

Effect of Cannabis Legalization on US Autism Incidence and Medium Term Projections

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ABSTRACT

Objective: In that cannabis use has been linked with the development of autism spectrum disorder like conditions in gestationally exposed children, we set out to explore the extent to which rising cannabis use might contribute to the rising autism epidemic.

Methods: Datasets from US Department of Education Individuals with Disabilities Act (IDEA), National Survey of Drug Use and Health, and CDC's Autism and Developmental Disabilities Monitoring (ADDM) Network were investigated. Data on legal status was derived from SAMHSA.

Results: IDEA had N=1,023 and ADDM N=87. Modelling of IDEA consistently showed that models quadratic-in-time out-performed linear-only models (ANOVA $p < 2.0 \times 10^{-16}$). In both datasets liberalization of cannabis legislation was associated with increased ASD ($p < 10^{-9}$ and $p < 0.05$ respectively). Slopes of: ASD *vs.* time, Cannabis *vs.* time and ASD *vs.* cannabis curves were shown to be related on graphical analysis by geofacet plots and tanglegrams (entanglement=0.3326). CDC's ADDM network quoted US autism incidence 168/10,000 in 2014. IDEA projections indicated rates 108.57, 131.67 and 166.49 in cannabis-illegal, -medical and -decriminalized states rising exponentially to 282.37, 396.91 and 455.54 by 2030.

Conclusion: ASD is the commonest form of cannabis-associated clinical teratology. Using two independent datasets and two categorization methods we confirmed that medical, decriminalized and legal cannabis regimes are associated with higher rates of ASD than illegal ones. Findings are consistent with molecular, cellular and epigenetic mechanisms. Formerly quadratic regression curves become exponential when projected forwards to 2030; predict a lower quantum than the 2014 ADDM CDC figure; and indicate a 60% excess of cases in legal states by 2030.

Keywords: Cannabis; Cannabinoids; Cannabidiol; Cannabinol; Cannabichromene; Tetrahydrocannabinol

Abbreviations: ADDM: Autism and Developmental Difficulties Monitoring from CDC; ASD: Autism Spectrum Disorder; CB1R: Cannabinoid Type 1 Receptor; CDC: Centers for Disease Control; IDEA: US Department of Education Individuals with Disabilities Act; NSDUH: National Survey of Drug Use and Health; Robo: Roundabout, a guidance molecule receptor for axonal growth cones and arterial endothelial tips; SAMHSA: Substance Abuse and Mental Health Services Administration; Slit: Slits 1-3, arterial and axonal guidance molecule and ligand for Robo; + : An additive operator for regression calculations; ~ : Tilde, a middle sign separating the two sides of a regression calculation; *: Asterisk, an operator used in regression calculations to include additive and interactive relationships.

INTRODUCTION

Recent reports from several sources indicate that the incidence of Autistic Spectrum Disorder (ASD) has been growing significantly in most USA jurisdictions in recent decades [1-3]. Although

the cause is not completely understood, periconceptual and perigestational exposures including genetic and epigenetic factors are believed to play an important role [4-6]. Older parents, affected siblings, time between births, exposure to some drugs, particularly anticonvulsants and SSRI antidepressants and folic acid deficiency

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have all been implicated [4-6]. So too has cannabinoid exposure [7,8].

This opens the possibility that the recent rise in the use of cannabinoids across the USA may be linked to the disturbing rise in the prevalence of autism [9]. Such a link achieves public health importance in the light of large numbers of pregnant American women who are exposed to cannabis, reaching 161,000 in 2017 [10], the frequent recommendation of cannabis dispensaries to pregnant users to consume cannabis during gestation [11], and the positive test or affirmation of cannabis use by 25% of Californian teenage mothers [12].

The USA provides a useful opportunity to epidemiologically assess the putative association of cannabis in autism pathogenesis as the Substance Abuse and Mental Health Services Administration (SAMHSA) report strong negative trends for all other drug use in USA, but strong upward trends in cannabis use across the country [10, 13]. This has the effect at the epidemiological level of isolating the effect of cannabis in statistical analyses.

Given that a number of leading USA public health organisations have published data showing that pro-cannabis legalization paradigms are associated with increased rates of cannabis use [14], we investigated if these trends in individual states cannabis use were associated with increased incidence of ASD. The reader should note that it is our view that a putative link between prenatal cannabis use and ASD is already established by both mechanistic and longitudinal epidemiological studies which have been published in the literature. The question we set out to address was to what extent these putative relationships might be reflected in the extant epidemiological data on this subject.

METHODS

Data

Data on autism incidence rates at eight years of age was obtained from two sources. The major source was the US Department of Education Individuals with Disabilities Act (IDEA) Network and was sourced from [3]. The Network for Autism and Developmental Disabilities Monitoring (ADDM) based at CDC was also accessed from [2,3]. The IDEA dataset includes 1,023 points in 51 US states including the District of Columbia at annual intervals from 1991-2011. The ADDM dataset includes 87 data points 2000-2014 in selected states in eight cycles at two yearly intervals. As one metric is derived from schools and the other from clinical services the two rates used are not directly comparable.

Data on drug use was sourced from the National Survey of Drug Use and Health (NSDUH), which is an annual household survey conducted by SAMHSA [10]. Data on the legal status of cannabis in the various US states was derived from two sources, firstly an internet search of historical sources, and secondly an address by the Director of SAMHSA on 4th February 2019 [15] which provided details on the legal status of cannabis by state at that time.

Statistics

Desktop R from CRAN v3.5.2 was used for all analyses which were done in R Studio 1.1.463, performing regressions and preparing graphs and maps. Continuous variables were log transformed to optimize normality assumptions as guided by the Shapiro test. Linear regression was conducted in the classical manner by progressive manual model reduction by deletion of the least

significant term. Model diagnostics were checked in each case in R. Geofaceted graphs were prepared using the geofacet package v0.1.9 and tanglegrams (interacting dendrograms) were prepared using dendextend v0.1.9 and cluster v2.0.7.1 and factoextra v1.0.5 amongst other packages. Bivariate choropleth maps were prepared using the colorplaner package v0.1.4 and ggplot2 v3.1.0. The R function predict in the stats package which comes with Base R was used for simple model forward projections. $p < 0.05$ was considered significant.

Ethics

Ethical permission to undertake this study was granted from the Human Research Ethics Committees of the Southcity Medical Centre and the University of Western Australia.

RESULTS

Figure 1 presents choropleth maps of cannabis use, ASD and both cannabis and autism together across USA by state. Figure 1C is a bivariate choropleth map. Purple and pink shading indicate regions where both cannabis and autism are high such as California, Oregon and Vermont. Most of the bivariate map is green indicating that both signals are simultaneously low.

The time courses of both cannabis and autism (IDEA data) are presented for each US state in Supplementary Figures 1-4. Supplementary Figure 1 shows the time course of autism in 25 states with names from A to M plotted on an ordinate axis which is constant throughout. Supplementary Figure 2 shows a similar plot for the remaining 24 states with names from M to W. Supplementary Figure 3 shows the last month cannabis use rate for states over time for the alphabetically first 25 US states A to M. Supplementary Figure 4 shows similar cannabis use data for states M to W.

Figure 2 is a geofaceted plot showing the time course of autism rates and cannabis use, both of which have been scaled to make them comparable. The advantage of this format is that the data for each state appears separately and overplotting does not occur. Readers who may be interested in a particular American state can readily examine the pattern in their state and how this compares to that seen in nearby states. The figure clearly shows evidence of rising cannabis use rates and concurrently rising autism states in most states. This pattern is emphasized by the inclusion of regression lines for each plot.

Figure 3 shows the IDEA data categorized by legal status firstly by data from SAMHSA (A) and secondly using historical documentation of when each state transitioned into medical or legal use derived from an internet search (B). In each case the figures show clear separation of the autism rate in each legal category. This graphical demonstration suggests analysis by transformed autism rate over time.

