, suggesting that Uber has a negative effect. Figures 7 and 8 display changes in mean DUI arrests per capita for all 4 and 3 of the treated counties, respectively. Once again, a post-treatment decline in drunk driving is observed. Regression estimates presented in Tables 7, 8 and 9 support the negative association visually suggested in the figures, estimating a moderately statistically significant, negative association between Uber entry and drunk driving. This association is consistent across both outcome variables (total DUIs and DUIs per capita), as well as specifications with and without time trends.

It is expected that Uber will have a stronger association with DUIs the longer it has been present, given that Uber's market penetration increases over time. I do not attempt to measure this relationship quantitatively through a correlation, but I visually suggest the relationship in Appendix 4. Models 5 and 6 presented in Tables 7 and 8 support this significant negative relationship between Uber trips per capita and DUI arrests per capita.

Table 7 presents regression estimates for three difference-in-difference specifications: total DUI arrests on Uber treatment (0/1), DUI arrests per capita on Uber treatment (0/1), and DUI arrests per capita on Uber trips per capita. Each specification is reported with and without county-specific, linear time trends. The UberX coefficients for Models 1 and 2 are interpreted as the change in the number of DUI arrests experienced as a result of Uber entry, and the coefficients for Models 3 and 4 are interpreted to be the change in number of DUI arrests per capita due to Uber entry. Model 1 estimates that DUIs fall by 11.507 as a result of Uber entry, significant at the 1% level. Adding time trends in Model 2 decreases the magnitude and significance of this estimate, although the coefficient remains negative and statistically distinguishable from 0. Model 3 estimates that Uber entry leads to 3.5 fewer DUIs per 100,000 residents, while Model 4 is the only specification that is not statistically different from 0.

Models 5 and 6 employ both per capita independent and dependent variables, potentially increasing the precision of estimates by incorporating Uber market penetration rather than just entry. The results from these models support the previous estimates of Models 1-4, showing that Uber trips per capita have a significant and negative association with DUIs. Coefficients are statistically distinguishable from 0 at the 5% and 1% levels, respectively.[21]

Table 8 replicates the analysis of Table 7, except Rock Island County is excluded from the sample. Figures 4 and 9 show that Rock Island's DUIs decrease at a faster rate than the other counties in the sample, both before and after Uber entry. This steep decreasing trend may indicate that law enforcement behavior or some other county-specific factor is influencing drunk driving arrests. In order to ensure that Rock Island's steep decreasing trend does not interfere with identification, Rock Island's 6,930 DUI arrests are dropped, and the same six models presented in Table 7 are run again.

The results from Table 8 show that regression estimates excluding Rock Island are consistent with the earlier estimates presented in Table 7. Again, results show that Uber has a moderately significant negative association on both total DUIs and DUIs per capita. Without Rock Island, Models 1 and 6 now estimate coefficients of lesser magnitude than those of Table 7, but of the same direction and comparable significance at the 1% level. Models 2 and 4, which include time trends, now estimate coefficients of larger magnitude, with Model 4 estimating that there are 3 fewer DUIs per 100,000 residents as a result of Uber entry. Model 3 is no longer statistically distinguishable from zero.

From these results, I estimate that Uber entry reduces drunk driving, examined both through total DUIs and DUIs per capita. Specifications that incorporate linear time trends estimate a reduction of 3-4 DUIs as a result of Uber entry, while specifications that omit these trends show Uber reduces 7-11 DUIs, in absolute terms. About 3 DUIs per 100,000 county residents are reduced in per capita terms.

[21] Models 3-6, which employ per capita variables, are weighted according to county population. All standard errors are clustered at the county level, except for the results reported in Table 10 (due to the small number of clusters that would result).

To interpret these results on a percentage basis, I compare the estimated reduction in DUIs to the average number of DUIs in counties that eventually experience Uber entry before treatment, as presented in Table 5. The average number of DUIs per month-year is about 57, so on a percentage basis, a reduction of 3-4 DUIs involves a 5.37-7.29% decline in DUI arrests (with time trends), and a reduction of 7-11 DUIs involves a 12.98-20% decline in DUI arrests (without time trends). In comparison, Martin-Buck (2017) estimates that DUI arrests fall by 8.7-9.2% in cities with low to moderate transit usage as a result of Uber entry.[22] His estimate falls directly between those presented here.

5.1. IMPACT OF UBER BY AGE

I shift my analysis from the association between Uber and total DUIs to DUIs segmented by age cohort to examine whether the negative effect of Uber on drunk driving is observed across all age groups. The four age cohorts examined are individuals younger than 24, 24-29, 30-40, and individuals 41 and older.

The only specification used is total DUI arrests on Uber entry (0/1)—the same specification as Models 1 and 2 from Tables 7 and 8. Estimates are reported with and without time trends. The UberX coefficient is now interpreted as the change in DUIs that the specified age cohort experiences as a result of Uber entry. All models that do not include time trends show that the impact of Uber on drunk driving is negative and statistically distinguishable from 0.

The magnitude of the UberX coefficient is the largest for the youngest age cohort, but this difference among cohorts is understood to be less than a full DUI. In contrast to speculation that Uber will only significantly impact the youngest age cohort due to differences in mobile phone usage, the results show that Uber has a fairly significant impact on reducing DUIs across all age demographics, although the loss of significance with the introduction of county-specific, linear time trends in Models 2, 4, and 6 tempers this interpretation.

[22] Martin-Buck (2017) examines cities while I examine counties. The extent to which our estimates are comparable depends how much of a county's population lies outside of its largest city(s), which I do not calculate. This geographic difference could also explain why some estimated magnitudes are larger.

Martin-Buck (2017) is the only other study to investigate the potentially heterogeneous effects of ridesharing by demographic. He examines whether males aged 21-44 experience a greater reduction in DUIs as a result of rideshare entry. Martin-Buck (2017) estimates that ridesharing does not have a substantively different effect on drunk driving arrests for males aged 21-44. This aligns with my results, as I estimate a negative effect shared across age demographics, with each age cohort examined experiencing approximately 2-3 fewer DUIs in total.

5.2. ENDOGENOUS ENTRY

It is possible that drunk driving behavior is fundamentally different between the counties that Uber chooses to enter and those it does not. To account for the possibility of endogenous entry, I limit the sample to the four counties that Uber eventually enters, exploiting the variation in date of Uber entry (2015, 2016 and 2017). The same three models presented in Tables 7 and 8, both with and without time trends, are presented in Table 10.

