Financial Incentives and Autism Diagnoses:
An Ohio Autism Scholarship Program Case Study

Samantha Wronski

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Abstract

In recent years, as the definition of autism has expanded to include a “spectrum” of disorders (ASDs), the prevalence of ASDs have increased drastically – from 4 to 10 per 10,000 children in the early 1990s to 30 to 50 per 10,000, or about 1%, in the 2000s. In order to address this problem, several state-level programs have been started and made available to any child with an ASD diagnosis. One such program, the Ohio Autism Scholarship Program (ASP), started providing up to $20,000 per year for families with formally-diagnosed ASD children to purchase services at any program-approved facility in 2004. The literature finds that programs relying on an ASD diagnosis for funding or services have the ability to influence diagnostic conclusions. This analysis builds upon these largely observational studies by quantifying the impact of one such diagnosis-dependent autism resource – the Ohio ASP - on autism rates. Currently, Ohio ASP funding can be utilized in roughly half of Ohio counties where approved providers exist. In order to determine whether changes in autism rates are attributable to the Ohio ASP, I perform both state and Ohio county difference-in-difference regression analyses controlling for general autism trends over time. At this time, it appears that the impact of the ASP on autism rates is insignificant or inconclusive. This is important to note for stakeholders who are concerned that such financial incentives may lead to false-ASD diagnoses and, in turn, strain the resources available for the children most in need of them.

Introduction

In 1956, Leo Kanner and Leon Eisenberg presented the first formal set of criteria for the diagnosis of autism. Since then, the concept of autism has broadened with the evolution of Rutter's three behavioral domains in 1978 and the subsequent uses of the terms "Pervasive Developmental Disorder" (PDD) and, more recently, the greater-encompassing "Autism Spectrum Disorder" (ASD) (Blaxill, 2004). Autism itself is a PDD involving deficits in all three of Rutter's domains (communication, social skills, and repetitive behaviors or interests) before the age of 36 months (WHO, 1994; APA, 1994). Although the core definition of autism has remained relatively stable since these three domains were established, the widely used "Autism Spectrum Disorders" now constitutes an array of conditions in addition to autism, including not otherwise specified PDDs (PDD-NOS) and a large list of related disorders such as Asperger's syndrome (about 14 to 19% of ASD population), childhood disintegrative disorder, and Rett's syndrome (Blaxill, 2004).

As these significant changes in diagnostic criteria took place, the prevalence of autism increased drastically – from 4 to 10 per 10,000 children in the early 1990s to 30 to 50 per 10,000 in the first half of this decade (Barbaresi et al., 2006) and shows no sign of plateauing (Hertz-Pizziotto & Delwiche, 2009). The Centers for Disease Control and Prevention (CDC) reported an average of 1 in 110 children or 1% autism prevalence in 2006, with increases ranging from 27 to 95 (with an average of 57) percent since 2002 among the 16 Autism and Developmental Disabilities Monitoring (ADDM) network communities in the United States (2010). The ADDM Network sites obtained these estimates using data from health and education records of reporting communities, which comprise eight percent of the U.S. population of eight year olds (CDC, 2010); the range that they obtained reflects the breadth of change in autism rates experienced by the communities. When concerned researchers questioned this increase they found that it not only coincided with the aforementioned broadening of diagnostic criteria, but with the increased availability of educational services and increased awareness of autism as well (Barbaresi et al., 2006).

One obvious question is: "How much of this increase in autism is 'real?'" In their study of autism in California, Hertz-Pizziotto and Delwiche (2009) find that changes in diagnostic criteria, earlier ages at diagnosis, and the inclusion of milder cases explain, albeit not fully (2.2-, 1.56-, and 1.24-fold increases in autism incidence, respectively, out of a total 7- to 8-fold incidence increase from 1990 to 2006) the observed increase in autism incidence. Differential migration, or leaving the state due to an autism diagnosis, only played a minor or nonexistent role. They conclude with a call for further research in order to clarify the extent to which a continued rise in the incident rate represents a true increase in the occurrence of autism (Hertz-Pizziotto & Delwiche, 2009).

This study examines the role that newly-introduced increases in services and incentives for diagnoses play in inflating the prevalence of autism. First, I examine the impact of the unique Ohio Autism Scholarship Program (ASP) on the rates of autism at the state level using Ohio, nearby states, and all other "far" states as comparison groups. Next, I examine the impact of the ASP on the rates of autism within Ohio, where the program is in effect to varying degrees by county depending on program provider availability. This analysis is substantiated by Shattuck and Grosse's (2007) reports of research which found that programs (like Ohio's), which use an ASD diagnosis to determine eligibility for funding or services, have the potential to influence clinical diagnostic conclusions.

Literature Review

Below I detail the literature identifying pre-natal parental factors, post-natal childhood environmental factors, and external societal factors as potential causes for the rise in autism rates. The consensus is that while autism is a debilitating disorder, there are promising, albeit expensive, services available which can improve the outcomes of children as long as they have a diagnosis of autism. As such, the literature shows that parents and physicians have an incentive to obtain a formal autism diagnosis for their child. The ASP in Ohio, which I discuss, is one such way services and autism diagnoses have been linked to create an incentive for diagnosis and potentially contribute to some of the increase in autism rates.

Causes of Autism

I. Pre-Natal Factors

Before two people even decide to have a baby, there are several environmental factors that can place them at a higher risk of parenting an autistic child. Low socioeconomic status, high mother and/or father age, and parental schizoid traits have been identified as such potential factors (Larsson et al., 2005; Kelly, 2009). More proximally to conception and delivery, genetic abnormalities (Dombeck & Reynolds, 2006), fetal neurotoxins (Newschaffer et al., 2002), maternal illness (Chess, 1977), low age and/or birthweight (Larsson et al., 2005), and breech presentation (Bilder et al., 2009) have also been associated with autism.

II. Post-Natal Environmental Factors

Perhaps one of the most contentious and hard-to-research areas explores the impact of environmental determinants like loneliness and staying indoors on the development of autism.

