An Exploration on the Social Benefit of the Minimum Legal Drinking Age

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Abstract

The United States of America imposes a minimum legal drinking age of 21 years old on its citizens. The effectiveness of this minimum age will be measured in terms of community safety. Using data from the National Institute of Health and Safety, the effectiveness of the minimum drinking age is tested in preventing underage drinking. Finding that a reduction of 7.6% in underage drinking can attributed to the law, the paper then addresses if the law is an effective reducer of crime. Using California crime rates for various crimes, a strong connection established between drinking and increases in crime rates. There is an increase of 104.8 arrests per 10,000 person-years attributed to turning 21, which can be tied to the legal drinking age. This leads us to the interpretation that minimum legal drinking age effectively reduces the amount of alcohol consumed by underage individuals and in hand reduces crime that would be attributed to alcohol consumption. An IV estimate is produced in order to observe a local treatment effect of the MLDA on crime rates, as a method to create a more quantifiable effect estimate. The IV estimate produces a local treatment effect of 893 arrests per 10,000 person years, however this estimate is put under scrutiny due to limitations of the information used.

1 Introduction

The United States of America has a long history of debate surrounding the safety of alcohol consumption. With historical policy ranging from allowing 18 year old's to drink, to a nationwide ban for individuals of all ages. While other countries may have drinking laws allowing for individuals to beginning legally consuming alcohol as young as 16, there are fundamental differences between these countries and the United States. The minimum legal drinking age, referenced as MLDA, was established to be 21 years old by congress in 1984 through the National Minimum Drinking Age Act. Since then, there have been calls to lower the minimum legal drinking age. With groups such as the Amethyst Initiative stating the MLDA is ineffective as lowering underage drinking. Counter arguments for keeping the MLDA at 21 are focused on maintaining safety and reducing crime. The paper will address if the MLDA is an effective way to reduce drinking in underage individuals, and if the MLDA reduces crime.

Data from the National Health Interview Survey, NHIS, as well as national crime rates are used to determine the answers to our questions. The NHIS provides information on individuals age and if they have consumed alcohol within the last month. This gives a basis for estimating the drinking participation for various ages. The crime data is assembled from the California monthly citation and arrest register, giving information on arrest rates for individuals. We are able to observe the age and crime being arrested for. This data includes arrests for a selection of crimes, some alcohol related and some non-alcohol related, as well as a total arrests column.

Using data from the NHIS we are able to create a regression discontinuity in order to approximate the difference the MLDA makes in drinking rates. While we see a clear difference when comparing prior to 21 drinking rates and post 21 drinking rates, of approximated 7.9

percentage points. While there is a significant reduction in drinking assigned to the MLDA, we still see approximately 51.6% of individuals are have drank alcohol prior to turning 21. The large portion of underage drinking still occurring is an important aspect of the argument of the MLDA's effectiveness.

From arrest data we are able to use a difference in differences approach to view the change in crime rates of individuals pre and post turning 21. Here we assume that turning 21 has nearly no other effects on an individual besides allowing for them to legally drink alcohol. With this assumption in hand, then we are able to assign these changes in arrest rates to the MLDA. Here we observe a strong jump in nearly all types of crime. DUI, drunk risk to self, and aggravated assault appear to maintain higher levels after turning 21, however the other categories, disorderly conduct and vagrancy, robbery, and simple assault, all appear to return to their prior levels given time.

Our results indicate that the MLDA does have a meaningful reduction in underage drinking, and reduces the crime rate overall. We can then discuss the assumptions needed for an IV estimate. Performing an IV estimate using the NHIS data as a first stage with arrest data as a reduced form. While the MLDA evidently does not eliminate underage drinking or drinking related crime, it does serve as a significant tool in reducing these factors. However to address the questions raised, the MLDA does reduce drinking in underage individuals and does reduce crime.

2 Data

The data used in this paper comes from the National Institute of Health and Safety, or NHIS, and national arrest data. The data used from the NHIS contains characteristic variables, including age, alongside various drinking metrics. Important data entries in the NHIS data include are an individuals days till turning 21, whether or not they have drank alcohol within the last moth, and what percent of days they report having drank alcohol. This data allows for us to compare drinking rates and various demographics, however not without flaw. Due to the self reported nature of this data, we understand that bias is most likely contained in the data. It is understandable that individuals may not want to identify themselves as having consumed alcohol or may downplay how frequently they consume alcohol. Additionally, binge drinking is commonly seen as an undesirable behavior, encouraging individuals to under report their true amount of drinks consumed. Finally, we could see bias due to the nature of alcohol consumption, where an individual who partook in consuming alcohol may not accurately remember the their drinking habits. We observe an introduction of classical measurement error as well with the NHIS data regarding birth dates. Due to privacy regards, the NHIS protects birth dates and introduces slight changes to birth dates. This implies that the slope estimates will be slightly lower that what they should be.