Table 1 presents some of the regressions from Figure 3A, many of which achieve high levels of statistical significance. Figure 3A appears to be of quadratic form and one notes in Table 1 that the R-squared values are higher for regressions quadratic in time rising from about 0.78 to about 0.82. This superiority is confirmed at Anova testing (AIC-linear=321.89, AIC-Quadratic=272.30, $dF=1$, $F=185.63$, $p < 2.0 \times 10^{-16}$).

Table 2 presents the results of the linear regressions from Figure 3B.

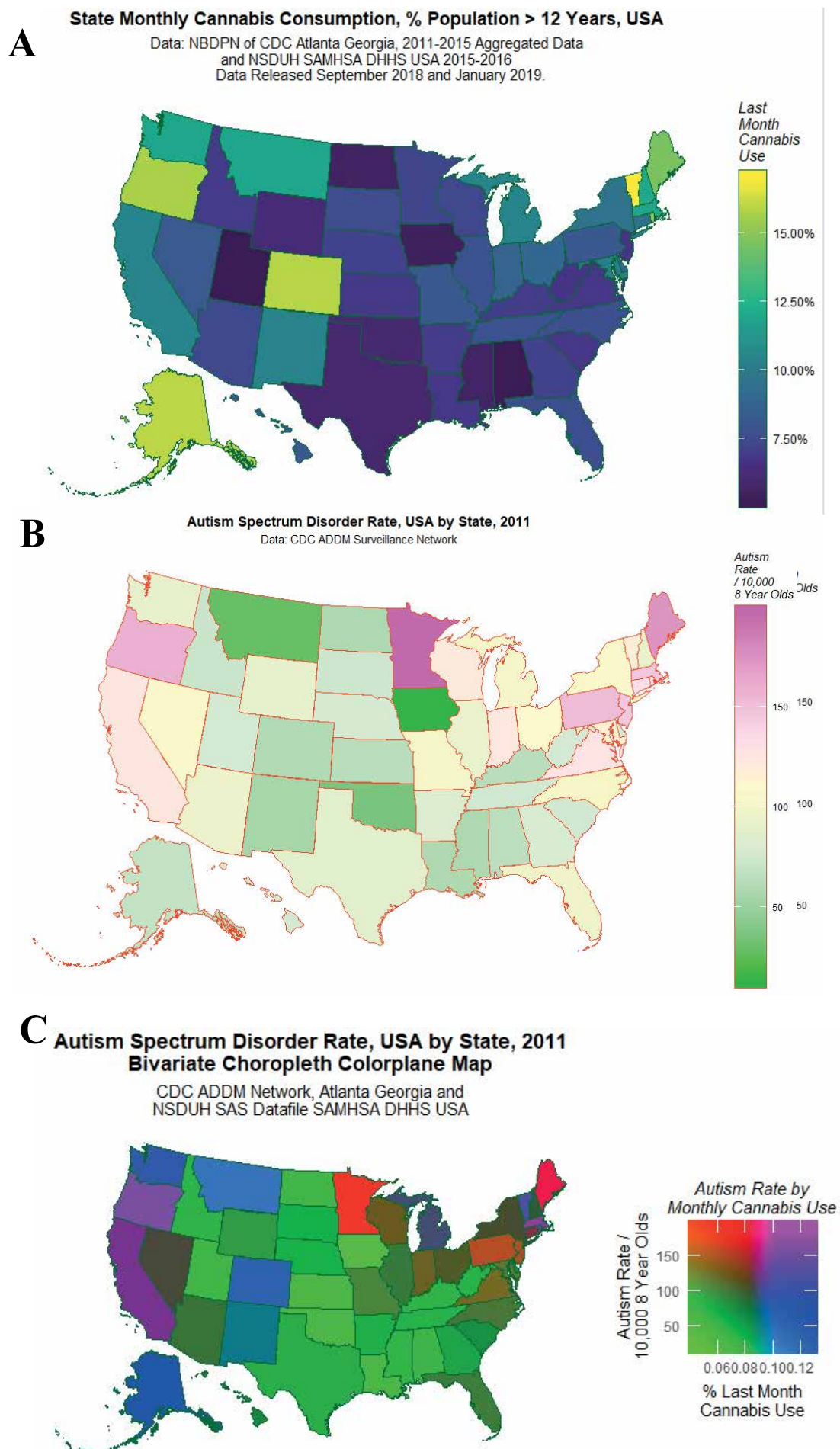


Figure 1: Maps of A: Cannabis Use, B: Autism, C: Cannabis use and autism together by USA state.

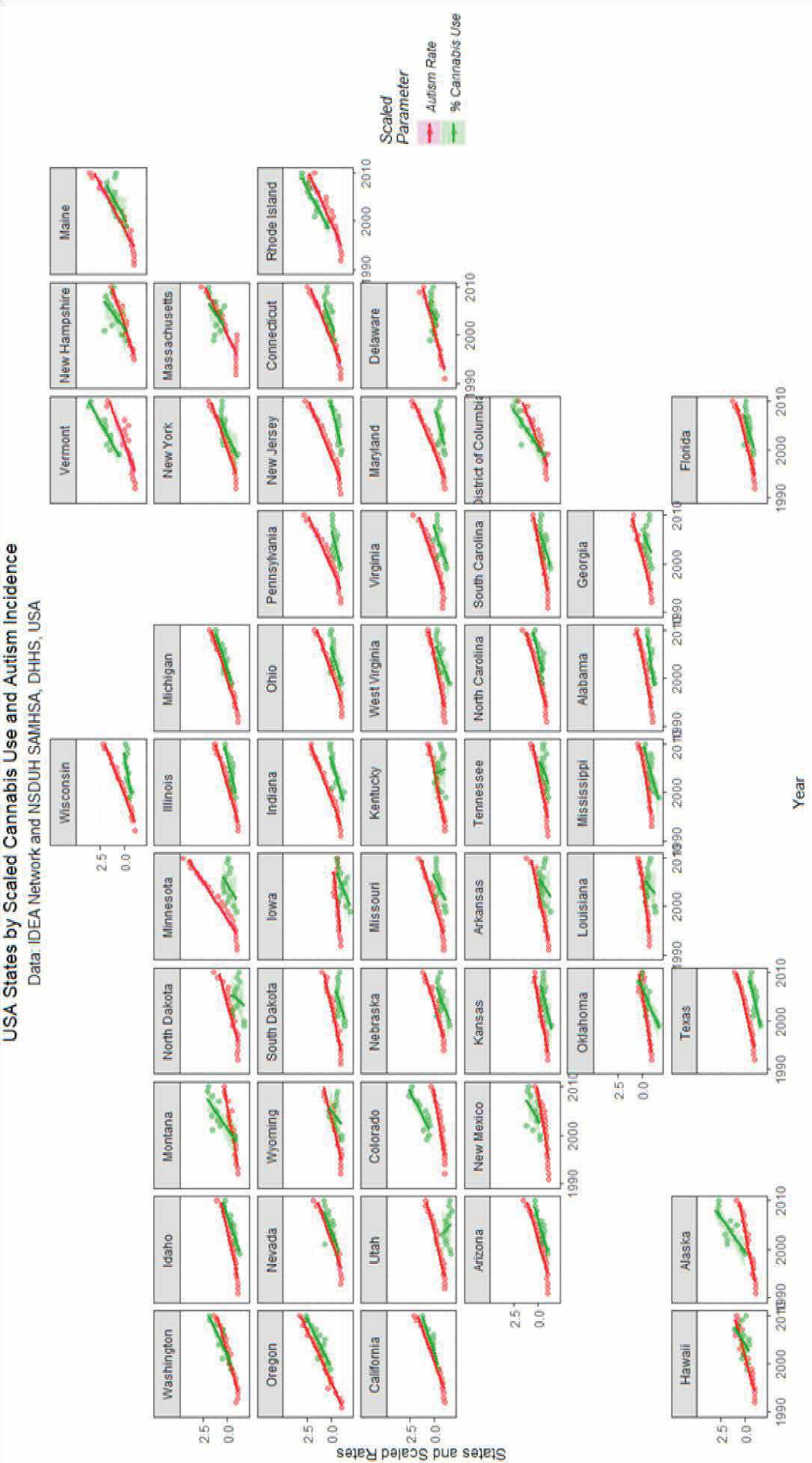


Figure 2: Geo-facetted charts of cannabis use and autism by US State.