Lasgaard et al. (2010) found that the occurrence of loneliness is high among adolescent boys with ASD and suggests perceived social support as an important protective factor. Another study, by Waldman et al. (2008), used precipitation rates as a proxy for staying indoors and found that county-level autism prevalence rates and counts among school-aged children were positively associated with a county's mean annual precipitation. The same authors, using natural experiments in a separate study, found support for the hypothesis that early childhood television-watching is a trigger for autism.

Factors Influencing ASD Reporting Rates

Croen et al. (2002) address the issue that is central to this study: Whether the observed increase in prevalence of ASD reflects a true increase in incidence or if it is an artifact of improved recognition and detection combined with a broadening of the diagnostic definition and expanding social services to meet the needs of ASD children. They examined the impact of external societal factors, such as increased services and ASD awareness, improvements in case recognition and diagnostic changes, on autism prevalence in California and concluded that these factors may indeed account for the observed increase in autism prevalence in the state. The researchers provide the example of how intensive autism intervention programs, such as the behavioral treatment program developed by Lovaas in 1987 which became more widely available during the early 1990s, gave families an incentive to enter the service delivery system in order to gain financial support for costly behavioral interventions. Croen et al. (2002) assert that "in an era when other disorders in the autistic spectrum became more widely recognized and interventions became more available, pressure may have increasingly been put on the system to give children with Asperger's disorder and PDD-NOS a diagnosis of full syndrome autism so that they could qualify for regional center services" (p. 214).

Implications of Autism and Treatment Options

There are significant financial costs involved in the treatment of autism. Ganz (as cited in Datz, 2006) estimates that the annual indirect costs for autistic individuals and their parents range from more than $39,000 to nearly $130,000. It is currently estimated the average cost of caring for one person with autism for life is $3.2 million (Vanderbilt, 2009). Moreover, autism currently costs the U.S. more than $90 billion per year, and that cost is projected to double by 2017 due to the growing population of those affected (Vanderbilt, 2009).

One of the most promising treatment options for children with autism or PDD is early intensive intervention based on the principles of applied behavior analysis (ABA); normal or near-normal functioning or significant gains in measured intelligence or other aspects of development have been attributed to this type of intervention (Jacobson et al., 1998). Significant savings have been attributed to early intensive behavioral intervention (EIBI). At varying rates of effectiveness and in constant dollars, Jacobson et al. (1998) found that lifetime cost savings ranged from $187,000 to $203,000 per child for ages 3 to 22 years, and from $656,000 to $1,082,000 per child for ages 3 to 55 years in 1998. Indeed, among limited studies of various ASD therapies, expensive EIBI showed improved outcomes for some children (Caronna & Halfon, 2003). Nevertheless, children with autism require lifelong care, services, and supervision. Educational services for autistic children are among the most intensively staffed and expensive forms of special education available under the Individuals with Disabilities Education Act (Jacobson et al., 1998).

The national Individuals with Disabilities Education Act (IDEA) helps to remedy the immense family financial burden of autism by establishing Part C (P.L. 108-446) to provide an Early Intervention Program for infants and toddlers with disabilities and behavioral problems

(Stahmer & Mandell, 2007). The voluntary Part C program established in 1990 has nevertheless gained participation from all states and, because of its flexible nature, has manifested itself in different ways depending on state determination for eligibility of services and what services are provided (Stahmer & Mandell, 2007). Although it has not been systematically examined, Mandell and Palmer (as cited in Stahmer & Mandell, 2007, p.30) suspect that these state policy variations may account for some of the 8-fold difference across states in the number of children ages 6–21 years receiving special education services for ASD.

A variety of distinct statewide programs for autism exist ranging from waivers and housing options for autistic adults in Pennsylvania to autism vouchers or scholarship programs for autistic youth in states like Florida and Ohio. Medicaid waivers that provide community supports for eligible individuals with autism are available in Maryland, Colorado, Indiana, Massachusetts, and Wisconsin. According to Caronna and Halfon (2003), combined with the decreasing stigma associated with ASD due to a broader array of disorders being included in the spectrum over the past decade, there has been an incentive for diagnosis in states where federally sponsored Social Security Insurance benefits rely on the autism label. Not surprisingly, some enhanced educational and treatment services through IDEA also rely on an autism diagnosis.

Psychiatrists and psychologists hired by the parents of autistic children understand that diagnosis greatly influences placement in appropriate educational programs. As such, they might have to ask parents to accept a certain (potentially stronger) diagnosis, even if it is undesirable, in order to get a child into the most appropriate class (Grinker, 2007). In New York State, the difference between an ASD diagnosis and Asperger's Disorder or PDD-NOS diagnosis means that children will be eligible for different special education programs, even if, according to psychiatrist Margaret Herzig, they would all probably be better served in an autism class. Further, physicians have been pressured to respond to the incentive by making earlier ASD diagnoses, even in young children (<5 years) who have mild symptoms (Caronna & Halfon, 2003). Prior to 1990, such diagnoses were rare; however, more recently an increasing number of children are being diagnosed with autism, with numbers particularly growing among younger children and children with milder symptoms. Despite these pressures of earlier ASD diagnosis, a Gurney et al. study (as cited in Caronna & Halfon, 2003, p. 620) suggests that a significant proportion (at least half) of children are receiving an ASD diagnosis after the ages of 5 or 6 years. Additional incentives to identify children with ASD may also be present among older children in the school system that might have a range of behavioral problems and mixed cognitive deficits and would benefit from ASD diagnosis-dependent special education services. In addition to earlier diagnoses, a shift to autism diagnoses from other diagnoses (such as mental retardation) has also been occurring (Caronna & Halfon, 2003). This substitution effect occurs when reporting only a primary diagnosis of autism confers eligibility for services. Caronna and Halfon (2003) note that due to changing stigma and incentives, more children with both ASD and mental retardation are being categorized as having ASD. This hypothesis was supported in a 1999 California report showing a tremendous jump in children receiving special services with a primary diagnosis of ASD concurrent with a decrease in children receiving services with a primary diagnosis of mental retardation (Caronna & Halfon, 2003).