Arrest data allows for us to observe crime rates per 10,000 person-years according to age. This data is sourced from California's Monthly Arrest and Citation Register from 1979 to 2006. We focus on the rates for individuals ranging from age 19 to 23. The arrest data frames crime rates in terms of days until turning 21, allowing for our analysis to center turning 21 at 0. Important features of the data focused on alcohol related crimes are DUI, drunk risk to ones self, and violation of liquor laws. Each of these crimes are tied directly alcohol consumption, as being charged with any of them required consuming alcohol. We also have data on total crime rate, both simple and aggravated assault, and disorderly conduct. While these crimes do not need alcohol to be committed, it is worth exploring the natural tie between alcohol consumption and these crimes. As this data is taken from national crime rates, it is unlikely to have any bias introduced during its collection process. Using this data we are able to explore the alterations in crime rates following individuals turning 21.

3 Empirical Methods

Upon using both the NHIS and arrests data to create graphs of age against having drank alcohol and age against all arrests, a regression discontinuity became a clear choice. The first step of the process was to group the data into more manageable data points. Given thousands of observations in our data sets, NHIS and arrest data, the we started by selecting a bin size and bandwidth for our regressions. The approach used to find a proper bin size was through graphing the NHIS data of age against our drinks alcohol variable at a variety of bin sizes. Using a variety of sizes ranging from 10 to 200, I selected a bin size of 50, what I felt to be a mix of visually acceptable while still providing an adequate amount of plotted points. The bandwidth was selected in a similar manner. Graphs exploring various bandwidths were created in order to aid in the visual decision making process. Here we also must be conscious of selecting a bandwidth size that is not too small, as to ensure prior trends are not being excluded. The bandwidth size selected was 2 years on either side of 21, giving us a range from 19 to 23. A larger bandwidth size captures changes in patterns that may be leftover from turning 18, and a smaller bandwidth does not give adequate information. The same bandwidth and age range were used for both sets of data to give an equivalent comparison, y range was adjusted for visual clarity. The y range of .45 to 0.7 for the MLDA data was selected in as to give a small amount of white space between the top and bottom data points and the top and bottom of the graphs. In the Crime data we used a y range of 0 to 300 for displaying alcohol related crimes and 0 to 100 for non-alcohol related crimes, as these ensured all respective points were included.

With a selected bin and bandwidth, the focus shifts to running our regression discontinuity. We estimate the treatment effect of the MLDA on drinking using the NHIS data through the following regression equation:

$$Drinks\_Alcohol_i = \rho_0 + \rho_1 * Over21_i + g * (Age_i - 21) + \epsilon_i$$

. We can address the variables at play, starting with our estimated variable, $Drinks\_Alcohol_i$. In our NHIS data regressions, $Drinks\_Alcohol_i$ represents the percentage likelihood of an individual partaking in alcohol consumption within the last month at a given age. Entering the right hand side, ρ_0 is our intercept. This intercept would be the expected value at 19 of our regressions as our bandwidth begins at age 19. Moving to $\rho_1 * Over21_i$, we are able to understand this as defining the new intercept for individuals who are 21 and over. The discrete binary variable, $Over21_i$ is either 0 or 1 depending on if the individual, i, is under 21 or over 21 respectively. So when an individual is over 21 we find our new intercept as $\rho_0 + \rho_1$. Continuing, $g * (Age_i)$ is a placeholder representation of the expansion of the equation with respect to age into its linear, quadratic or cubic forms. Finally we have our error term, ϵ_i, which is representative of non observable characteristics.

Moving to the arrest data, we estimate the effects on crime rates in regards to turning 21. In our arrest data we have $Arrests_i$ representing the estimated amount of crimes committed by individuals of a certain age on amounts of per 10,000 person-years. As our desired output we establish the general equation for regression equations over the arrest data:

$$Arrests_a = \phi_0 + \phi_1 * Over21_a + h * (Age_a - 21) + \nu_a$$

. The equation for arrest data differs from that of the NHIS data due to the facts the arrest data uses crimes in terms of grouping. The age range of input and bin size are identical for both regressions, however the y range varies due to different magnitudes. The variables ϕ_0 is the intercept at age 19, and we find the intercept at age 21 through $\phi_0 + \phi_1$. The regression gives us a visible discontinuity through the use of the $Over21_a$ variable, which is a discrete variable taking the value of 0 if the age is below 21 and 1 if the age is over 21. The general form of $h * (Age_a - 21)$ is representative of the linear, quadratic and cubic expansions of this regression. A cubic polynomial was used in the final approximations. After a visual comparison of linear, quadratic and cubic, it was apparent that the cubic best fit the data without over or understating the effects. we must include an error term for omitted variables, ν_a.