Table 10 tells a different story than the previous three tables discussed; all estimates of the association between Uber and drunk driving except for Model 6 are indistinguishable from 0. Table 10, in contrast to the results previously discussed, suggests that Uber market entry and Uber activity does not reduce drunk driving.

Although the results presented in Table 10 deserve consideration, they do not invalidate the findings presented earlier. Limiting the sample to only four counties results in a loss of power, in addition to there only being three entry dates to exploit. Furthermore, the post-treatment observation period is relatively short, given that Uber entered the counties recently. So, while Table 10 suggests that the counties Uber chooses to enter may differ fundamentally in observed drunk driving behavior, the small sample size, lack of variation in treatment timing, and short observation period impacts identification efforts.

Figure 6.

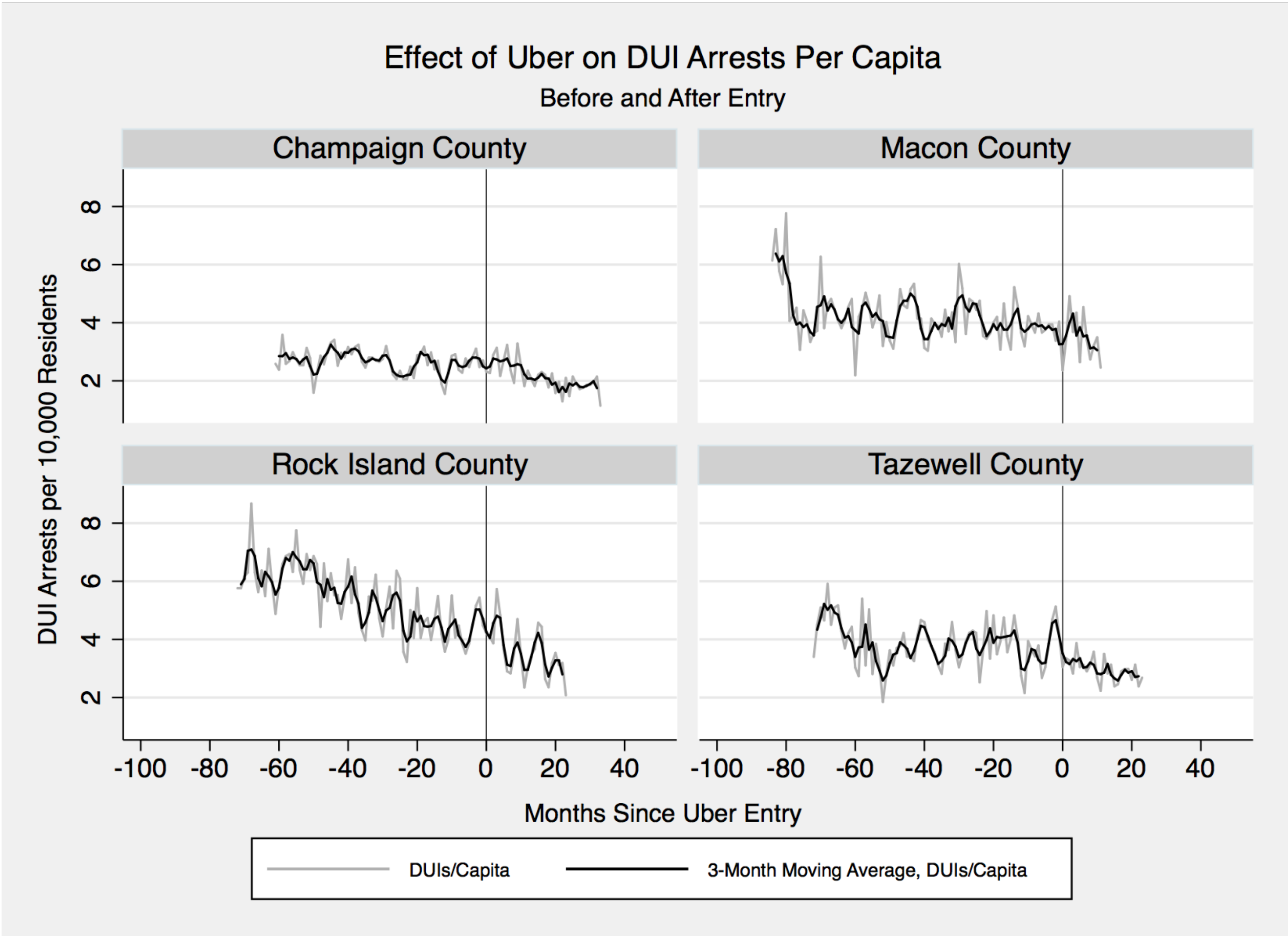


Figure 6 illustrates the effect of Uber on DUI arrests per capita in the four counties that experience Uber entry in the sample. DUIs per capita is on a per 10,000 residents basis. Observations are by month-year. Period 0 and the solid vertical line identify the month-year of Uber entry in the county. The light lines show DUIs/capita, while the dark lines show the 3-month moving average of DUIs/capita. Positive numbers identify the months after treatment, while negative numbers identify the months before treatment.

Figure 7.