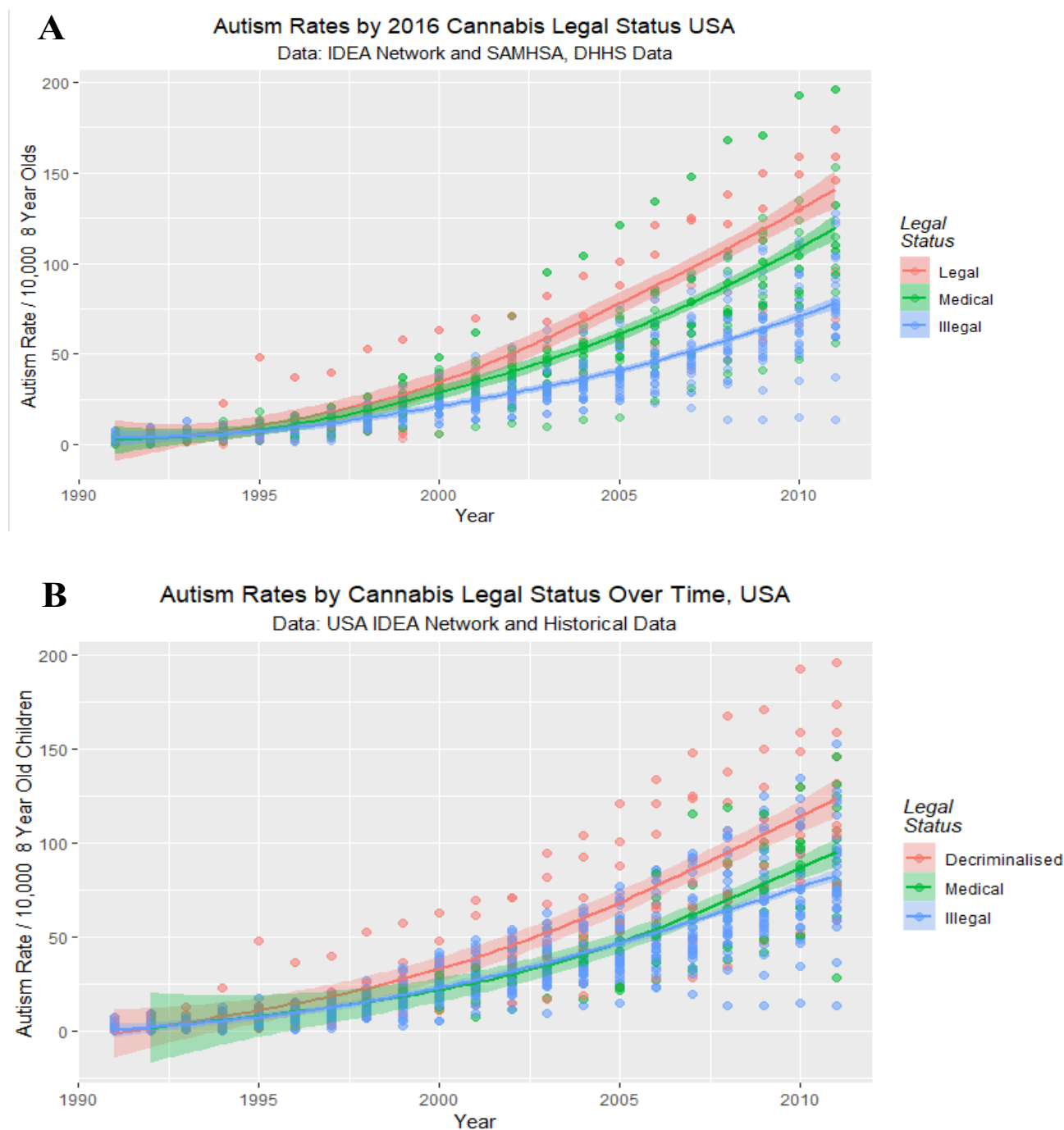


Figure 3: Graphs of Autism by US state by cannabis legal status using A: SAMHSA described legal status and B: historical legal status.

Again quadratic models are superior (ANOVA: AIC-linear=306.43, AIC-Quadratic=255.23, $dF=3$, $F=51.19$, $p<2.0\times10^{-16}$).

Figure 4 shows some graphical dissections of the ADDM data on autism incidence. Figure 4A shows the ASD rate over time for the fifteen states in the CDC ADDM network with individual regression lines of best fit. Figure 4B shows similar data with a loess localized polynomial curve fitted to all the states as one whole dataset. Figure 4C presents the same data with a single least squares regression line for all the data. Figure 4D is a similar plot but this time with the states categorized into states where cannabis is illegal and states where cannabis is legal for medical or recreational use. Panel D illustrates a dichotomized stratification of legal status which is shown in Table 3 to be significant.

Since it has been shown that cannabis legalization is associated

with more widespread cannabis use [14] it is of interest to consider the relationship between the slope of the cannabis use curves and the slopes of the autism rise. Figure 5 is a geofaceted plot which presents the very important data of the autism rate as a function of community uptake of cannabis by state. Several important features stand out from this graph. States charted in red and pink, particularly Maine, Minnesota, Oregon and Ohio seem either to have higher levels of autism or to be rising more steeply. Secondly in most cases the slopes of the regression lines showing the relation between the autism rate and cannabis use rate is positive irrespective of the legal status of cannabis. This is a very important finding indeed.

This finding is so important that it is again investigated in Figure 6 which compares the slopes of the regression lines by state for autism against time squared against each line's intercept on a single plot. This is a common plot used by statisticians to investigate models.

Table 1: Linear Regression of IDEA Database on 2018 Cannabis Status.

Parameter	Parameters				Model			
	Est.	Std. Error	t value	Pr (> t)	Adj. R Sq	F	df	P
IDEA								
Linear Models								
<i>Log (Autism_Rate)-Status</i>								
Status Medical	0.2031	0.0826	2.46	0.01	0.0047	3.418	21,020	0.03317
Status Legal	0.1785	0.1052	1.696	0.09				
<i>Log (Autism_Rate)-Time+Status</i>								
Year	0.1806	0.003	60.947	<2.0E-16	0.7855	1249	31,019	<2.0E-16
Status Medical	0.2001	0.0383	5.221	0.00				
Status Legal	0.1494	0.0489	3.059	0.00				
<i>Log (Autism_Rate)-Time * Status</i>								
Year	0.1661	0.0043	38.27	<2.0E-16	0.7896	768.1	51,017	<2.0E-16
Year: Status Legal	0.0334	0.0083	4.003	0.00				
Status Legal	-66.59	16.67	-3.994	0.00				
Year: Status Medical	0.0235	0.0065	3.632	0.00				
Status Medical	-46.88	12.96	-3.616	0.00				
Quadratic Models								
<i>Log(Autism_Rate)-(Time)²+Status</i>								
Time	36.7204	0.5433	67.585	<2.0E-16	0.8192	1159	41,018	<2.0E-16
(Time) ²	-7.5797	0.5487	-13.815	<2.0E-16				
Status_Medical	0.1995	0.0352	5.67	9.80E-06				
Status_Legal	0.1433	0.0449	3.194	0.00				
<i>Log(Autism_Rate)-(Time)² * Status</i>								
Time	33.6271	0.7911	42.504	<2.0E-16	0.8242	600	81,014	<2.0E-16
(Time) ²	-6.4559	0.8011	-8.058	2.2E-15				
Status_Medical	0.1855	0.0349	5.322	1.30E-07				
Status_Legal	0.1253	0.0446	2.809	0.0051				
Time: Status_Legal	5.0561	1.1815	4.28	2.1E-05				
(Time) ² : Status_Medical	-2.5638	1.1928	-2.149	0.0319				
Time: Status_Legal	7.1735	1.5269	4.698	3.0E-06				

Table 2: Linear Regression of IDEA Database on Historical Cannabis Status.