Using the two regressions we have created a first stage and reduced form estimate for the effectiveness of the MLDA on reducing crime. The first stage is given by the measurement of the discontinuity in drinking rates for age 21. We can then scale our crime reduction estimate from the arrest data regression to estimate the local effect of crime reduction.This allows us to create an IV estimate of the effects of the MLDA on reducing crime. By using the following equation for IV estimates:

$$IV = \frac{Reduced\ Form}{First\ Stage}$$

The IV estimate produces a scaled estimate of the reduced form in attempt to observe what the local effect of the MLDA is. Because we do not expect perfect compliance with the MLDA, and would like to measure what the effect of the MLDA is on crime, we scale the crime rate estimate by the effectiveness of the MLDA. Using the IV estimate gives a better idea of what the effectiveness of the MLDA would be if enforced over the population. However due to the nature of the population being observed, we can only say this estimate is accurate for the population of individuals who comply with the MLDA. The individuals who follow the MLDA are being estimated by this IV process.

4 Results

Beginning with our analysis on the effectiveness of the MLDA, we will be using the NHIS data. We can split our data into two categories, observations on individuals age 19 up to 21, and individuals age 21 to 23. From this data we generate two cubic regressions, one for each side of age 21. The regressions estimate the percentage of individuals who drink at given age. There is a visual discontinuity shown in Figure 1, with a noticeable increase in population of alcohol drinkers post turning 21. The regression coefficients of both cubic functions are displayed in table 1. Here we see a statistically significant correlation between being under 21 and not drinking alcohol. The level of alcohol consumption is statistically significant at a p value of less than 0.01, indicating high correlation between being over 21 and drinking alcohol. The t-stat of our observation appears at 2.69, an alternative description of our statistical significance. The increase observed alcohol drinking at 21 in the regression is estimated at approximately 7.9%. The regression estimates that approximated 53.2% of individuals under 21 will have consumed alcohol, and approximated 62% of individuals will have consumed alcohol after turning 21. Now we must ask the question if the MLDA can be attributed to this reduction in alcohol consumption prior to age 21. When considering what changes occur upon turning 21, there appear to be very few beyond the legal consumption of alcohol. Because of the limited effects of turning 21 beyond legal alcohol consumption, it encourages the idea that the MLDA is the force at hand when viewing a lowered amount of underage drinking.

Our initial question set out measure the portion of underage drinking the MLDA effectively stops. With our regressions we estimated that 7.9% of the population is likely not drinking alcohol due to the MLDA. While the appears to be ineffective in stopping a very large portion of the population, there is still an undeniable increase attributed due to turning 21. With this information we are able to continue to estimate the crime reduction effects of the MLDA. It is important that we established a measurable reduction in alcohol consumption attributed to the MLDA to establish relationships in , with this in mind we can view changes in crime rates.

Through the use of arrest data and the NHIS we can approach measuring the effect of the MLDA on reducing crime rates. We would like to begin with ensuring that the NHIS data is properly balanced, to ensure there is not large amounts of bias prior to exploring the other regressions. In table 2 we have a balance table to observe regressions run on the characteristics provided in the NHIS data. Importantly, we can observe that the data contains balanced observations for individuals before and after 21. There are no characteristics that we see a statistically significant difference in observations at the cut off of 21 years old. We must also address the issue of multiple inference. With 4 independent variables being observed, at a 0.05 confidence level, we have $1-(1-0.05)^4 = 0.1855$, or an 18.55% chance of failing to capture one of the true means. This would mean that there is a chance one of the variables does have a statistically significant increase but we failed to capture it in our data, and while 18.55% may be unlikely it is very far from impossible. Assuming the NHIS data is not heavily skewed, and aware of the potential for errors, we can continue to measuring the effects of turning 21 on crime rates, especially those related to alcohol. In figure 2 the crime rate per 10,000 person-years is plotted against age. While a seemingly downward trend is evident, at turning 21 there is a very large discontinuity. With evidence of an upward shock in all crime at turning 21 years old, it is important to observe if any certain types of crime are overtly responsible for this increase. We divide the types of crimes into two categories, alcohol related and other. Alcohol related crimes are crimes in which alcohol are typically tied into being charged with, for this data we have: DUI (driving under the influence), drunk risk to self, and disorderly conduct/vagrancy. In figure 3 the two types of crime are graphed with linear regressions paired onto both sides of 21. These graphs allow for easy visualization on the effects of turning 21 and alcohol related crimes. As expected there is an increase in alcohol related crimes, predictably through the increase in alcohol drinkers upon turning 21 as seen through the NHIS data.