Externalities and Ethical Implications of Increased Autism Treatment, Services, and Awareness

Certainly, advances made in the detection, treatment, and provision of services for autism have improved child outcomes and better helped families cope with the challenges of the disorder. Yet, as alluded to previously, the increased attention and resources for tackling autism may have also provided some physicians and families with an incentive to provide an autism diagnosis. Caronna and Halfon (2003) express concern that the broad and flexibly-interpreted autism "spectrum" diagnosis may lead to a misallocation of educational resources away from children with more severe autism and autistic children with greater financial need. Unfortunately, the ability of financial incentives to drive autism diagnoses is a reality (Grinker, 2007). For example, in Maryland, a Medicaid waiver will allow an *autistic* child to receive intensive supports and medical care even if his or her family is not near the poverty line, but will offer nothing to a child with *mental retardation living in the same financial circumstances* (Grinker, 2007). Ohio's autism scholarship program works in a similar way in that it requires an autism diagnosis to qualify a child for service eligibility. And as Shattuck and Grosse note, "whether program eligibility hinges on a diagnosis of autism can significantly influence the capacity of service systems to accurately determine who has autism" (2007). There is reason to suspect that, when faced with these incentives, service systems will take advantage of the "soft" (as opposed to "hard" straightforward physical impairment) diagnostic nature of autism and, in turn, yield related increases in autism prevalence. Indeed, Lester and Kelman (1997) have found that the ways diagnoses are interpreted "as well as, or instead of, actual disease prevalence" are related to variation in state-level learning disability (LD) diagnostic levels. Because this relationship was found most strongly among soft LD diagnoses, there is reason to suspect that autism may respond similarly to diagnostic practices.

One factor that can influence a state's autism diagnostic practices is the availability of financial or fiscal incentives for diagnosis. Stahmer and Mandell (2007) revealed that the limited number of studies of the effects of policy variation on service delivery find education policies and level of aid for children with disabilities highly predictive of the proportion of identified learning disabilities. One such study, by Cullen (2003), which examined the elasticity of student disability rates with respect to the generosity of state reimbursements, found that when Texas state aid was varied as a result of a policy change, fiscal incentives explained “nearly 40% of the recent growth in student disability rates.” Because changes in the size and characteristics of beneficiary populations affect not only ultimate costs but also may undermine stated policy objectives, Cullen believes that understanding the relationship between social insurance program generosity and caseloads is essential for program design.

Other factors that can also impact autism diagnoses are insurance reimbursement and treatment possibilities (Grinker, 2007). An example of the former is provided through a personal anecdote from Grinker; he lost hundreds of dollars during the first few months of his daughter’s autism diagnosis because the speech therapist had submitted the bills under the diagnosis code of “Mixed Receptive-Expressive Language Disorder.” After the code was changed to autism, the insurance company suddenly started to reimburse him. Indeed, insurance coverage and reimbursement as well as economic issues were factors reported by a majority of respondents in a Rushton et al. (2002) survey as reasons for alternative coding. Further, the survey found that over two thirds of providers reported ever using an alternate diagnostic code, and many reported common use (monthly-weekly) (Rushton et al, 2002). Approximately 10% used alternate diagnostic codes on a daily basis (Rushton et al., 2002). A statistically significant 52.5 to 23.9 percent of physicians ($p < .001$; range reflects the maximum and minimum among different medical specialty averages) ever using alternative coding did so for an autism spectrum disorder (Rushton et al., 2002).

Another motivation for alternative coding is access to treatment possibilities that are diagnosis-dependent. Doctors will make an ASD diagnosis, even when they were not certain that it is the correct diagnosis, for the purposes of educational ASD ascertainment, so the child can access additional educational resources (Skellern et al., 2005) or for the purposes of medication prescription (Grinker, 2007). In a survey of Australian clinicians, Skellern et al. (2005) found that 58 percent (60 doctors) reported on at least one occasion providing an uncertain ASD diagnosis, with most (56 out of 60) reporting that the child's existing symptoms were only upgraded for the purposes of ASD ascertainment.

Using Skellern et al.’s (2005) data, Shattuck and Grosse (2007) assert that Ohio’s ASP and similar programs, which give families a lump sum to pay for therapeutic intervention outside the public special education system and rely on an ASD diagnosis for funding or services, have been found to influence clinical diagnostic conclusions. Despite the unknown effectiveness of the program, parent satisfaction seems to drive the desire to take advantage of the financial incentive; parents of the 178 students participating in the program at the start of 2004-2005 report being highly satisfied (Shattuck & Grosse, 2007). Nevertheless, Shattuck and Grosse (2007) note that school district officials were concerned that the Ohio program – which, with no new appropriations and funded from state and local budgets - could generate a “negative financial impact, including the need to reduce services to other children in special education.” It was these concerns that led a Wisconsin bill for a similar autism scholarship program to be defeated in 2006.

In all of these scenarios there is a concern that the increasing resources for coping with autism could be exploited. Because there is often a disconnect between those who implement the policy and those who determine eligibility for the policy, gaps may be created between the intended user of a particular treatment, service, or medication, and the ultimate recipient. Given the particular flexibility of the autism "spectrum" diagnosis, this can make determination of budget and resource allocation extremely difficult for policy makers.

Key Findings

Although a variety of pre-natal and post-natal environmental factors have been identified as being associated with autism, little is known about the actual causes of autism. As such, it may be hard for parents to avoid the development of autism that will ultimately disable and financially burden their child, and family, for life. With seemingly little to be done to prevent autism from developing, resources have been devoted to developing effective early intervention therapies to overcome the symptoms of the disorder. When a parent's only choice to improve his or her child's future is autism-diagnosis-dependent services and financial resources, they may opt for - or even actively pursue - an autism diagnosis for the child. Indeed, the reported literature establishes a strong case for the argument that diagnoses may be getting "upgraded" to formal autism in the face of financial and/or service incentives. Yet, a weakness of many of these studies is that they fail to formally quantify the impact that diagnosis-dependent service availability or financial resources have on autism rates. Many are simply observational in nature. I will further the literature in my study by attempting to quantify the impact of one such diagnosis-dependent autism resource – the Ohio ASP – on autism rates.