Parameter	Parameters				Model			
	Est.	Std. Error	t value	Pr (> t)	Adj. R Sq	F	df	P
IDEA-Historical Data								
Linear Models								
<i>Autism ~ Year</i>								
Year	5.026	0.1136	44.257	<2.0E-16	0.644	1959	11,081	<2.0E-16
<i>Autism ~ Year * Status</i>								
Year	4.2146	0.1238	34.0467	<2.0E-16	0.7129	538.4	51,077	<2.0E-16
Status Medical	-4539.2	569.84	-7.9658	0.00				
Status Decriminalised	-4539.2	569.84	-7.9658	0.00				
Year: Status Medical	2.2761	0.2847	7.9947	0.00				
Year: Status Decriminalised	2.2761	0.2847	7.9947	0.00				
<i>Log (Autism) ~ Year</i>								
Year								
<i>Log (Autism) ~ Year * Status</i>								
Year	0.1821	0.003	60.2368	<2.0E-16	0.7766	1255	31,079	<2.0E-16
Year: Status Medical	0.0001	0	5.6809	0.00				
Year: Status Decriminalised	0.0001	0	5.6809	0.00				
Quadratic Models								

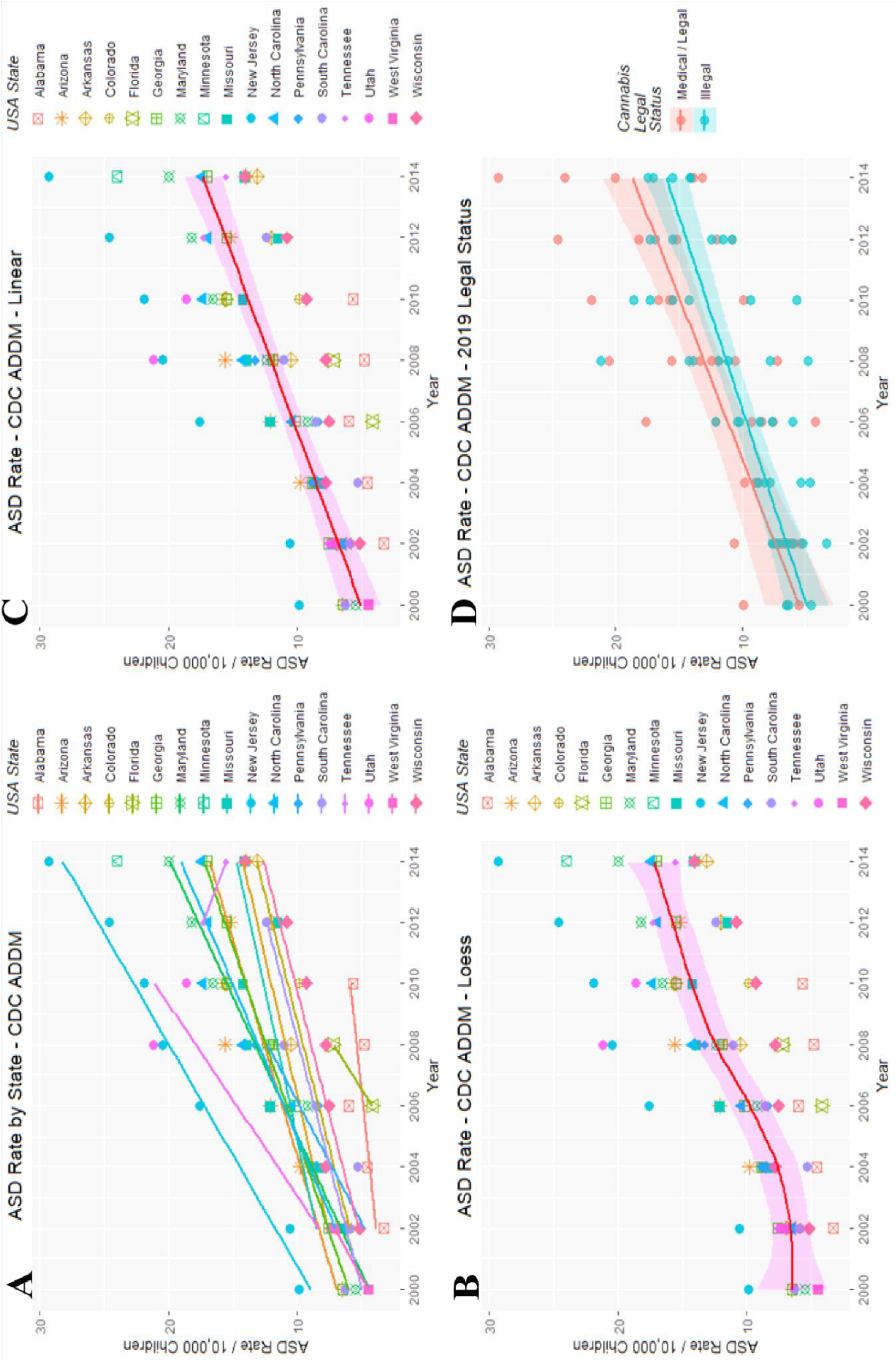


Figure 4: Graphs of Autism from the CDC ADDM network A: by US state, B: with a loess curve of best fit applied, C: with a straight line least squares regression line fitted, and D: categorized into dichotomous cannabis legal status groups.