Observing a visual increase in crimes after turning 21, now it is appropriate to explore the statistical significance of turning 21 on crimes. In table 3 we generate cubic regressions over each crime recorded in regards to age. We add a control variable for birthday, which indicates if it was an individuals birthday. The reasoning for controlling for birthday comes from the idea that it is common practice to engage in binge drinking, visiting bars or partying, all of which may encourage an individual to commit a crime. Within table 3, we observe a statistically significant effect of turning 21 on each crime. The highest t-stat observed is accounted for by Liqor Law Violations with a t-stat of -52.21, accounting for a very seriously correlated decrease in arrests. We have a t-stat of 11.98 for DUI, followed by drunk risk to self at 6.04. Our other alcohol related crime, liquor law violations sees a decrease upon turning 21, presumably due to a decrease in underage drinking arrests. While disorderly conduct, our last of the three alcohol related crimes saw a statistically significant increase, the magnitude of the t-stat was comparable to other crimes. Simple assault sees the highest t-stat of the non-alcohol related crimes, with a t-stat of 5.41. The t-stat for all arrests comes in at 6.7, representing that turning 21 does have an effect on the number of arrests. It is clear that a statistically significant relationship between crimes and turning 21 exists.

Incorporation of the birthday variable is evidently more significant in the arrest data than in the NHIS data. There is a clear trend of an increase in arrests on an individuals 21st birthday compared to being 21. All crimes see a statistically significant increase except for robbery. Because we are accounting a birthday variable we are able to increase the legitimacy of our results, as this effect is being properly accounted for. The various factors that come into play of turning 21 make it difficult to attribute the increase in crime directly to the MLDA. Activities such as visiting bars and going to clubs open individuals to a variety of other factors that very well may increase their likelihood of committing a crime. However when observing the alcohol related crimes, it is evident that a reduction is made in individuals under 21. Because alcohol is a key part of the crimes, we are able to better explain that the MLDA is effective at reducing crime, especially those related to alcohol. The total crime increase observed after turning 21 comes out to be an increase of approximately 105 arrests per 10,000 person-years.

5 Conclusion

Evidently, the consumption of alcohol is partially responsible for an increase in crimes. We are also able to view the MLDA producing an effective reduction in alcohol consumption for approximately 7.9% of the population immediately before turning 21. We use this information in combination to produce an answer to the questions raised in the beginning of the paper. The MLDA is effective at reducing the alcohol consumption rate, accounting for a difference of 7.9% as mentioned. We address the second question, and interpret the MLDA as method of reducing crime by approximately 105 arrests per 10,000 person-years. Due to the low amount of compliance with the MLDA, observing nearly 51% of individuals having drank alcohol recently before turning 21, we turn to an IV estimate to produce a local treatment effect. The IV will allow us to observe what the effects of the MLDA are on individuals who follow the law, not drinking until turning 21. Before performing an IV regression we must address if certain assumption about the data are met. First we can assume that the MLDA's effect on alcohol consumption does have an effect on crimes that have a correlation to alcohol consumption. However we run into an issue when we must assume that there is no correlation between the MLDA and the outcome variable, the arrest rate. The MLDA is a factor of violation of liquor laws, directly effecting a portion of the arrest rate. With these precautions raised, we can still perform an IV regression using the NHIS regression's difference in intercepts at 21 as our first stage and the difference in estimated arrest rates as our reduced form. For all arrests, this provides us with an estimated local treatment effect of 893.74328 per 10,000 person-years. In terms of a per person arrest rate, we view an 8.9% increase in likelihood of being arrested for a crime after turning 21. However, it is important to raise doubts when discussing the IV estimator. Due to possible bias implemented within our NHIS data and turning 21 having effects beyond legal alcohol consumption, we must question the validity of our estimate. Without narrowing of our effects displayed within the reduced form estimates to only alcohol consumption, it is misleading to perform an IV estimate. Instead it is more proper to keep our estimates separated, leaving the question of the MLDA's effect on crime rates to be unable to be answered properly using the data selected.