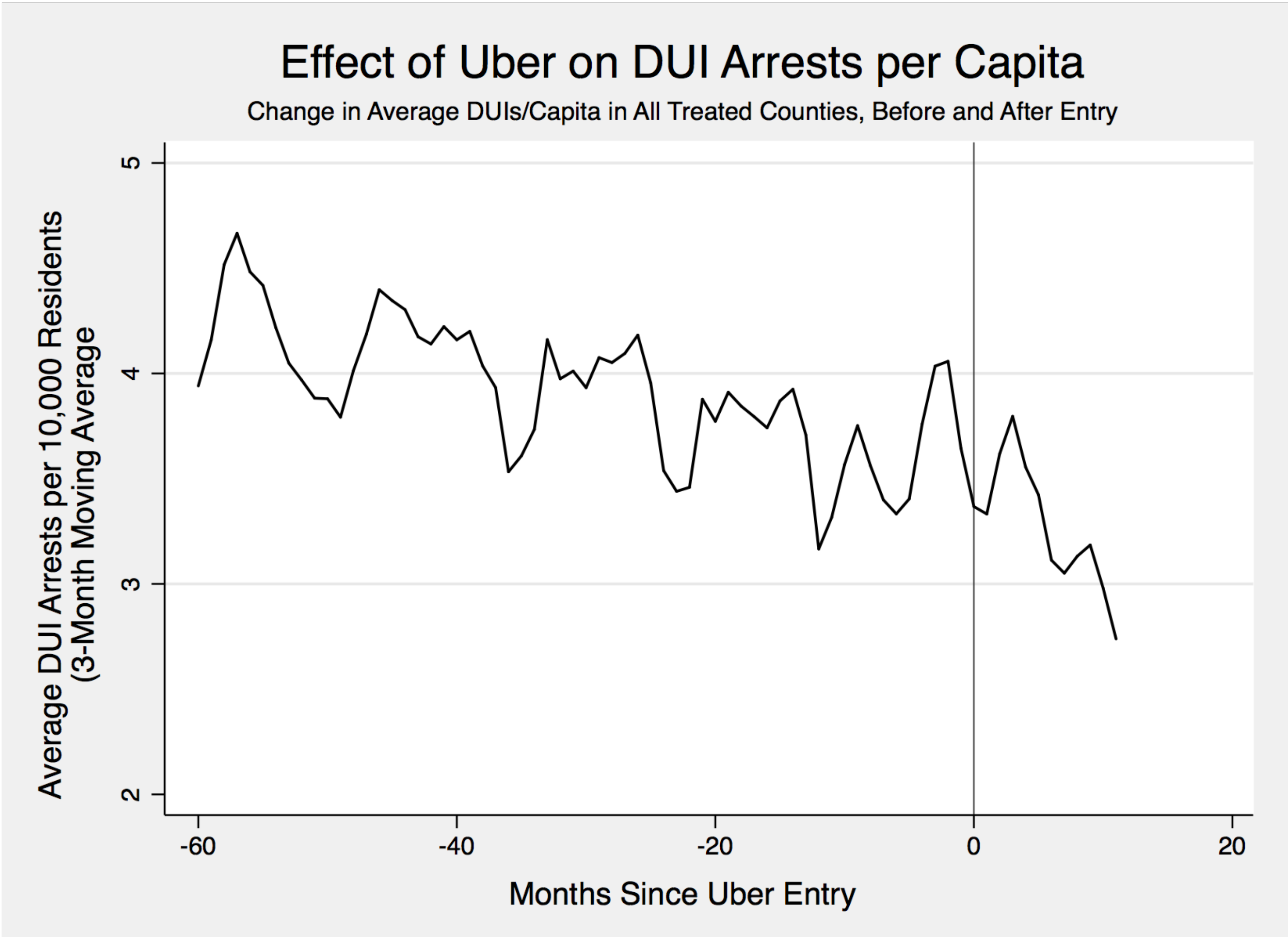


Figure 7 illustrates the effect of Uber on mean DUI arrests per capita of the 4 counties that experience Uber entry in the sample. DUIs per capita is on a per 10,000 residents basis, and shown here as a 3-month moving average. Observations are by month-year. Period 0 and the solid vertical line identify the month-year of Uber entry in the county. Positive numbers identify the months after treatment, while negative numbers identify the months before treatment. On both the pre-and post treatment sides, the line is truncated to accommodate the county with the shortest observation period. For example, while Champaign, Rock Island, and Tazewell have post-treatment periods that extend farther than 12 months, the line must be truncated at 12 months to accommodate Macon County.

Figure 8.