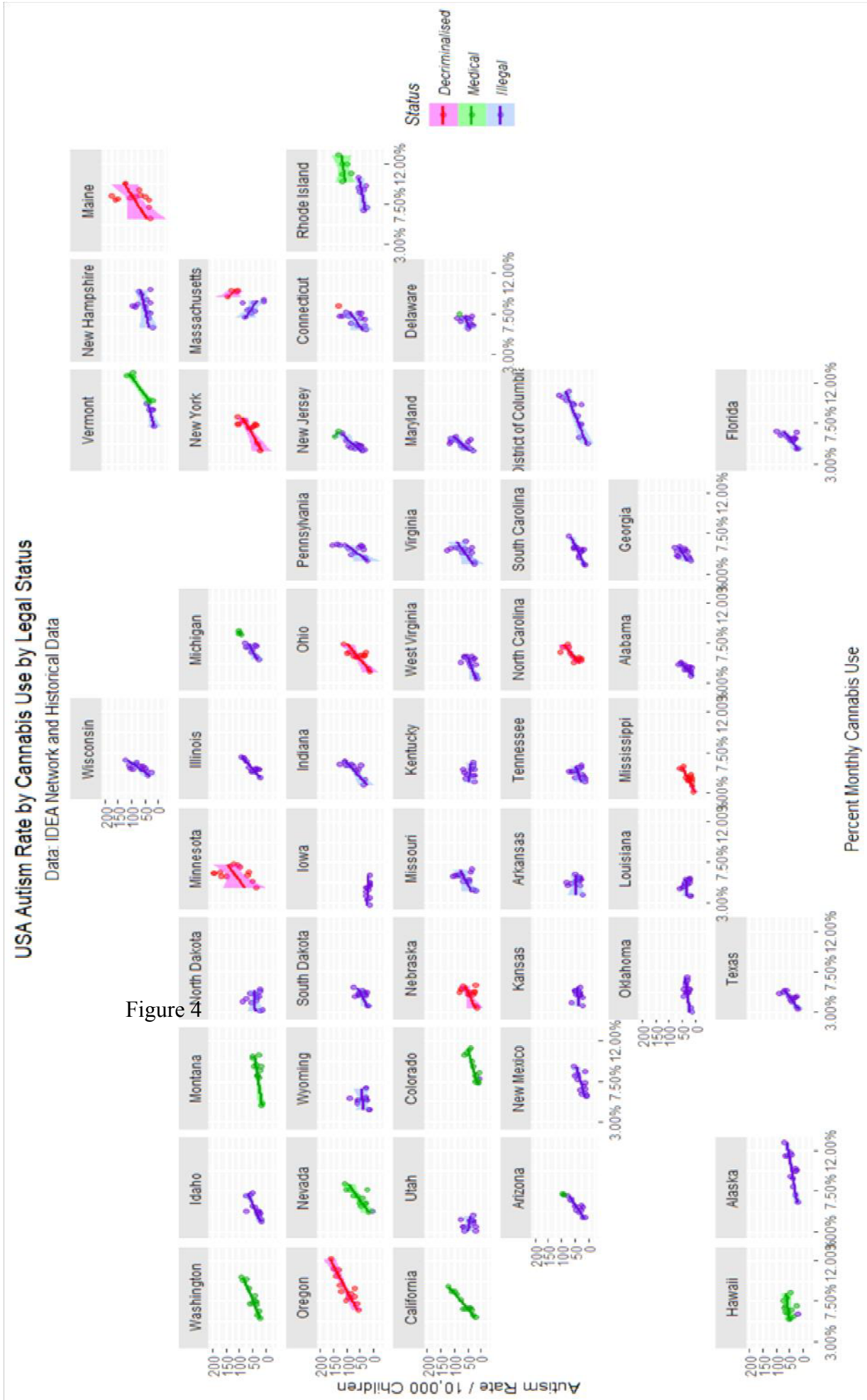


Figure 4

Figure 5: Geofacetted charts of autism rates as a function of cannabis consumption rates by US state.

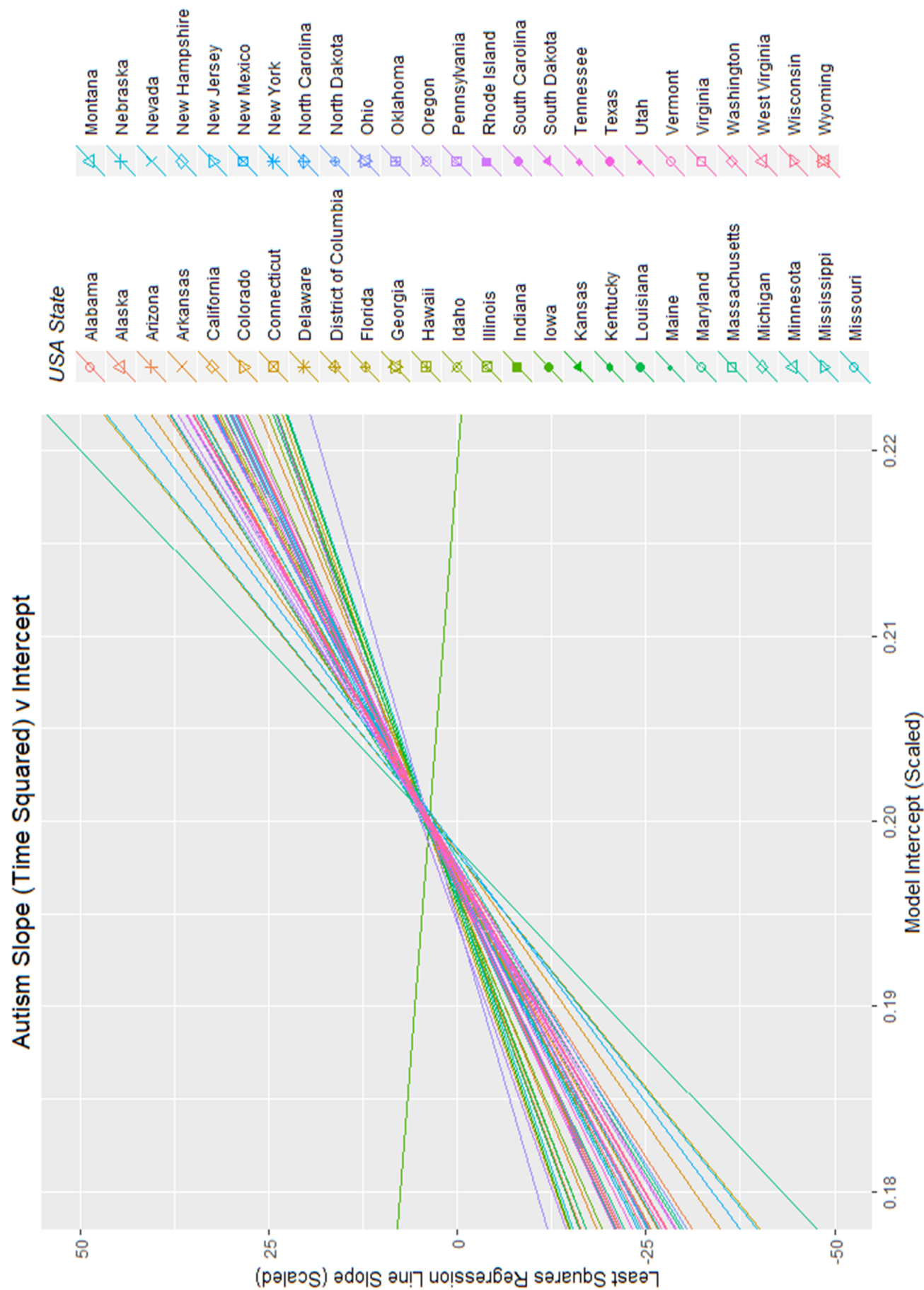


Figure 6: Graph comparing the slopes of the regression lines of autism against the square of time by US state. The regression line for Iowa stands out as a notable exception.

The negative slope in Iowa stands out prominently when the data is presented in this manner. The slope of the autism rate against time (squared) is noted to be positive in 48 of 49 states.

If cannabis use and autism were causally related it might be reasonable to suppose that the rates of rise of the slopes of the two regression lines might be roughly parallel. Figure 7 plots two interacting cluster dendrograms classifying the slope of the autism