6 Figures

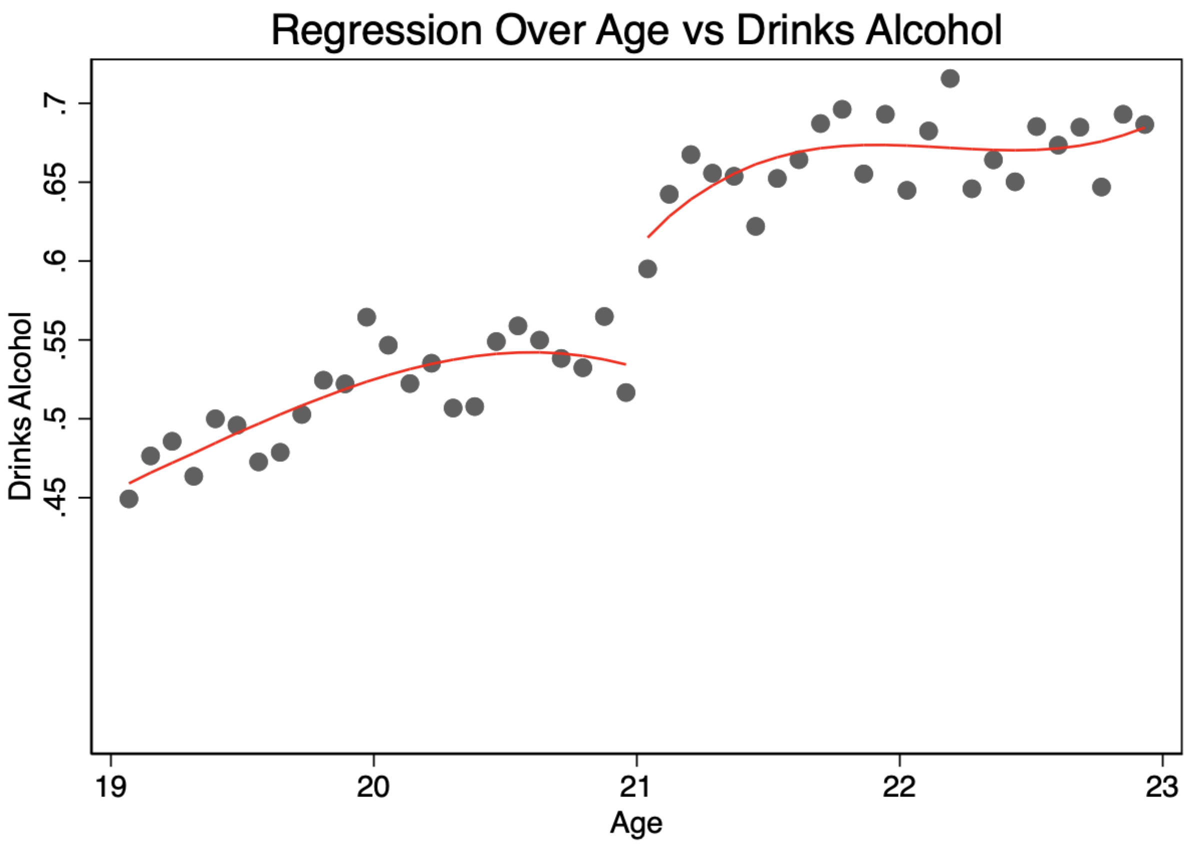

Figure 1: Age profile of having drank alcohol in the last month

Table 1: Linear, Quadratic and Cubic Regression Coeffecients

	(1) Drinks Alcohol	(2) Drinks Alcohol	(3) Drinks Alcohol	(4) Drinks Alcohol	(5) Drinks Alcohol	(6) Drinks Alcohol
Over 21	0.0866***	0.0866***	0.0908***	0.0901***	0.0815**	0.0794**
	(6.09)	(6.07)	(4.22)	(4.16)	(2.80)	(2.69)
Age	0.0439***	0.0439***	-0.0236	-0.0236	-0.0509	-0.0509
	(4.76)	(4.76)	(-0.64)	(-0.64)	(-0.55)	(-0.55)
Age*Over 21	-0.0243*	-0.0243	0.0969	0.0982*	0.207	0.215
	(-1.96)	(-1.96)	(1.95)	(1.96)	(1.65)	(1.70)
Age^2			-0.0340	-0.0340	-0.0681	-0.0681
			(-1.89)	(-1.89)	(-0.63)	(-0.63)
$Age^2 * $ Over 21			0.00727	0.00673	-0.0618	-0.0695
			(0.30)	(0.28)	(-0.43)	(-0.48)
Age^3					-0.0114	-0.0114
					(-0.32)	(-0.32)
$Age^3 * $ Over 21					0.0457	0.0479
					(0.96)	(1.00)
Birthday		0.00192		0.0206		0.0360
		(0.02)		(0.25)		(0.43)
Constant	0.559***	0.559***	0.536***	0.536***	0.532***	0.532***
	(53.44)	(53.43)	(34.03)	(34.03)	(24.92)	(24.92)
Observations	18801	18801	18801	18801	18801	18801
R^2	0.025	0.025	0.025	0.025	0.025	0.025

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Characteristics Coeffecient Comparisions