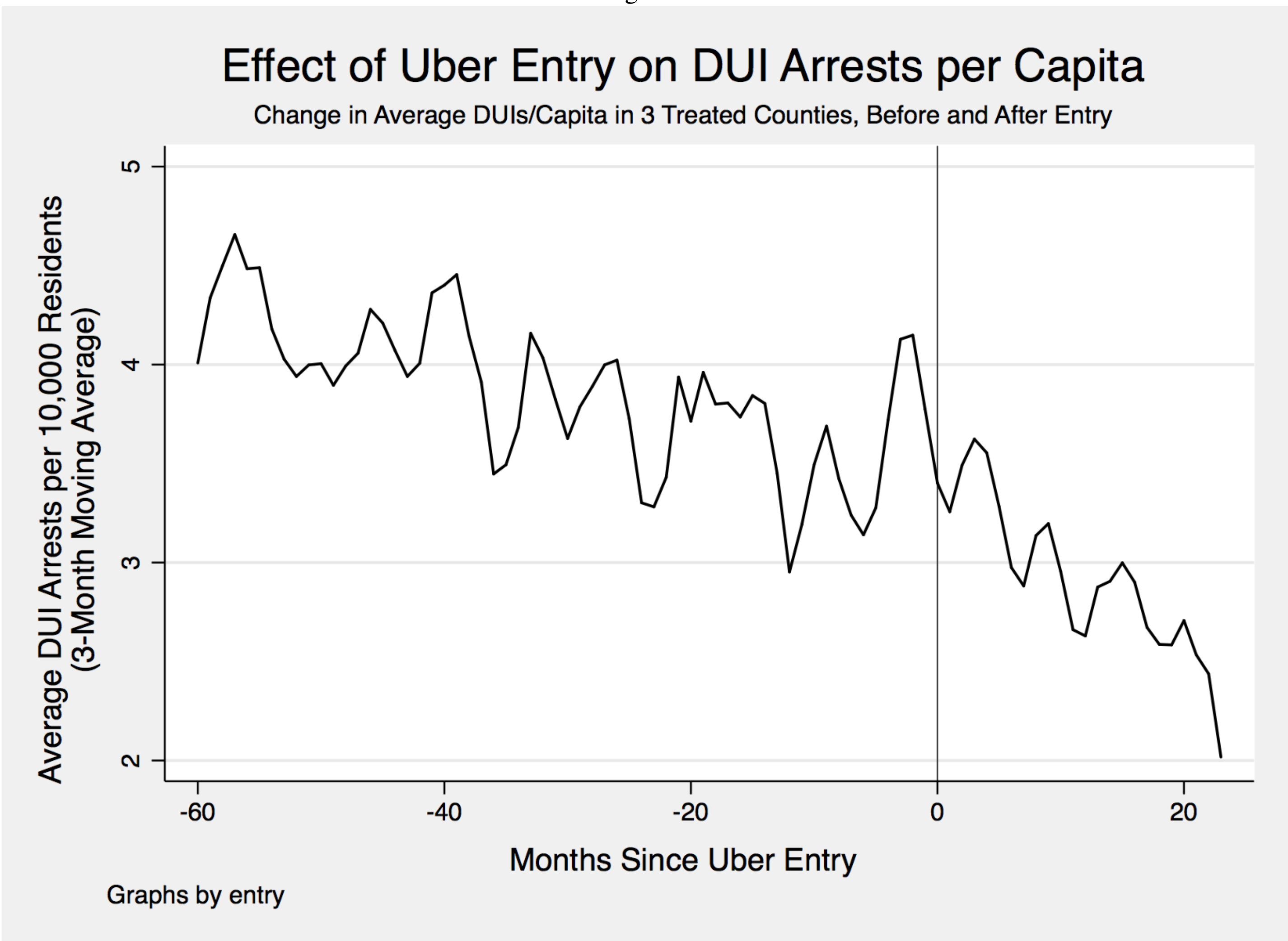


Figure 8 illustrates the effect of Uber on mean DUI arrests per capita for 3 of the counties that experience Uber entry in the sample (Champaign, Rock Island, and Tazewell). Macon is excluded in order to show a longer post-treatment observation period. DUIs per capita is on a per 10,000 residents basis, and shown here as a 3-month moving average. Observations are by month-year. Period 0 and the solid vertical line identify the month-year of Uber entry in the county. Positive numbers identify the months after treatment, while negative numbers identify the months before treatment.

6. DISCUSSION

6.1. ALCOHOL AND DECISION MAKING

I find that Uber entry has a moderately significant impact on reducing drunk driving. The difference-in-differences method employed shows that 3-11 DUIs are prevented as a result of Uber market entry, and about 3 DUIs per 100,000 county residents are prevented. On a percentage basis, a reduction of 3-4 DUIs (with time trends) shows a 5.37-7.29% decline in overall DUIs, and a reduction of 7-11 DUIs (without time trends), shows a 12.98-20% decline. This negative effect is shared across age demographics, as I estimate that each age cohort examined experiences 2-3 fewer DUIs.

It is not surprising that introducing a cheaper and more convenient mode of transportation would lead to fewer individuals making the risky decision to drive drunk. However, it is likely that an estimate of 11 DUIs, or a 20% reduction, is overestimated, a result biased by the steep downward slope of Rock Island. On the other hand, considering an estimated reduction of only 3-4 DUIs, the question arises why the estimated impact of Uber on drunk driving is not larger. To make sense of the magnitudes estimated, an understanding of the mechanisms that influence an individual's decision to drive drunk is required.[23]

A number of factors that influence an individual's decision to drive drunk are speculated, including: the perceived probability of being apprehended, the severity of resulting punishments, the disruption in quality of life or inability to work due to license suspension, peer influence, and the risks of causing harm to oneself, property, or others. These considerations, however, are unobserved in the dataset.

The ridesharing platform is understood to reduce the frictions involved in finding and paying for transit, as the app allows the user to instantaneously pair with a driver and pay through the device. In some instances, ridesharing may be cheaper than alternative forms of transportation, effectively lowering the cost of going out. Yet, comparing the price of driving oneself and the price of ordering a rideshare,

[23] Mechanisms are discussed in brief, but a complete analysis is beyond the scope of this essay.

driving oneself will always be cheaper; only when the perceived risks of engaging in drunk driving outweigh the difference in cost between options will an individual choose to rideshare.

If an individual is unable to accurately assess their level of intoxication and the risks of drunk driving accurately, ridesharing may never be an attractive option. It is possible that ridesharing will only be a substitute transit option for those individuals already choosing not to drive drunk (Brazil and Kirk 2016). Jackson and Owens (2011), the primary study cited to explain the association between transportation decisions and drinking, examine how extending the hours of public transit service impacts DUI arrests in Washington DC. They find considerable heterogeneity across geographic areas: areas where bars are within walking distance to transit stations experience increases in alcohol related arrests and decreases in DUI arrests, but no signs of behavioral change are observed elsewhere.

It is also possible that initial transportation decisions are made before the individual goes out and becomes intoxicated. This means the unimpaired individual weighs perceived risks, and then can plan to take (or not take) transit home. As Martin-Buck (2017) argues, all else equal, improving the ease and convenience of alternative transportation will weakly reduce the number of individuals who optimally choose to drive drunk. With this understanding in mind, estimated magnitudes on the lower end (3-7 total, or a 5.37-12.98% decline) seem reasonable.

6.2. RESOLVING IDENTIFICATION CHALLENGES

Despite using an ideal datasets that observes the number of Uber trips since market entry in fifteen counties, challenges to identifying the association between ridesharing and drunk driving remain. Three identification shortcomings, specifically the influence of law enforcement behavior, the short post-treatment observation period, and the impact of other ridesharing companies, are discussed. I conclude with a discussion of the policy consequences of my findings.

This study employs DUI arrests as the outcome variable to represent drunk driving behavior. Because law enforcement capacity is a county-specific factor that varies over time, this may interfere with identification, potentially biasing results (as was discussed in Section 5). The FBI Uniform Crime

Reporting database reports that in 2014, there were 1.1 million arrests for driving under the influence, while the CDC estimates that over the same time period, there were 121 million incidents of drunk driving (Brazil and Kirk 2016). These statistics make the case that police officers capture drunk drivers according to their enforcement capacity, with officer shortages or a reduction in resources liable to have a significant impact on the number of DUI arrests in a county (Belcher 2017). Further examination of the association between ridesharing and drunk driving could incorporate data on the number of officers in traffic roles over the observation period by county in order to control for changes in enforcement capacity over time.

Another issue with using DUI arrests as an outcome variable is that the population of DUI offenders may not be independently distributed across demographics. For example, if police strategically target certain neighborhoods or roadways, it may lead to low income individuals being disproportionately likely to be arrested for drunk driving. If Uber has a higher usage rate among high income individuals that can afford rideshares, then the association between Uber and drunk driving will be underestimated. Palsson (2017) addresses this possibility when investigating the impact of Uber on public transportation, observing that Uber is likely to have a stronger effect in larger cities where transit riders tend to be wealthier and able to pay Uber fares. Data on the demographics of DUI offenders, such as income and race, could be incorporated in future research in order to extend this initial exploration on the heterogeneous impact of Uber beyond age.

Using arrest data as an outcome variable has shortcomings, but employing fatal crashes as an outcome variable has limitations as well. Previous studies that have used fatal and alcohol-impaired crashes are constrained by the number of crashes observed. Dills and Mulholland (2017), examining counties nationwide, note that about 60% of month-year observations in their sample report zero fatal crashes. Brazil and Kirk (2016), who study the 100 most populated metropolitan areas in the US, also report extreme skewness of traffic fatality data, which includes many observations with few or no fatalities. A dilemma arises: identifying the relationship between ridesharing and drunk driving is especially compelling in low population density regions where Uber is not just a cheaper and more convenient alternative to a taxi or public transportation. These regions, however, lack fatal crash observations, while using arrest data leaves estimates vulnerable to the law enforcement biases described. Neither variable clearly presents itself as the correct choice.