A Program Case Study: The Ohio Autism Scholarship Program

The Ohio Autism Scholarship Program allows the Ohio State Department of Education to pay a scholarship to the parents of a qualified child with autism (2010). The non-means-tested program currently provides parents of children with an autism spectrum disorder public funds of up to $20,000 per year (and up to $7,000 per quarter) to purchase education or treatment at private schools or other approved facilities (Van Lier, 2008). Although families of all income levels are eligible, their child must have an Autism Spectrum Disorder (ASD) diagnosis in his or her Individualized Education Plan (IEP), the written document that outlines the child's education needs. Van Lier (2008) states that "preschool-age children must be evaluated by a physician or psychologist using criteria for autism spectrum disorder in the 4th edition of the Diagnostic and Statistical Manual of Mental Disorders, and must have deficits in communication and adaptive behavior and 'at least three observations that document behavior consistent with autism conducted by a nonfamily member who is knowledgeable about autism." In fiscal year 2007, approximately 50 percent of all program participants were preschoolers (Van Lier, 2008). Even so, children up to age 21 (and as young as 3) can qualify for the program, so long as they are enrolled or eligible to enroll in their school district of residence at any level from preschool to 12th grade in accordance with the Ohio Revised Code (Van Lier, 2008). This program is one of only four of its kind in the United States; Florida, Utah, and Arizona possess similar scholarships.

Another stipulation of the program is that scholarship funds be used at one or more providers on an approved list. The number of approved providers in the program has grown from 200 in 32 of Ohio's 88 counties in October 2007 to 243 in 38 Ohio counties according to the most recent Department of Education reports. The number of students using the program has also grown since its inception from 70 students in 2003 to 1,495 students in 2010. Providers wishing to be approved in the program must apply through the Office of Exceptional Children of the Ohio State Department of Education.

Statement of Major Research Questions

The major research question to be explored in this study is:Do financial incentives for families affect autism diagnoses?

Specifically, I will be exploring the question of whether programs that provide a financial incentive for children to be diagnosed with autism affect the number of formal autism diagnoses.

Furthermore, I will be examining how autism incidence rates compare (1) between Ohio and nearby and far states that have not implemented the program and (2) within Ohio between counties have been able to utilize the program to varying degrees due to provider availability.

Statement of Hypotheses to be Tested

H1: Holding all other factors constant and allowing for differences in baseline autism rates, Ohio's autism incidence rates will be greater than those of other states with the implementation of the Scholarship program in 2004.

H2: Ohio counties with providers in which the program can actually be implemented will experience a greater than average increase in autism rates during the years of the policy (2004-2009) relative to Ohio counties with no providers, controlling for socio-economic factors in the county.

Motivation: If financial incentives affect diagnoses, I would expect Ohio's autism rates to jump where comparison states' rates have not because the Scholarship program provides parents with the impetus to obtain an ASD school diagnosis for their child, whereas parents in comparison states do not experience a change in financial incentive. Through the Autism Scholarship Program, Ohio has made a link between diagnosis and access to services that may be less salient in other states.

Methods

Description of Data Set

State Analysis: The state-level analysis utilizes data from the 2005 Interim State Population Projections of the U.S. Census Bureau Population Division to estimate the overall state population of 3 to 22-year-olds from 2000 to 2008 for each U.S. state. The dataset consists of estimates for the population at each age (from 0 to 85+) for the year 2000 and for each year from 2004 to 2030. Because the state autism counts from U.S. Special Education data are only available from 2000 to 2008 for ages 3 to 22, I linearly interpolate the population of 3 to 22-year-olds for the years 2001 to 2003. The autism count data are a part of a larger set of child count data collected annually by the U.S. Department of Education, Office of Special Education Programs (OSEP) in accordance with Section 618 of Individual with Disabilities Education Act (IDEA). Each state collects its own data and submits those data to the OSEP, where it is, in turn, used to prepare reports for the US Congress. The data are made publically available on thoughtfulhouse.org.

Ohio County Analysis: Online data are available from the Power User Reports of the Ohio State Department of Education Interactive Local Report Card (iLRC). Data from this database include enrollment and demographics of students at the state, district, and school building levels for each school year. The number of autistic children aged 3 to 21 is available for each year from 1995 to 2010 on a school building level in county datasets. A separate iLRC dataset on total enrollment for each school (at the building level) in a county is also available for 1995 to 2010. It is therefore necessary to sum these school level autism enrollment counts and divide them by summed school enrollment totals in order to calculate county-level autism rates for a given year.

A list of approved 2006-2007 ASP providers provided by School Choice Ohio is also used to determine if counties have providers and, if so, how many. This list is updated annually, with 2010-2011 being the most current sample available. Although the number of providers in a county can change from year to year, making a provider county a non-provider county and vice-versa, these post-policy yearly changes are not integral to this analysis, which is why I have not included yearly provider count data. Ideally, pre-policy data should be included to show how providers responded to the policy by moving into many counties that have a large potential patient population. Because such data are unavailable, I utilize the earliest list of approved providers available, from two years after the ASP began operation.

Description of Dependent/Outcome Variables

State Analysis: Because rates can be skewed if a state population is small, a negative binomial regression will be performed using autism counts and adjusting for population size. Thus, two dependent variables are observed separately. The unit of observation in the ordinary least squares (OLS) regression is the mean autism rate for 3-22 year-olds per 100,000 children age 3-22 for state in a given year from 2000 to 2008. For example, if the state was Ohio and the year was 2004, then the outcome variable would represent the mean autism rate for Ohio in 2004. States are categorized according to whether they are near or far from Ohio (defined further below). The second unit of observation in the negative binomial regression is the mean autism count among 3-22 year-olds for a state in a given year from 2000 to 2008, controlling for the state’s 3-22 year-old population in that given year.