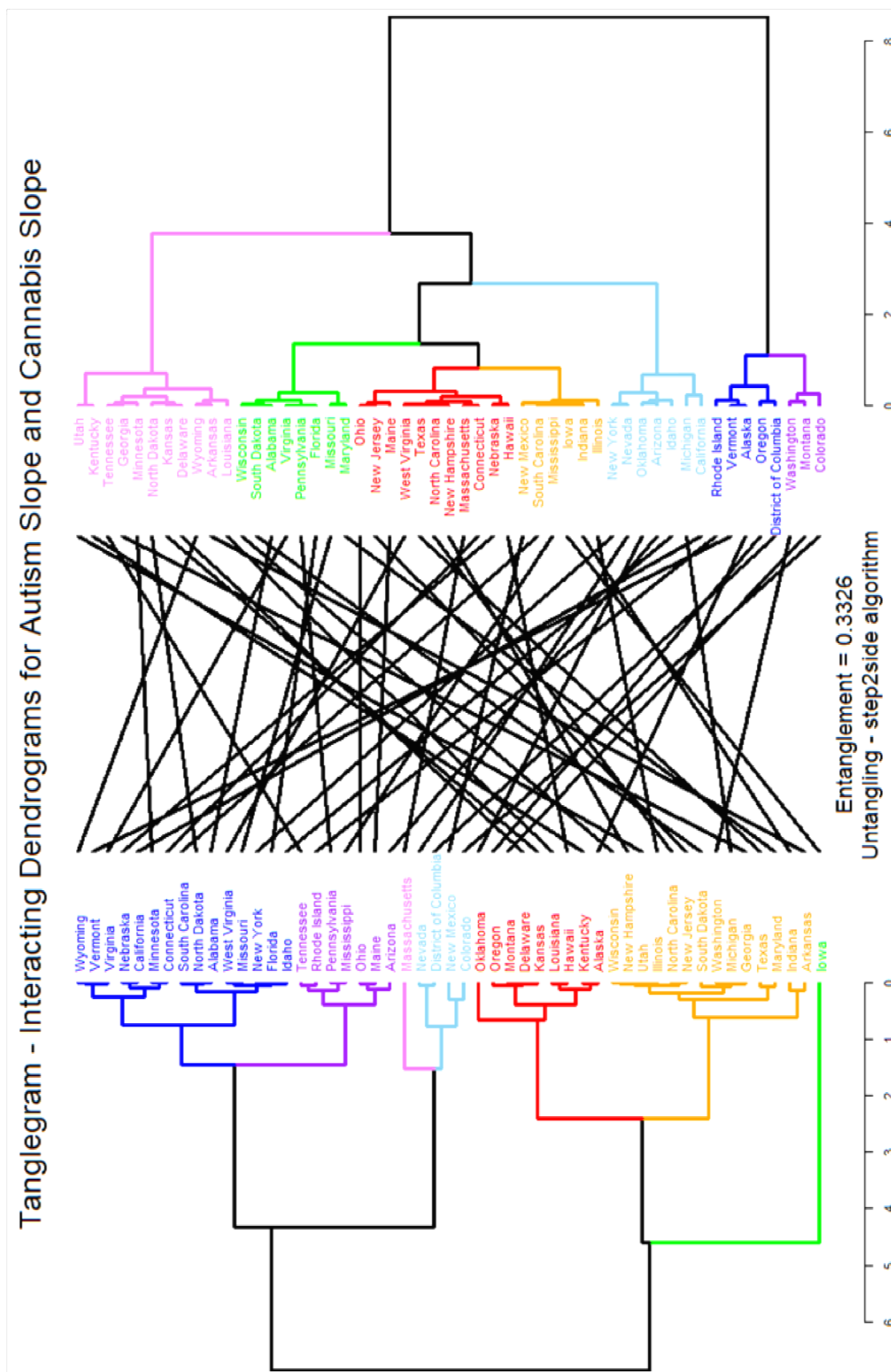


Figure 7: Tanglegram / Interacting Dendrograms showing the classification of slopes of the regression lines for autism (left dendrogram) with the regression line slopes for cannabis (right dendrogram). Compared using Wards algorithm to maximize agglomerative coefficient. After disentangling the tanglegram with the step2side algorithm the entanglement coefficient is 0.3326 indicating fair to moderate entanglement of the two parameters.

regression lines on the left and cannabis use regression slope on the right. The dendrograms have been drawn using Ward's algorithm to perform hierarchical clustering which achieved the highest agglomerative coefficient (AC=0.9727 v 0.9657 from the complete method with all the others lower). When an untangling algorithm (step 2 side) is applied to these two dendrograms the two are shown to be fairly-to-moderately entangled (entanglement coefficient=0.3326). This coefficient is a measure of the statistical relationship between the two dendrograms.

Figure 8 again presents the IDEA autism frequency data by time together with the various applicable quadratic equations for the curves of best fit for each legal condition. In each case the curve of best fit is shown for each legal category of cannabis use.

One notes that ascertainment of rates of autism can be very delayed after birth and it is not uncommon to wait until children are eight years of age before finalizing such a diagnosis. This introduces a protracted delay into case finding and tracking of the epidemic. Hence the IDEA dataset finishes in 2011, but we are already at 2019 at the time of writing.

Since the IDEA dataset is so rich it lends itself to simple forward projections. This has been done using the predict function from the stats package in R. Figure 9 shows that the previously quadratic curves now appear to be exponential, and this is confirmed on formal testing (equations presented on the figure for each legal category; R-squared for exponential models for decriminalization, medicalization and illegal status are 0.9671, 0.9719 and 0.9385

Table 3: Linear Regression of ADDM Database on Historical Cannabis Status.

Parameter	Parameters				Model			
	Est.	Std. Error	t value	Pr (> t)	Adj. R Sq	F	df	P
IDEA-Historical Data								
Linear Models								
<i>Log (Autism_Rate) ~ Status</i>								
Status_Medical/Legal	0.179	0.0995	1.7987	0.0756	0.0253	3.235	1,85	0.0756
<i>Log (Autism_Rate) ~ Time+Status</i>								
Year	0.079	0.0076	10.3666	<2.0E-16	0.5673	57.38	2,84	<2.0E-16
Status_Medical/Legal	0.1361	0.0664	2.0482	0.0437				
<i>Log (Autism_Rate) ~ Time*Status</i>								
Year	0.079	0.0076	10.3666	<2.0E-16	0.5673	57.38	2,84	<2.0E-16
Status_Medical/Legal	0.1361	0.0664	2.0482	0.0437				

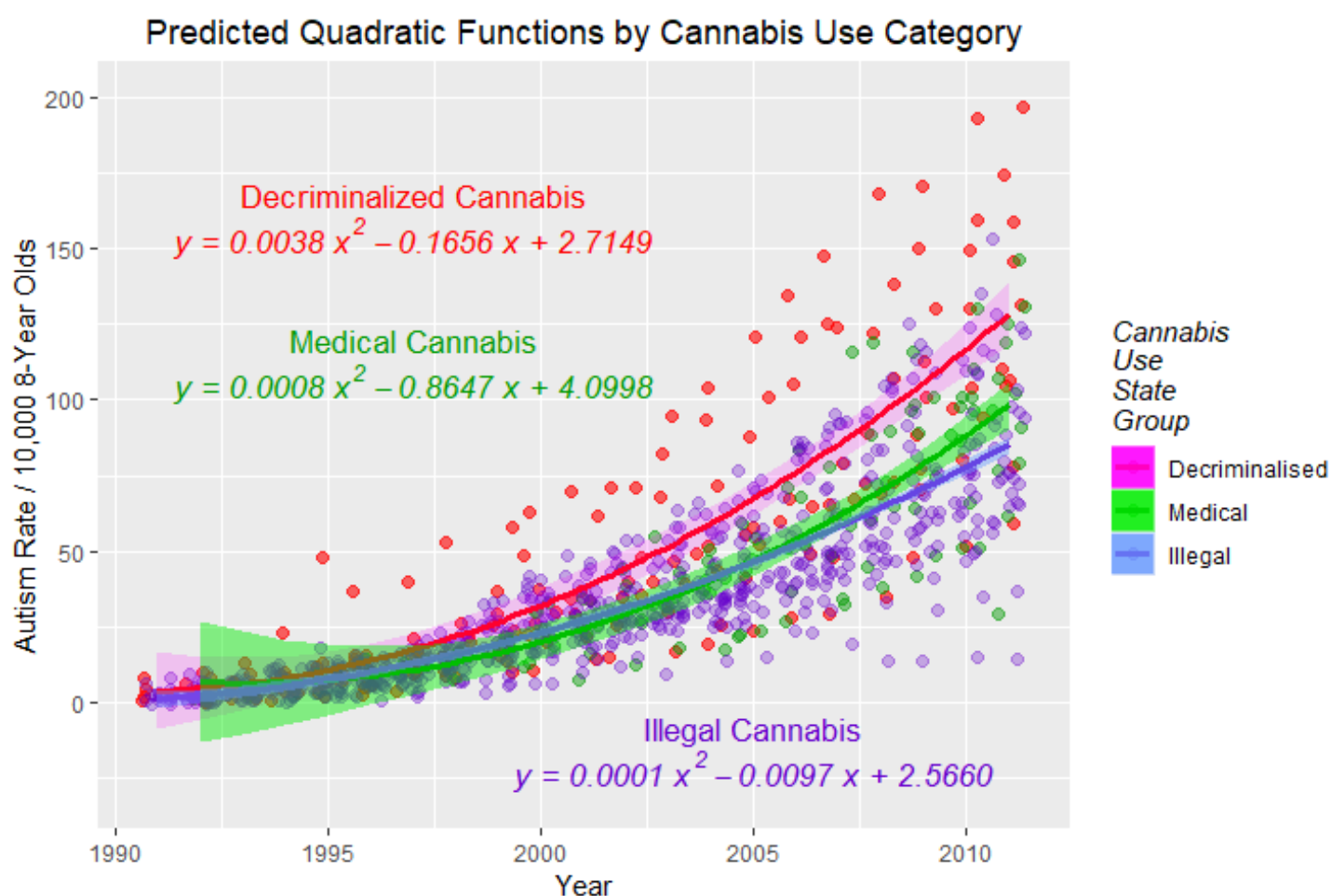


Figure 8: Graph of IDEA autism with historical legal status showing quadratic equations for the best fit regression lines.