Second, post-treatment observation periods are relatively short in the sample analyzed, given that Uber entered many of the counties recently. Macon County, for example, experienced Uber entry in 2017. Palsson (2017) observes that Uber entry decisions are strongly correlated with population, and this leads to Uber as a whole not being present in regions of low population density for very long. Analysis of the counties sampled may be more compelling given more time to observe their post-treatment state.

Lastly, the entry of other ridesharing companies, specifically Lyft, may impact identification efforts. I use local news sources to estimate when Lyft enters the largest city in each county that experiences significant Uber entry. I find that in all cases, Lyft enters after Uber.[24] This means there is no premature ridesharing in treated counties, but I concede that the UberX coefficient may also capture the additional effect of Lyft. This does not impact my overarching question of how ridesharing effects drunk driving. Market penetration coefficients would underestimate the number of trips occurring in each county.

Regarding the control counties, I am unable to validate whether Lyft is or is not present in each one. Because Uber is the more dominant ridesharing company and Lyft has been observed to follow Uber entry (both in this dataset and across the nation), I reasonably assume that Lyft is not present in counties that are used as controls—but I concede that this is imprecisely estimated. Overall, I conclude that incorporating treatment information from Lyft would not significantly change the estimates presented.

6.3. IMPLICATIONS FOR POLICY AND WELFARE

With rideshares guaranteeing a safe way home, some individuals may have less incentive to drink responsibly, leading to increases in nuisance crimes like public intoxication as a result of Uber market entry. These countervailing effects may offset some of the welfare benefits of reducing drunk driving

[24] https://blog.lyft.com/posts/champaign; Fox Illinois News Team 2017; Colon 2017; Lusvardi 2017.

episodes, but the association is unclear. Some individuals may choose to drink more, but as Jackson and Owens (2011) point out, increased transit options may shift drinking behavior from the home to the bar. Since the marginal cost of alcohol higher at the bar (paying per drink rather than paying per bottle), the impact on consumption behavior remains ambiguous. A complete picture of the welfare consequences of Uber entry would examine these countervailing effects, but such an analysis is beyond the scope of this essay.

In conclusion, lawmakers must weigh a number of factors when making policy decisions that impact ridesharing, including the potential for changes in tax revenue from effected public transit ridership, changes to the number of cars on the road, and the creation or disruption of employment opportunities. The intensity of these factors varies by city, many of which have approached ridesharing in their own unique way. In Chicago, for example, Mayor Rahm Emanuel has implemented a 15-cent rideshare tax to generate revenue (Byrne 2017), while other policymakers have proposed subsidizing rideshares as a method to curb drunk driving (Reilly 2015; Radin 2017).

In this essay, I empirically show that ridesharing has the ability to reduce drunk driving. This finding deserves consideration when making policy choices that make it easier or harder for ridesharing companies to operate in a county. Furthermore, because I observe that the impact of ridesharing is shared across age groups, policy decisions implicating ridesharing companies are understood to not only involve the youngest constituents, but all residents.

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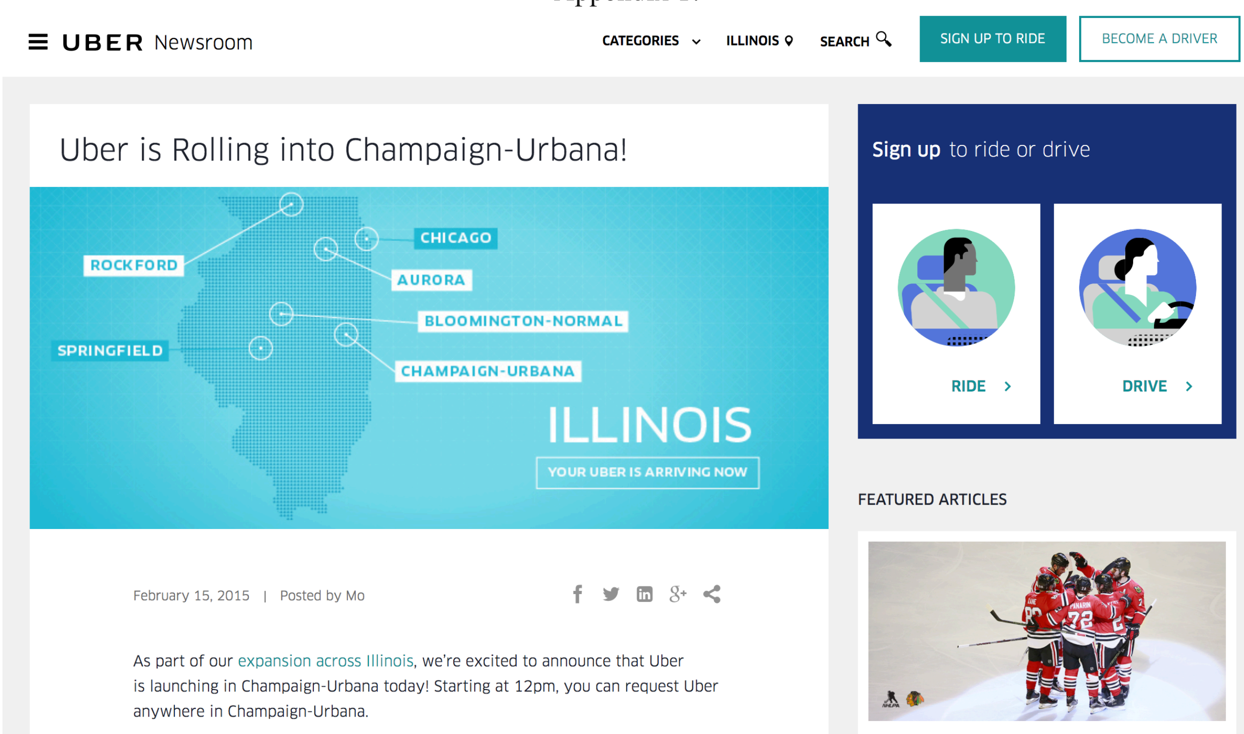
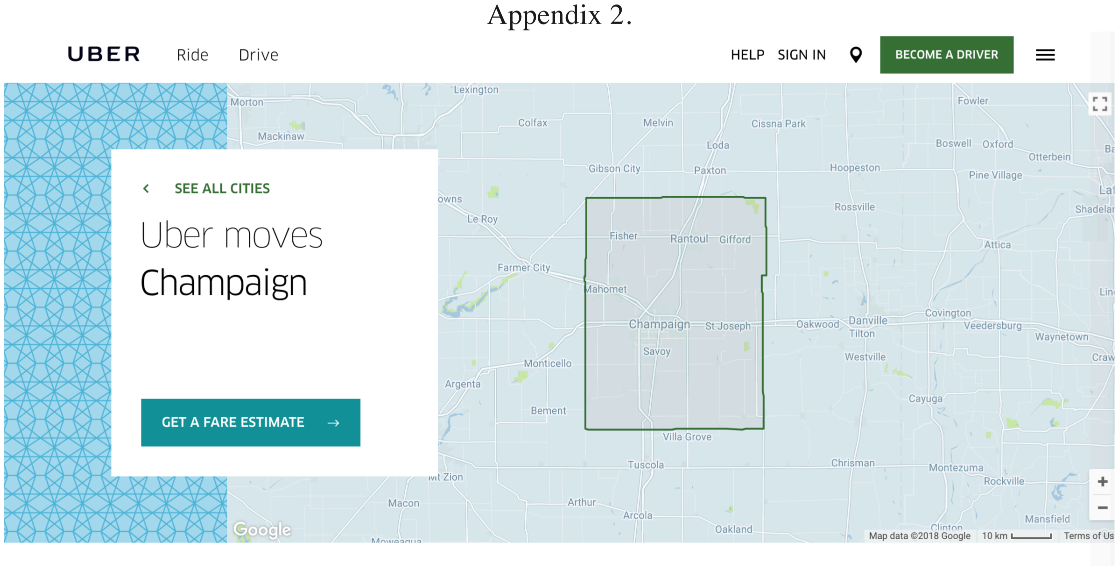
APPENDIX