Ohio County Analysis: Just as in the state analysis, it is important to observe both autism rates and counts. The unit of observation in the OLS regression is the mean autism rate for 3-21 year-olds per 100,000 students age 3-21 for a county in a given year from 1995 to 2010. For example, if the county was Cuyahoga and the year was 2004, then the outcome variable would represent the mean autism rate for Cuyahoga County in 2004. Counties are categorized according to whether they had no provider, any provider, or more than one provider in 2006. In the negative binomial regression, we observe the mean autism count among 3-21 year-olds for a county in a given year, controlling for the total 3-21 year-old student enrollment in that year.

Description of Explanatory Variables

State Analysis:

Near – A dummy variable (1 or 0) that indicates whether a state is near Ohio (within 200 miles) or not. The variable is equal to 0 for Ohio.

Far – A dummy variable (1 or 0) that indicates whether a state is far from Ohio (beyond 200 miles) or not. The variable is equal to 0 for Ohio.

Timetrend – A variable that codes for the year. It is equal to 0 in 2000, 1 in 2001, and so on.

Post – A dummy variable (1 or 0) that indicates whether the year is before (2000-2003) or after (2004-2008) the Ohio ASP was enacted.

Posttime – An interaction term generated by multiplying post by timetrend.

Posttimenear – An interaction term generated by multiplying post by timetrend and near.

Posttimefar – An interaction term generated by multiplying post by timetrend and far.

Ohio County Analysis:

Provider – A dummy variable (1 or 0) that indicates whether a county has any approved scholarship program providers or not.

Providerhigh – A dummy variable (1 or 0) that indicates whether a county has more than 1 provider or not.

Timetrend – A variable that codes for the year. It is equal to 0 in 1995, 1 in 1996, and so on.

Post– A dummy variable (1 or 0) that indicates whether the year is before (1995-2003) or after (2004-2010) the Ohio ASP was enacted.

Posttime – An interaction term generated by multiplying post by timetrend.

Posttimeprovider – An interaction term generated by multiplying post by timetrend and provider.

Posttimehigh– An interaction term generated by multiplying post by timetrend and providerhigh.*Specification of Empirical Model*

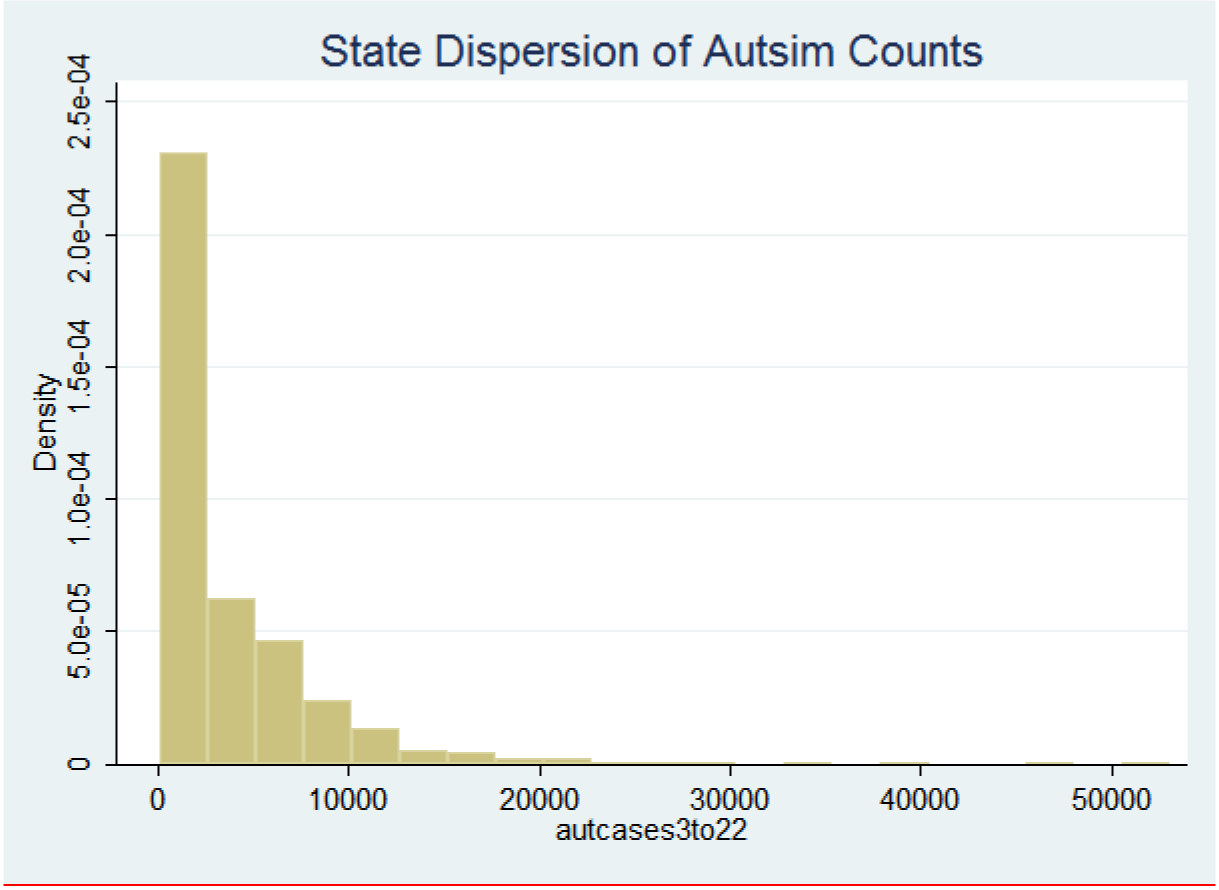
In order to determine whether changes in autism rates or counts are attributable to the Ohio ASP, I perform both a state and Ohio county analysis. Both analyses include two regressions: an OLS model observing mean autism rates, and a negative binomial regression observing mean autism counts. The state analysis allows me to see if the ASP was associated with an increase in autism rates in Ohio relative to other states that have not enacted the policy. Distinguishing between states that are near versus far from Ohio allows me to observe whether families who live in states near to Ohio may move to Ohio to take advantage of the program, over families living in states that are far away who are more unlikely to do so. Either way, results from the OLS and negative binomial regression should complement each other. The county analysis is less definitive than the state analysis for determining whether the ASP caused autism rates to increase. This is because an increase in autism rates observed among Ohio provider counties relative to non-provider counties may be misleading and actually reflect a re-distribution of autism cases within Ohio. Perhaps the policy causes families with autistic children that would have otherwise been randomly dispersed throughout Ohio counties to move, or simply drive, to counties with providers where they can utilize the financial incentive of the ASP. Alone, the county analysis can only show how the provider market may have responded to changes in the demand for autism services. If this analysis shows an increase in autism rates and counts for high provider counties and there was an overall increase in autism rates and counts in Ohio relative to other states, only then can the hypothesis be supported.