	(1) Graduated Highschool	(2) Employed	(3) Hispanic	(4) Black	(5) White
Over 21	0.0203	0.0304	0.0138	-0.0251	-0.00273
	(0.89)	(1.07)	(0.55)	(-1.18)	(-0.09)
Age	0.0182	-0.0305	-0.106	0.0543	0.0956
	(0.24)	(-0.34)	(-1.33)	(0.81)	(1.04)
Age*Over 21	-0.00405	0.0788	0.0882	-0.0588	-0.0976
	(-0.04)	(0.64)	(0.81)	(-0.64)	(-0.77)
Age^2	0.0585	-0.0578	-0.133	0.0507	0.129
	(0.67)	(-0.55)	(-1.44)	(0.65)	(1.20)
$Age^2 * $ Over 21	-0.0583	0.0458	0.140	-0.0250	-0.122
	(-0.50)	(0.32)	(1.11)	(-0.24)	(-0.83)
Age^3	0.0341	-0.00710	-0.0449	0.0155	0.0431
	(1.17)	(-0.20)	(-1.47)	(0.61)	(1.22)
$Age^3 * $ Over 21	-0.0373	0.00978	0.0455	-0.0272	-0.0466
	(-0.98)	(0.21)	(1.10)	(-0.78)	(-0.96)
Constant	0.806***	0.615***	0.224***	0.166***	0.571***
	(47.37)	(29.58)	(12.35)	(10.58)	(26.92)
Observations	18801	18801	18801	18801	18801
R^2	0.003	0.014	0.000	0.000	0.000