Appendix 1.



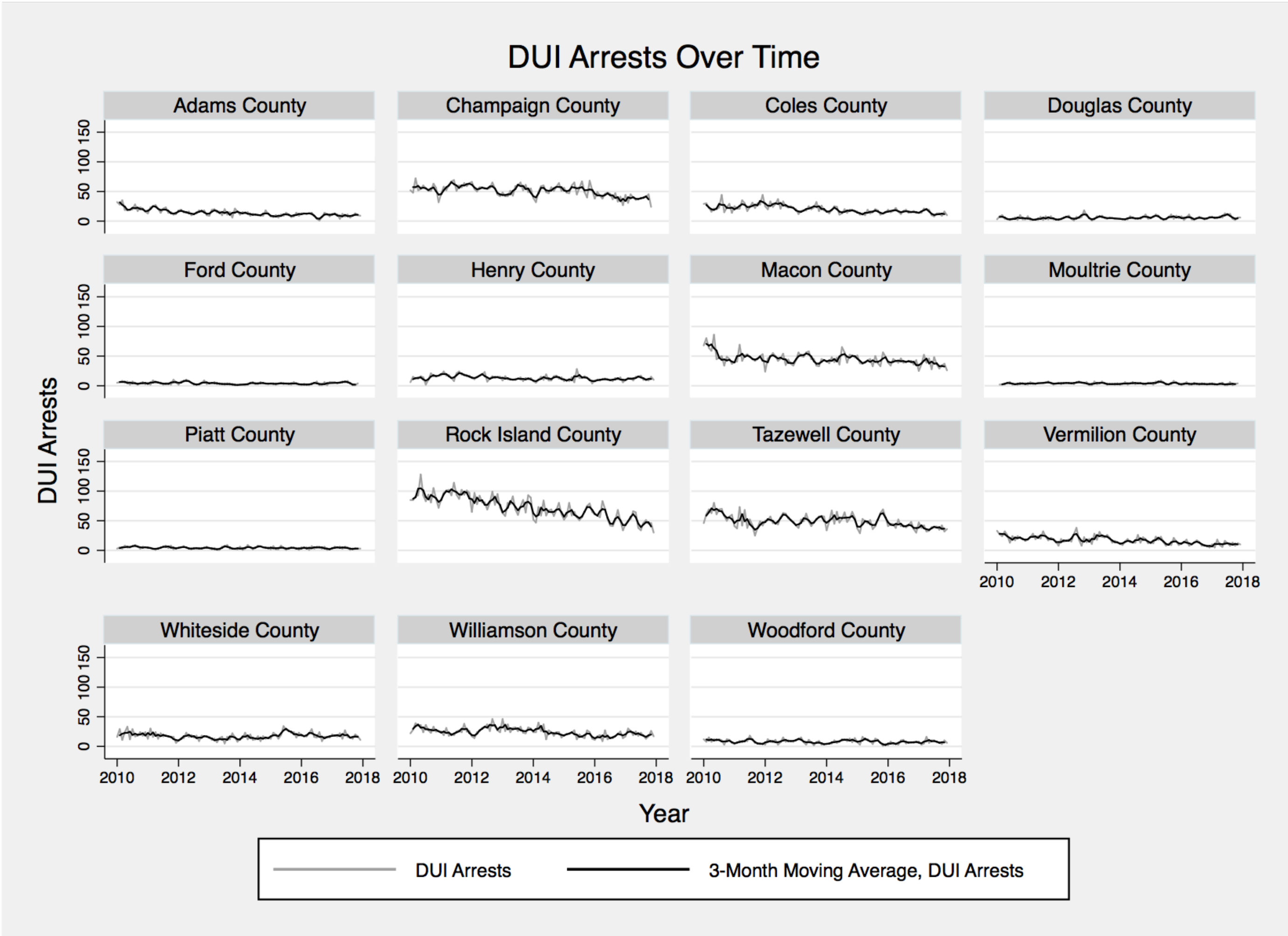
Appendix 1 shows the initial announcement on the Uber blog of market entry in Champaign-Urbana, emphasizing service just for the city.
https://newsroom.uber.com/us-illinois/uber-is-rolling-into-champaign-urbana/

Appendix 2.