For the following analysis model descriptions, please refer to the regression equations at the bottom of each section to see where variables discussed appear in the regression.

<u>State Analysis:</u> I will determine whether Ohio's autism rate changes differently relative to other states, particularly after the Autism Scholarship Program was put into effect in 2004. I assume that no other significant changes have taken place that would make the states incomparable and verify that comparison states have not enacted any policies or made any other changes that might impact autism rates. Two groups of comparison states will be created using dummy variables: (1) states close to Ohio (within 200 miles, includes Indiana, Kentucky, Michigan, New York, North Carolina, Pennsylvania, Tennessee, Virginia, and West Virginia) and (2) all other far states. Since Ohio falls into neither category, the dummy for each group will equal 0 for Ohio. Mean autism rates are then formed for these groups for each year (. The "near" and "far" indicator variables allow the autism rates to differ between Ohio and these two groups of states. The coefficient on the timetrend variable (indicates the average annual increase in the autism rate nationally. This allows me to conduct a difference-in-difference approach and control for the fact that autism rates were not the same between Ohio and near and far states. Using the timetrend variable, I am allowing for a national trend of increasing autism rates to occur. The coefficient indicates whether the autism rate increased at a greater rate nationally after the policy relative to before; the coefficients and measure whether the autism rate increased at a different rate in the near and far states after the ASP relative to Ohio. If my hypothesis is correct that the Ohio policy was associated with unique increases in autism rates relative to other states, then the coefficients on will be negative and statistically significant. The post ( ) variable is included in the regression to help with the interpretation of the posttime interaction variables of interest. With these explanatory variables, the dependent variable of mean autism rate for a state's category (near, far, or Ohio) in a given year is estimated.

A similar negative binomial regression (nbreg) using the data on the number of cases of age 3-22 autism is performed. This is essential because OLS regressions are limited in their ability to estimate count data. It is important to also look at autism counts because rates can easily be skewed if the state is small or scarcely populated and a few cases are left out. Another way to think about it is that the autism rates in the more populated states will be more accurate than in the less populated sates. Further, the nbreg model will be a better fit for the over-dispersion shown in the outcome variable of autism counts and even rates. A simple histogram (Figure 1) confirms the highly skewed-right nature of the data. Although the histogram depicts autism counts, the same skew pattern can be seen for autism rates.

Figure 1: Skewed-Right Dispersion of State Autism Count Data



By using autism counts in a negative binomial regression, one is able to adjust for the population size. The dependent variable observed here is the average number of autism cases of autism for 3-22 year olds in a given year in a given state. As with the OLS regression, I will focus on interpreting the coefficients . The nbreg regression is conceptually the same as the OLS regressions, except for the outcome variable and the inclusion of the total population of 3 to 22 year-olds in a state.

Ohio County Analysis: I will determine whether there are significant differences in the change in autism rates within Ohio by comparing the roughly 43% of counties that have approved providers with the roughly 57% of counties that do not currently have any approved providers with which the Autism Scholarship Program can be utilized. A subset group of high provider counties will be arbitrarily created that consists of counties with more than 1 provider, since one could argue that counties with only one provider offer little added choice to parents and more closely share the experiences of a county without any providers at all. I perform two similar, but separate regressions: first (A) comparing the autism rates in a given year between a group of counties that have any number of providers with the counties that have no providers, and second (B) comparing the autism rates in a given year between a group of counties that have a "high" (>1) number of providers with all other counties. These two regressions are necessary because if both the provider variable and high provider variable were included in one regression, there would be overlap and interpretation of the coefficients would be difficult. Because application to the Ohio ASP relies on a school diagnosis of an ASD, this analysis looks at school-reported autism enrollment rates. Mean autism rates are then formed for the groups (depending on which regression version is used) for each year (. The timetrend variable (measures the average annual increase in autism rates statewide. This allows me to conduct a difference-in-difference approach and control for the fact that autism rates were not the same between non-provider, provider, and high provider counties. The timetrend variable of the state analysis is used similarly here, controlling for the potential statewide increasing trend in autism rates. The posttime coefficient indicates whether the autism rate increased at a greater rate statewide after the policy relative to before. , depending on the version of the equation, measures whether the autism rate increase at a different rate in (a) the provider counties relative to the non-provider counties or (b) the high provider counties relative to all other counties. If my hypothesis is correct that the Ohio policy was, in fact, associated with increases in autism rates in provider counties where the policy could easily be used relative to non-provider counties, then the coefficients (for both versions of) will be positive and statistically significant. The post