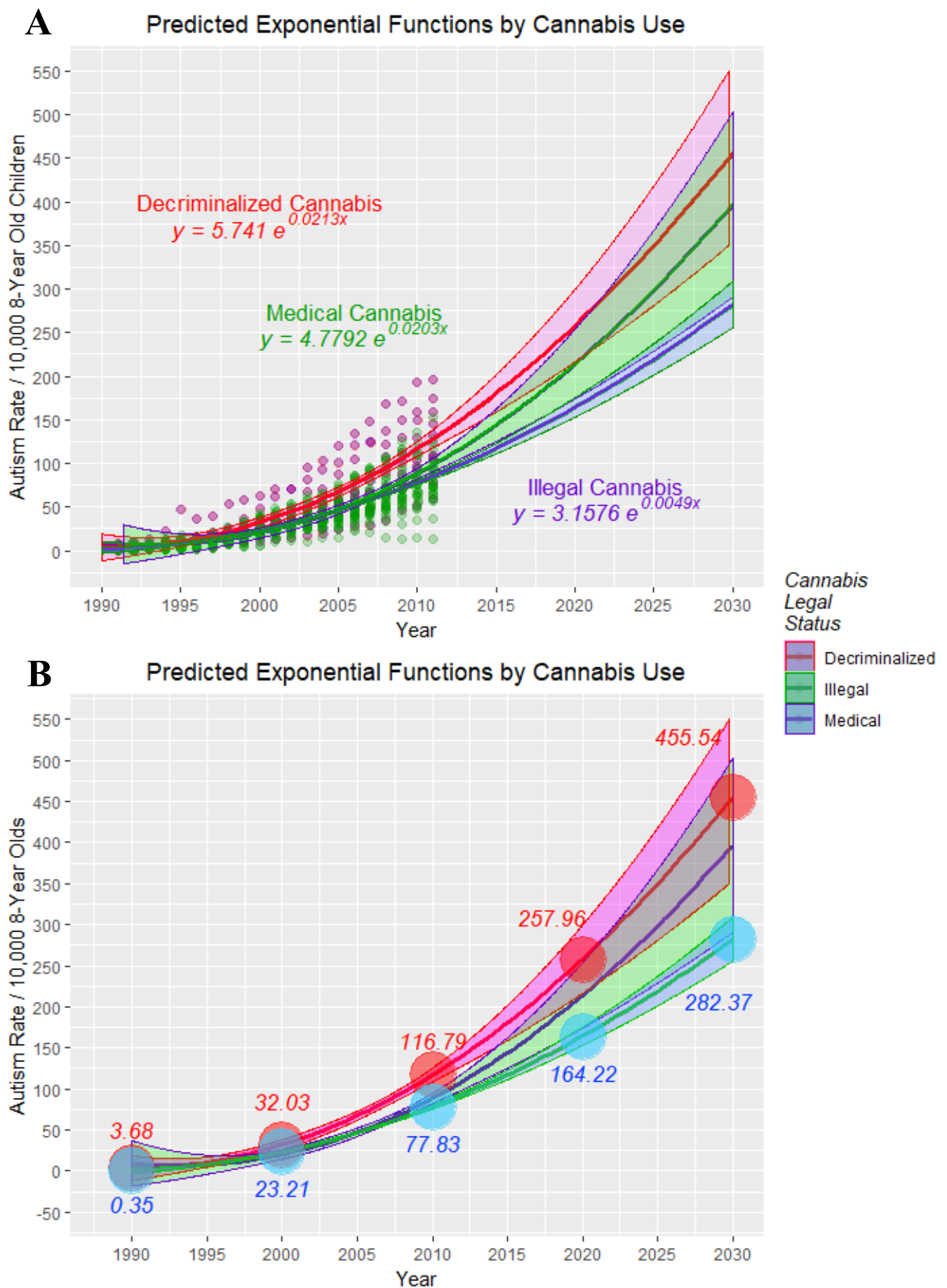


Figure 9: Projections of ASD to 2030 based on presently available IDEA data. A: Includes exponential equations of best fit, B: Placing numbers on the calculated curves at decadal points.

Table 4: Linear Regression of IDEA Database on Historical Cannabis Status.

Year	Decriminalised	Medical	Illegal
1990	3.68	9.4	0.35
1991	3.98	7.89	1.21
1992	4.84	6.96	2.38
1993	6.26	6.6	3.87
1994	8.25	6.81	5.68
1995	10.8	7.6	7.81
1996	13.92	8.97	10.25
1997	17.6	10.9	13.01
1998	21.85	13.41	16.09
1999	26.66	16.5	19.49
2000	32.03	20.16	23.21
2001	37.97	24.39	27.24
2002	44.47	29.2	31.59
2003	51.54	34.58	36.26
2004	59.17	40.53	41.24
2005	67.36	47.06	46.55
2006	76.12	54.17	52.17
2007	85.44	61.85	58.11
2008	95.33	70.1	64.36
2009	105.78	78.93	70.94
2010	116.79	88.33	77.83
2011	128.37	98.3	85.04
2012	140.51	108.85	92.56
2013	153.22	119.97	100.41
2014	166.49	131.67	108.57
2015	180.33	143.94	117.05
2016	194.72	156.79	125.85
2017	209.69	170.21	134.96
2018	225.21	184.2	144.4
2019	241.31	198.77	154.15
2020	257.96	213.91	164.22
2021	275.18	229.63	174.6
2022	292.96	245.92	185.31
2023	311.31	262.78	196.33
2024	330.22	280.22	207.67
2025	349.7	289.24	219.32
2026	369.74	316.82	231.3
2027	390.34	335.99	243.59
2028	411.51	355.72	256.2
2029	433.34	376.03	269.13
2030	455.54	396.91	282.37

whilst those for quadratic models are 0.8205, 0.7949 and 0.7990 respectively; ANOVA testing is not suitable as degrees of freedom are equal in all models). One notes the very high applicable R-squared (0.94 – 0.97) for each legal condition implying that the curves of best fit account for nearly all the variance in the trend model.

When these curves are projected outwards into the medium term the data shown in Figure 9B and Table 4 is obtained. Data in Table 4 is highlighted at each decadal point to make it easier to discern the longitudinal trends. One notes a report from the CDC [2] that

the 2014 incidence of ASD in the ADDM network was 1.68%. This is a little above the estimates presented in Table 4 for all three legal conditions, suggesting that the estimates presented there are somewhat underestimates.

Figure 9A presents the applicable exponential equations for the predicted curves and the known data on its left hand side. Figure 9B highlights the growth in ASD rates for the two extreme groups decriminalization and illegal status. Indeed one notes that in 2030 the two rates are predicted to be 455.54/10,000 compared to 282.37/10,000 or 60.75% larger under the decriminalization regime.

It is noted again that these calculations somewhat underestimate the most recent CDC ADDM estimate of ASD incidence of 1.68% in 2014 [2]. This in turn implies that these modest projection calculations likely err on the conservative side. As mentioned although these modest projections extend out to 2030, one notes that we are already at 2019. The lag in data acquisition reflects the time needed to diagnose ASD which are often not finalized until 8 years of age. This also gives us pause since if it is accepted that many of the causes of ASD occur during gestational or prenatal life which then this implies that most of the input of genetic and environmental causes have already occurred at this point, since 2019 plus 8 years is 2027 which is almost 2030 already.

DISCUSSION

The USA appears to be undergoing a significant social transformation in recent years in relation to addiction in general and to cannabis use in particular. Indeed America's addiction epidemics have been at the heart of two recent Surgeons General's reports to the nation [16,17].