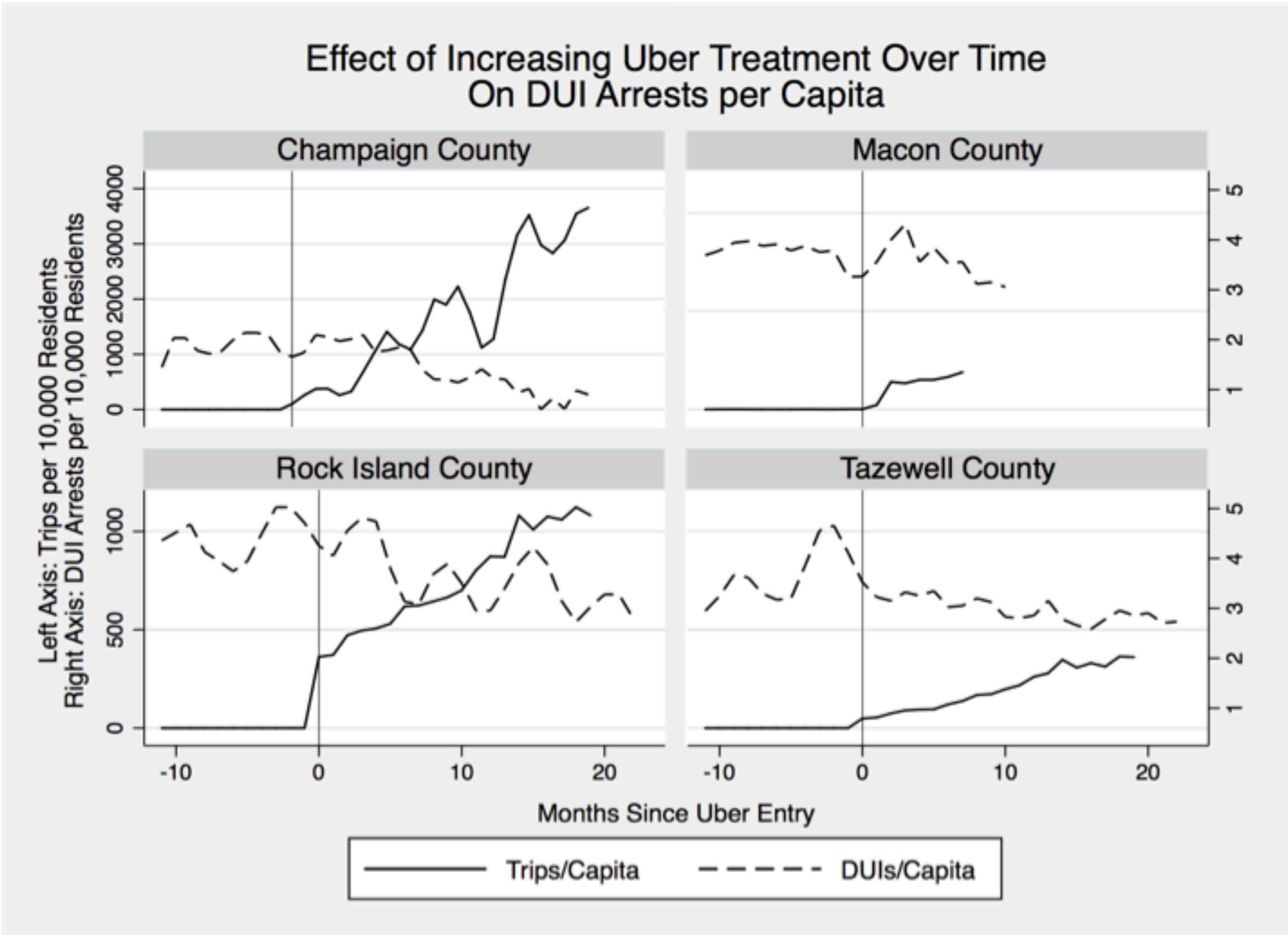
Appendix 2 shows the current service area displayed on the Uber website, emphasizing service throughout the whole county.
https://www.uber.com/cities/champaign

Appendix 3.



Appendix 3 shows total DUI Arrests from 2010-2017 for all counties sampled. Observations are by month-year. The light lines show DUIs/capita, while the dark lines show the 3-month moving average of total DUIs.

Appendix 4.



Appendix 4 shows UberX trips per capita over time for the 4 counties that experience significant Uber activity, as represented by the solid line corresponding to the left axis, and DUI arrests per capita, as represented by the dashed line corresponding to the right axis. Both per capita variables are on a per 10,000 residents basis. Observations are by month-year. Period 0 and the solid vertical line identify the month-year of Uber entry in the county. Positive numbers identify the months after treatment, while negative numbers identify the months before treatment. The figure suggests that greater market penetration over time leads to larger decreases in DUIs.

Table 1: DUI Arrests by County, 2010-2017

County	**DUI Arrests**	**% of Total**
Adams	1,350	4.05%
Champaign*	4,825	14.46%
Coles	1,925	5.77%
Douglas	528	1.58%
Ford	385	1.15%
Henry	1,243	3.73%
Macon*	4,314	12.93%
Moultrie	352	1.05%
Piatt	411	1.23%
Rock Island*	6,930	20.77%
Tazewell*	4,706	14.10%
Vermilion	1,620	4.86%
Whiteside	1,669	5.00%
Williamson	2,334	6.99%
Woodford	775	2.32%
Observations	33,367	100%

Asterisks(*) identify counties with eventual Uber entry.
Source: Champaign County State's Attorney and Public Records

Table 2: DUI Arrests by Age Cohort, 2010-2017

Age Cohort	**DUI Arrests**	**% of Total**
<24	7,499	22.47%
24-29	7,805	23.39%
30-40	9,381	28.12%
41<	8,674	26%
Observations	33,359	100%

Percents do not sum to 100 because they are rounded at two digits.
Observations where age can not be identified are dropped.
Source: Champaign County State's Attorney and Public Records

Table 3: County Descriptive Statistics

County	**Population (2016)**	**Population per Square Mile**	**High School Diploma (%)**	**Median Age**	**Median Household Income**	**Unemployment Rate (2016)**
Adams	66,578	78.5	91.7	41.1	$48,065	4.8
Champaign*	208,419	201.8	94.7	29.5	$48,889	5.1
Coles	52,343	106	90.2	33.6	$38,800	5.9
Douglas	19,630	48	84	38	$52,984	4.7
Ford	13,575	29	88.8	43.4	$49,257	5.5
Henry	49,280	61.3	88.9	42.3	$54,757	6.1
Macon*	106,550	190.8	89.6	40.7	$47,477	6.6
Moultrie	14,827	44.2	84.1	40.7	$51,432	4.6
Piatt	16,560	38.1	95.2	43.3	$69,160	5.0
Rock Island*	144,784	345	88.6	40.1	$50,208	6.3
Tazewell*	134,385	208.6	92.8	40.6	$60,178	6.3
Vermilion	78,111	90.9	87.2	32.6	$43,552	7.2
Whiteside	56,536	85.5	88.7	42.8	$49,151	5.8
Williamson	67,560	157.9	90.2	40.9	$45,902	6.2
Woodford	39,140	73.3	94	40	$68,040	5.4

Asterisks(*) identify counties with eventual Uber entry.
Source: Median Age from American FactFinder, US Census Bureau. Unemployment Rate from Bureau of Labor Statistics. All other statistics from QuickFacts, US Census Bureau.