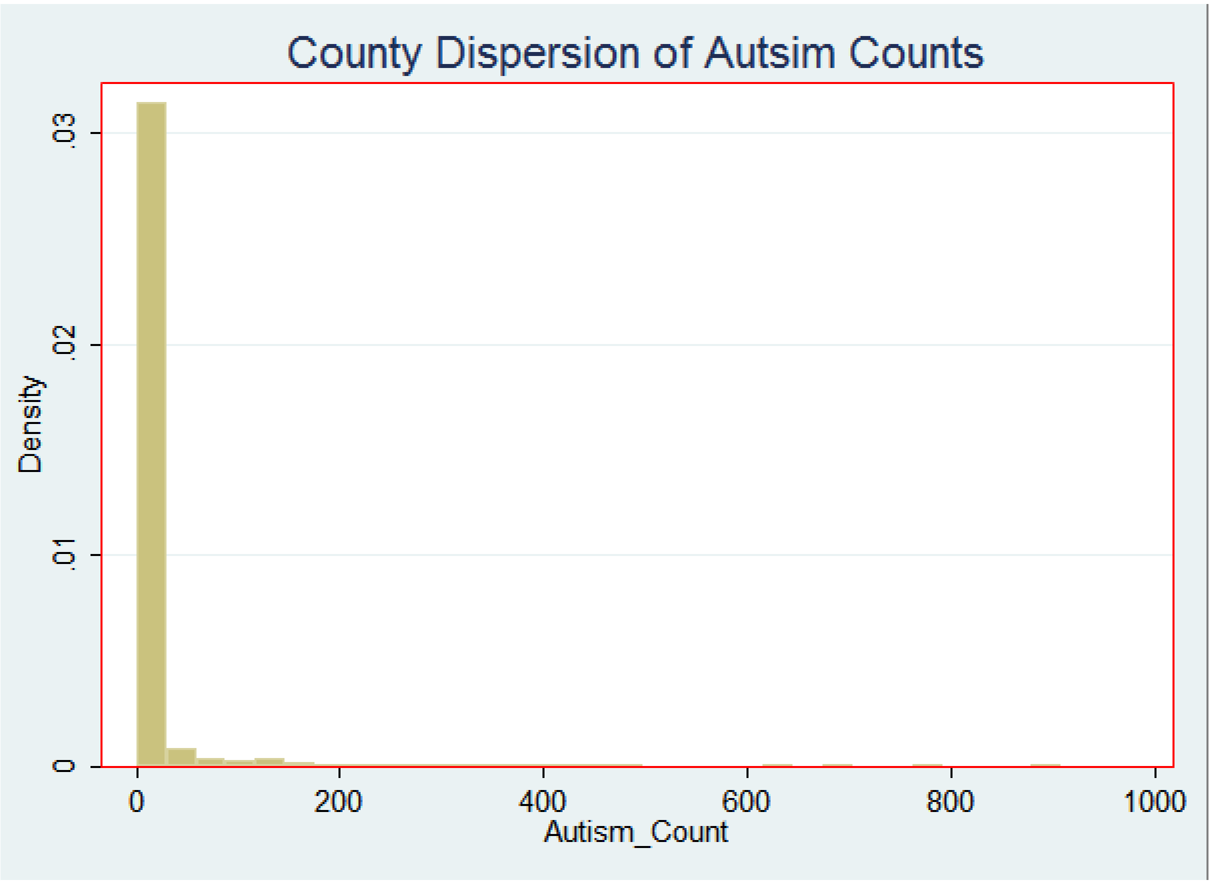
( ) variable is included in the regression to help with the interpretation of the posttime interaction variables of interest. With these explanatory variables, the dependent variable of mean autism rate for a county's category (non-provider, provider, or high provider) in a given year is estimated.

A. Comparing autism rates in counties that have any providers vs. counties with no providers:

B. Comparing autism rates in counties that have a "high" (>1) number of providers vs. all other counties:

For the same reasons as in the state analysis, I also perform a similar nbreg using the Ohio county autism count data. Similarly, adjustments are made for the county population size. The dependent variable observed here is the average number of autism cases in a given year in a given county. As with the OLS regression, it is important to focus on . The nbreg regressions are the same as the OLS regressions, except for the outcome variable and the inclusion of the number of students in the enrolled population of a county as an exposure. There are also two nbreg regressions, one using the provider group and the other using the high provider group as the point of comparison. The histogram (Figure 2) below shows that because the county autism count data is also over-dispersed and skewed right, the nbreg model is likely a better fit for this analysis. The autism rate data also displays similar skewed-right dispersion.

Figure 2: Skewed-Right Dispersion of County Autism Count Data



Descriptive Statistics

State Analysis: The state analysis included all 51 states (District of Columbia included), with 9 of 50 (Ohio is excluded) near states. Table 1 shows the number of observations, means, standard deviations, minimums and maximums for each variable in the analysis. Table 2 shows the mean autism rates per 100,000 3 to 22 year-olds for each state group (far, near, or Ohio) from 2000 to 2008; it corresponds to the Figure 3 graph. Figure 3 shows that the rates of autism in Ohio began much lower than the mean rates of near and far states but, by the time the Ohio ASP was enacted in 2004, Ohio's autism rates were the same as the far state rates and by the end of the period of observation in 2008, they were higher than both state groups. Table 3 depicts the mean number of autism cases for people aged 3 to 22 for each state group (far, near, or Ohio) from 2000 to

2008. The corresponding graph (Figure 4), shows that while autism counts were similar between Ohio and neighboring states, they began to diverge – with Ohio's counts exceeding those of nearby states – in 2001. The number of cases of autism was still higher in the Ohio area as compared with far states.

Table 1: State Analysis Descriptive Statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
year	459	2004	2.584806	2000	2008
Population	459	1675064	2365931	130366	3.36E+07
autcases	457	3958	5717.43	108	53050
autrate	457	226.7363	132.2971	9.117674	872.6781
near	459	0.1764706	0.381636	0	1
far	459	0.8039216	0.3974618	0	1
post	459	0.5555556	0.4974462	0	1
timetrend	459	4	2.584806	0	8
postnear	459	0.0980392	0.2976921	0	1
posttimenear	459	0.5882353	1.840339	0	8
posttimefar	459	2.679739	3.13242	0	8
posttime	459	3.333333	3.165728	0	8

Table 2: Mean Autism Rates per 100,000 3-22-year-olds by State Category

Mean Autism Rate	**Far**	**Near**	**Ohio**

2000	105.9061	116.5303	78.92518
2001	130.7824	138.2959	105.6981
2002	157.7807	164.4279	136.2092
2003	185.662	193.4411	172.614
2004	210.9585	226.1309	210.7582
2005	244.3266	263.2463	253.7616
2006	288.4065	304.8033	302.1811
2007	333.351	349.9618	325.4756
2008	366.1967	395.4299	403.8157