The present study confirms that increased rates of US state cannabis use related to increasingly liberal paradigms (medical cannabis, decriminalization and drug legalization) are associated with subsequent increased rates of ASD. Importantly, this correlation was consistently replicated using different indices of ASD are used (IDEA and ADDM) and when different metrics of cannabis legal status are employed (SAMHSA and historical survey data).

This study also demonstrates that most states show a positive relationship between the slope of the cannabis: time and the ASD: time curves on linear regression, geofacet and ggplot2 analysis; Iowa being a notable and prominent exception. Tanglegram analysis confirms that the two slopes are related in a fair to moderate way.

One notes that a few exceptions to the overall pattern do exist in some states. We feel that this may reflect the operation of other complex factors since it seems clear that many environmental and hereditary factors may well interfere with brain development.

The rich IDEA dataset also lends itself to medium term extrapolation. The historically quadratic ASD epidemics appear to be undergoing exponential transformation at present. The projection calculated is numerically somewhat below the latest CDC ADDM figure of 1.68% in 2014, but nevertheless shows that by 2030 the rate of ASD in cannabis decriminalized states is likely to be more than 60% higher than that in states where cannabis is not legal in any respect. The real nature of the cannabis effect is likely more significant than suggested by this analysis, as cannabis use is reported to be rising even in jurisdictions where it is presently illegal [10]. Notwithstanding the provisional nature

of any such projections, it is important to note that much of what will likely occur with autism incidence 2019-2027 has already been set in place given the long incubation time and time to diagnosis of autistic and developmental delays and their largely prenatal and perinatal aetiology.

We show here that at the state level there is a relationship between increased cannabis use and increasing rates of autism; that the slopes of the two epidemics are related; that the epidemic is presently undergoing a transformation from a quadratic growth phase to an exponential growth phase; and noted that this is consistent with numerous mechanistic studies indicating that cannabis is implicated in many key neurodevelopmental processes including myelination, proliferation and migration of foetal neuroblasts, axonal steering and path finding, synapse formation, exuberant outgrowth of the relatively massive human neocortex, fasciculation of white matter fibre tracts and oligodendrocyte physiology, neural stem cell niche maintenance, mitochondrial energetic and metabolic functions, dendritogenesis, microglial and immune maturation, synaptic pruning, and maintenance of the integrity of the genome, epigenome and epitranscriptome [18-44].

Moreover prenatal cannabis exposure has also been linked with many defects of cortical and executive functioning including reduced visual processing, attention span and concentration in all four longitudinal studies which examine this question [45-49]. One impressive longitudinal New Zealand study of 1,037 children followed from birth to age 38 years found progressive, serious and dose-related declines in IQ and a global decline in all measures of executive cortical functioning, which accrued with continued use and were obvious to external observers [45]. Cannabis has been shown to impair synapse formation [19,22] and induce dendritic pruning [21] which has been causally linked with the mechanisms of forgetting [50,51] and to adversely affect the slit/robo ratio [18,52,53] a key messenger-ligand pair controlling the extent of exuberant mammalian neocortical development [54,55]. All of these widespread neurocognitive cannabis-induced defects are consistent with its multifarious known mechanisms of action and its intimate involvement in virtually every step of brain and neural network formation.

Overall therefore our results, together with increasing reports from clinicians practising in high-cannabis areas of US [56,57] suggest that an increase in ASD is likely to be one of the more serious, and the commonest implications of increasing the availability of cannabis to the general population and particularly to both male and female adults of reproductive potential.

Reports from the National Births Defects Prevention Network of CDC have previously implicated cannabis use in causing anencephaly, gastroschisis, diaphragmatic hernia and oesophageal stenosis with or without tracheo-oesophageal fistula [58,59]. The American Academy of Pediatrics position statement on the aetiology of non-inherited heart disease previously noted that cannabis is associated with a doubling of the incidence of ventricular septal defect and Ebsteins anomaly [60]. And a large registry-controlled Hawaiian study in 2007 found that the incidence of 21 congenital defects was more common after cannabis exposure [61]. This novel study whose findings were much more serious than others, has since been validated by the latest American experience with atrial septal defect, the experience of many congenital anomalies in Colorado, and a recent experience of phocomelia in France [9].

However since ASD is more common than any of these other

disorders it seems likely that it will become by far the most common issue with cannabis teratogenesis and cannabis neuroteratogenesis.

There is a lengthy delay period between birth and diagnosis of ASD. Indeed, given that we are now in 2019 in eight years' time the year will be 2027, so given that much of the aetiology of ASD is believed to occur in or around birth, it would seem that much of this medium term trajectory has already been determined.

It is of interest to consider the generalizability of present findings. Several considerations are pertinent. Firstly USA is a large nation so its experience carries significant epidemiological weight. By many metrics USA is the world's leading nation and exercises considerable financial and cultural prowess. The bulk of cannabis sales occurs over the internet and it is a matter of record that many providers in California, Colorado, Canada and elsewhere have large mail order businesses [62]. Mail order seizures from Colorado show that interstate trafficking ranks in the thousands of kilograms [62]. California is said to grow eight times more cannabis than is consumed intrastate. NSDUH data indicate that in 2017 161,000 pregnant women in USA consumed cannabis and for 69,000 this was reported to be daily or near daily use [10,13]. Of particular concern it was recently reported that 69% of cannabis dispensaries in Colorado recommended cannabis use to pregnant females [11]. Almost 25% of pregnant females in California recently tested positive or admitted to cannabis use [12]. All these factors point in the same direction and indicate that US trends are likely to have both direct and indirect effects to spread the experience of a cannabis-autism link both within and outside the United States.

The present study has various strengths and weaknesses. Its strengths relate to the use of two major datasets for autism diagnosis and the use of two systems for the categorization of cannabis legal status. Moreover the study is set in the US which arguably has the best data on these parameters. Also the IDEA dataset is of not inconsiderable size being over 1,000 data points. The shortcomings of the study relate to its epidemiological and ecological design. Individual participant level data was not available to this work. These issues would be corrected by the conduct of a prospective case-control design study where data relevant to these matters could be collected prospectively. Since self-report is a generally unreliable basis on which to conduct such investigations more objective measures are required. In this regard the work of the group of David employing hair analysis to assess neonatal toxicological exposure is relevant [63]. It should be noted that it is possible that the cannabis industry may have indirect effects on brain growth and development, as the widespread use of highly potent pesticides to protect cannabis cultivars from animal predation is reported [64]. For example a number of citations have been made of carbofuran use, a highly potent and exquisitely toxic pesticide which has been banned in USA and many nations [64-68].

CONCLUSION

A substantial literature establishes that brain formation occurs by a complex and intricately orchestrated choreographed "dance" of molecules, genes and epigenetic regulation with new neuroblasts and glial cells coming "on line" and being wired into the expanding neural circuit. The evidence of this study suggests but does not prove that these delicate and spatiotemporally precisely coordinated events are materially, seriously and permanently impaired by prenatal cannabis exposure in the parents.

Our study has shown that ASD is more common in states which host

more liberal legislative paradigms (decriminalization, legalization and medicalization) relating to cannabis use. This relationship is robust to consideration with different datasets and with different methods of legal status assignment. Extrapolation of current quadratic ASD trends shows exponentiation of the epidemic, with the rate of ASD in cannabis-legal states likely 60% greater than those in cannabis-illegal states by 2030 under conservative assumptions. These epidemiological level findings are consistent with basic sciences mechanisms which have demonstrated that cannabinoids are critically involved in numerous key aspects of brain and neurological development. Together with the increasingly common presentation of such cases to clinicians practising in localities which see significant numbers of cannabis exposed patients these findings suggest that the autism epidemic will continue to accelerate in the medium term and that the increasing availability of cannabis is likely to have common and unforeseen and potentially serious long-term neurodevelopmental complications. Further detailed mechanistic case-control investigations are required.

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CONTRIBUTORS STATEMENT PAGE

Dr Reece designed the study, performed the statistical analysis and wrote the first draft.

Prof. Hulse reviewed the manuscript for important intellectual content and revised the draft. He also provided administrative, research support and assisted with statistical advice and oversight.

All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

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