Table 4: Comparison of County Descriptive Statistics

	No Uber Entry				**Uber Entry**			
	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum
Population (2016)	43,104	23,710	13,575	78,111	148,535	43,062	106,550	208,419
Population per Sq. Mile	73.9	36.8	29	157.9	236.6	72.7	190.8	345
High School Diploma (%)	89.4	3.5	84	95.2	91.4	2.8	88.6	94.7
Median Age	39.9	3.7	32.6	43.4	37.7	5.5	29.5	40.7
Median Household Income	\$51,918	\$9,351	\$38,800	\$69,160	\$51,691	\$5,767	\$47,477	\$60,178
Unemployment Rate (2016)	5.56	.8	4.6	7.2	6.1	.7	5.1	6.6
Total Counties	11				4			

Source: Median Age from American FactFinder, US Census Bureau. Unemployment Rate from Bureau of Labor Statistics. All other statistics from QuickFacts, US Census Bureau.

Table 5: Summary Statistics: DUI Arrests

	No Uber Entry	Uber Entry		
		0	1	All
Average Monthly DUI Arrests (per 10,000 residents)	2.75	4.10	2.87	3.80
Average Monthly DUI Arrests	12.00	57.55	44	54.22
Total Arrests (2010-2017)	12,591			20,768

Uber Entry refers to counties that Uber eventually enters.
0 identifies the time period before treatment in counties that Uber eventually enters.
1 identifies the treatment period in counties that Uber eventually enters.
Source: Champaign County State's Attorney and Public Records

Table 6: Population and Uber Entry

County	**Population** (2016)	**Uber Entry** (Date Observed)
Champaign	208,419	February, 2015
Rock Island	144,784	January, 2016
Tazewell	134,385	January, 2016
Macon	106,550	January, 2017
Vermilion	78,111	
Williamson	67,560	
Adams	66,578	
Whiteside	56,536	
Coles	52,343	
Henry	49,280	
Woodford	39,140	
Douglas	19,630	
Piatt	16,560	
Moultrie	14,827	
Ford	13,575	

Source: QuickFacts, US Census Bureau.

Table 7: Impact of Uber Market Entry on Drunk Driving Arrests

	All Counties Included, Outcome Variables Indicated					
	(Model 1) DUI Arrests	(Model 2) DUI Arrests	(Model 3) DUIs/Capita	(Model 4) DUIs/Capita	(Model 5) DUIs/Capita	(Model 6) DUIs/Capita
UberX	-11.507***	-3.091*	-0.355***	-0.198		
	(1.341)	(1.679)	(0.104)	(0.125)		
Trips/Capita					-0.00011**	-0.00026***
					(0.00005)	(0.00007)
County Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Time Trends		✓		✓		✓
N	1,432	1,432	1,432	1,432	1,432	1,432
R^2	0.906	0.928	0.669	0.72	0.666	0.721

Standard errors in parentheses. All errors clustered at the county level.

All per capita variables calculated on a per 10,000 residents basis.

Models 3-6 weighted according to county population.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Impact of Uber Market Entry on Drunk Driving Arrests

	Rock Island Excluded, Outcome Variables Indicated					
	(Model 1) DUI Arrests	(Model 2) DUI Arrests	(Model 3) DUIs/Capita	(Model 4) DUIs/Capita	(Model 5) DUIs/Capita	(Model 6) DUIs/Capita
UberX	-7.470***	-4.197**	-0.067	-0.311**		
	(1.170)	(1.827)	(0.088)	(0.132)		
Trips/Capita					-0.00003	-0.00023***
					(0.00004)	(0.00007)
County Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Time Trends		✓		✓		✓
N	1,336	1,336	1,336	1,336	1,336	1,336
R^2	0.894	0.905	0.546	0.579	0.546	0.58

Standard errors in parentheses. All errors clustered at the county level.
All per capita variables calculated on a per 10,000 residents basis.
Models 3-6 weighted according to county population.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Impact of Uber Market Entry on Drunk Driving Arrests by Age Cohort

	All Counties Included, All Outcome Variables: DUI Arrests							
	(Model 1) **<24**	(Model 2) **<24**	(Model 3) **24-29**	(Model 4) **24-29**	(Model 5) **30-40**	(Model 6) **30-40**	(Model 7) **41<**	(Model 8) **41<**
UberX	-3.277***	-0.214	-3.001***	-0.094	-2.567***	-1.078	-2.660***	-1.696**
	(0.525)	(0.696)	(0.530)	(0.679)	(0.492)	(0.744)	(0.463)	(0.758)
County Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Month-Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Time Trends		✓		✓		✓		✓
N	1,432	1,432	1,432	1,432	1,432	1,432	1,432	1,432
R^2	0.772	0.811	0.795	0.835	0.830	0.845	0.794	0.800

Standard errors in parentheses. All errors clustered at the county level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of Uber Market Entry on Drunk Driving Arrests

	Sample Limited to Counties Uber Eventually Enters, Outcome Variables Indicated					
	(Model 1) DUI Arrests	(Model 2) DUI Arrests	(Model 3) DUIs/Capita	(Model 4) DUIs/Capita	(Model 5) DUIs/Capita	(Model 6) DUIs/Capita
UberX	-0.114	1.571	-0.024	0.007		
	(2.737)	(2.574)	(0.206)	(0.195)		
Trips/Capita					0.000001	-0.002*
					(0.000066)	(0.00012)
County Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Time Trends		✓		✓		✓
N	383	383	383	383	383	383
R^2	0.726	0.799	0.768	0.827	0.768	0.828

Standard errors in parentheses.

All per capita variables calculated on a per 10,000 residents basis.

Models 3-6 weighted according to county population.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$