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

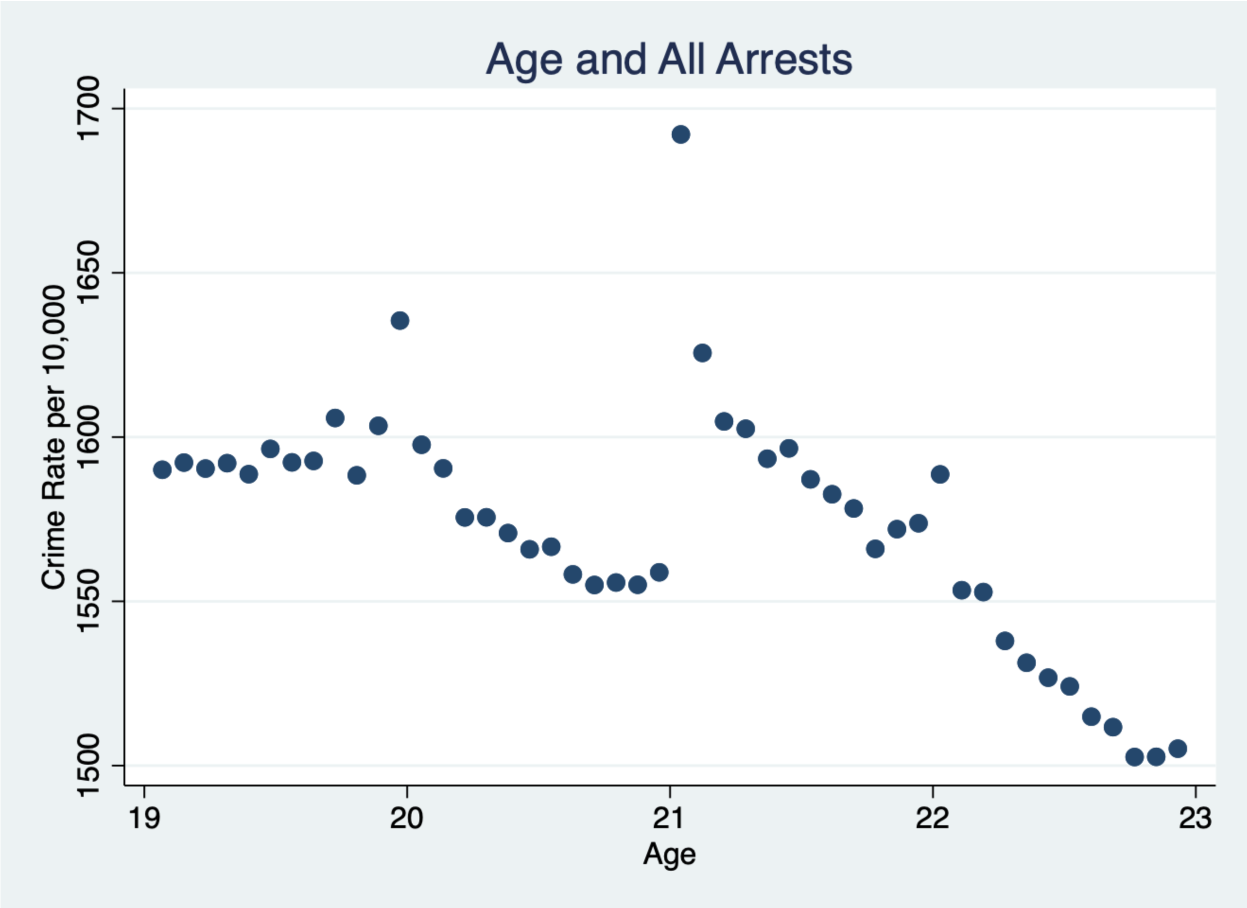

Figure 2: Age profile of drinking figure

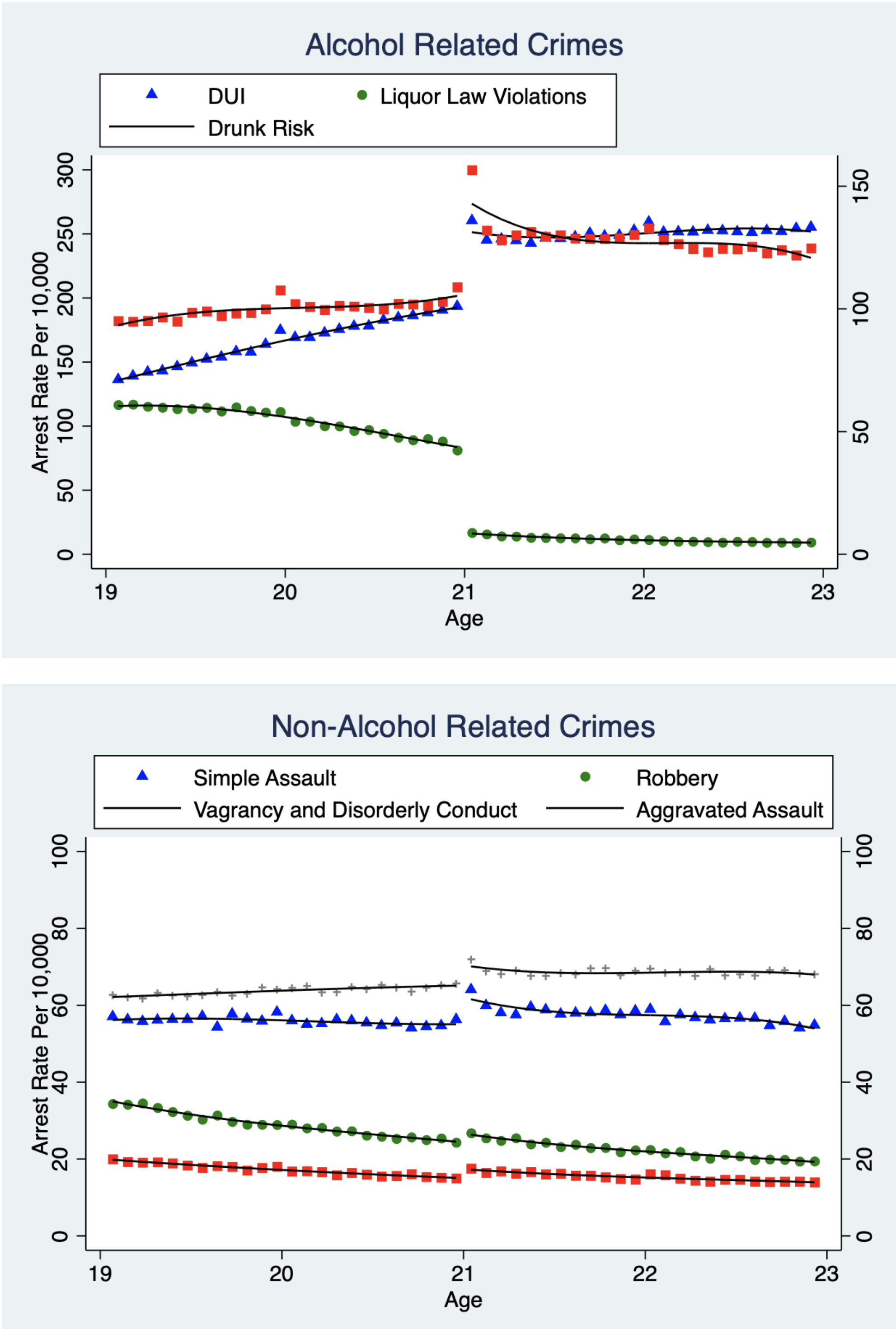

Figure 3: Crime Rates per 10,000 with cubic regressions overlaid

Table 3: Regressions of Different Arrests

	(1) DUI	(2) Drunk Risk to Self	(3) Liquor Law Violations	(4) Vagrancy	(5) Robbery	(6) Simple Assault	(7) Aggravated Assault	(8) All Arrests
Over 21	57.19***	36.35***	-65.65***	2.003***	2.161***	6.616***	4.776***	104.8***
	(11.98)	(6.04)	(-52.21)	(3.58)	(4.28)	(5.41)	(4.66)	(6.70)
Age	17.78**	9.394	-28.10***	-2.308	-4.048*	-1.569	-0.0174	-52.17*
	(3.25)	(1.82)	(-5.45)	(-1.56)	(-2.49)	(-0.62)	(-0.01)	(-2.43)
Age*Over 21	-34.00	-46.18*	19.57***	0.829	-2.475	-8.632	-4.265	-106.4
	(-1.85)	(-2.03)	(3.69)	(0.36)	(-1.07)	(-1.74)	(-0.96)	(-1.75)
Age^2	-11.49	6.371	-0.868	-0.492	-0.200	-0.516	-1.886	1.711
	(-1.72)	(1.04)	(-0.15)	(-0.29)	(-0.10)	(-0.17)	(-0.55)	(0.06)
$Age^3 * \text{Over 21}$	36.04	24.44	4.512	-0.179	2.780	10.08	6.054	91.31
	(1.90)	(1.06)	(0.74)	(-0.07)	(1.00)	(1.86)	(1.18)	(1.44)
Age^3	-2.991	2.147	2.286	-0.333	-0.477	-0.134	-0.608	8.559
	(-1.29)	(1.01)	(1.17)	(-0.59)	(-0.68)	(-0.13)	(-0.53)	(0.89)
agec_post_cu	-5.035	-10.93	-2.897	0.690	-0.114	-3.140	-0.602	-35.95
	(-0.88)	(-1.59)	(-1.44)	(0.83)	(-0.12)	(-1.82)	(-0.36)	(-1.85)
Birthday	126.0***	190.4***	4.889***	15.06***	4.961***	36.69***	23.21***	616.9***
	(27.25)	(32.25)	(16.20)	(33.96)	(13.03)	(33.99)	(28.98)	(41.10)
Constant	193.0***	105.2***	82.09***	14.98***	24.35***	54.81***	65.02***	1546.4***
	(164.01)	(90.62)	(67.25)	(43.74)	(73.47)	(95.30)	(101.60)	(354.90)
Observations	1460	1460	1460	1460	1460	1460	1460	1460
R^2	0.943	0.691	0.990	0.341	0.720	0.154	0.249	0.518

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1) DUI	(2) Drunk Risk to Self	(3) Liquor Law Violations	(4) Vagrancy	(5) Robbery	(6) Simple Assault	(7) Aggravated Assault	(8) All Arrests
Over 21	59.92***	40.48***	-65.54***	2.330***	2.269***	7.412***	5.280***	118.2***
	(11.20)	(5.71)	(-52.05)	(3.65)	(4.46)	(5.20)	(4.72)	(5.91)
Age	17.78**	9.394	-28.10***	-2.308	-4.048*	-1.569	-0.0174	-52.17*
	(3.25)	(1.82)	(-5.45)	(-1.56)	(-2.49)	(-0.62)	(-0.01)	(-2.43)
Age*Over 21	-44.26*	-61.68*	19.17***	-0.397	-2.879	-11.62*	-6.154	-156.6*
	(-2.16)	(-2.31)	(3.61)	(-0.15)	(-1.24)	(-2.05)	(-1.29)	(-2.05)
Age^2	-11.49	6.371	-0.868	-0.492	-0.200	-0.516	-1.886	1.711
	(-1.72)	(1.04)	(-0.15)	(-0.29)	(-0.10)	(-0.17)	(-0.55)	(0.06)
$Age^3 * \text{Over 21}$	46.30*	39.95	4.911	1.048	3.184	13.07*	7.945	141.6
	(2.20)	(1.48)	(0.81)	(0.37)	(1.14)	(2.15)	(1.47)	(1.80)
Age^3	-2.991	2.147	2.286	-0.333	-0.477	-0.134	-0.608	8.559
	(-1.29)	(1.02)	(1.17)	(-0.59)	(-0.68)	(-0.13)	(-0.53)	(0.89)
agec_post_cu	-8.032	-15.46	-3.013	0.332	-0.232	-4.013*	-1.154	-50.62*
	(-1.27)	(-1.93)	(-1.50)	(0.37)	(-0.25)	(-2.11)	(-0.66)	(-2.13)
Constant	193.0***	105.2***	82.09***	14.98***	24.35***	54.81***	65.02***	1546.4***
	(164.07)	(90.66)	(67.27)	(43.76)	(73.49)	(95.33)	(101.63)	(355.02)
Observations	1460	1460	1460	1460	1460	1460	1460	1460
R^2	0.938	0.622	0.990	0.321	0.719	0.113	0.236	0.426

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$