Figure 3: Mean Autism Rates per 100,000 3 to 22-year-olds by State Category

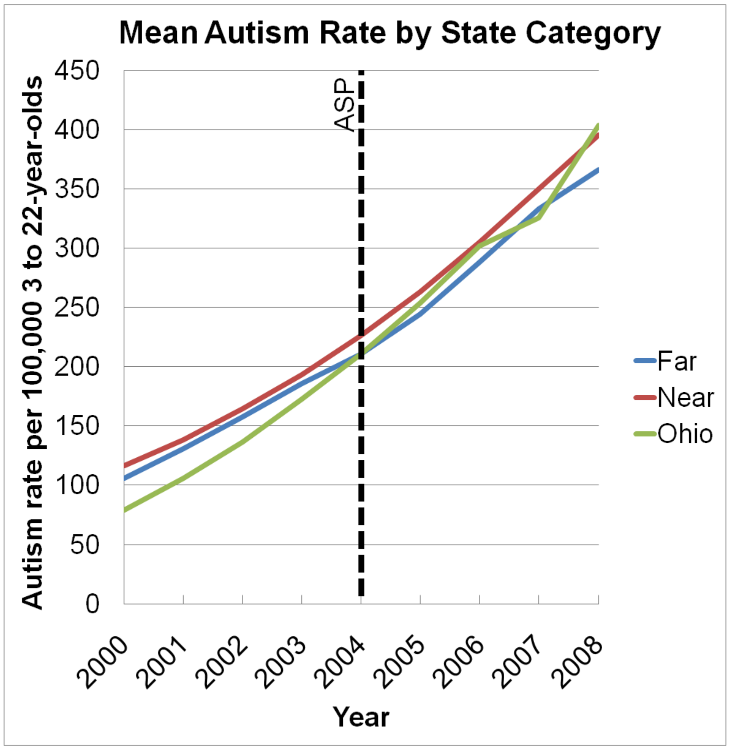
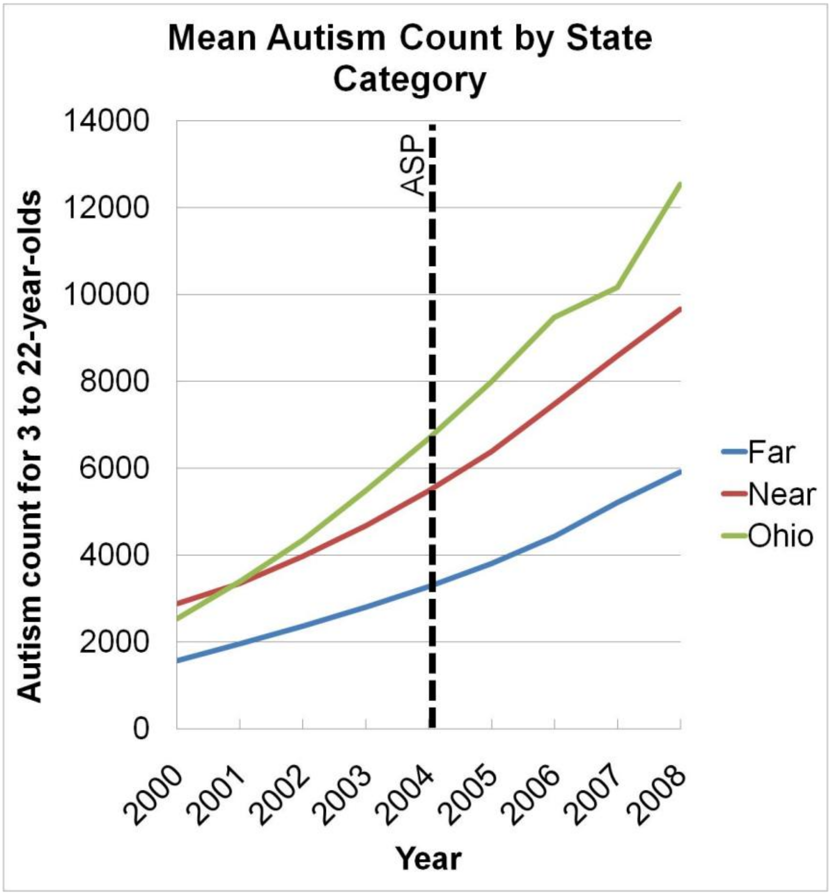


Table 3: Mean Autism Counts for 3-22-year-olds by State Category

Year	**Far**	**Near**	**Ohio**
2000	1574.66	2875.89	2543
2001	1965	3345.78	3391
2002	2361.15	3978.56	4351
2003	2809.44	4674.78	5490
2004	3276.83	5477.67	6674
2005	3809.8	6379.44	7993
2006	4425.49	7476.22	9469
2007	5214.75	8577.22	10155
2008	5913.28	9655	12537

Figure 4: Mean Autism Counts for 3 to 22-year-olds by State Category



Ohio County Analysis:

This analysis included all 88 of Ohio's counties. Table 4 shows the number of observations, means, standard deviations, minimums and maximums for each variable in the analysis. Table 5 shows the mean autism rates for each county group (non-provider, provider, high provider, low and no provider) from 1995 to 2010; it corresponds to the Figure 5 graph. Figure 5 shows that from 1995-1997 no Ohio counties have any cases of autism. From 1997-2002 provider counties are the only counties to have cases of autism, while non-provider counties continue to have 0 cases. Although some pre-policy differences existed between all 4 provider type county groups, the increase in autism rates is still far more rapid in the provider county groups relative to the no provider counties after the policy was enacted in 2004, particularly for the high provider counties (> 1). The purple line (# Providers ≤ 1) shows that the mean autism rates in low provider counties are very similar to no provider counties and follow a very similar trend, supporting the legitimacy of categorizing the low provider counties with the no provider counties. Table 6 and Figure 6 depict the same information for autism counts. As you can see from the graph in Figure 6, the trends in autism counts could be characterized similarly as the trends in autism rates.

Table 4: Ohio County Analysis Descriptive Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Year	1320	2002	4.322131	1995	2009
Policy_Year	1320	0.4666667	0.4990767	0	1
Provider	1320	0.3522727	0.4778594	0	1
NumProviders	247	0.8421053	4.482505	0	43
Total_Enro~d	1320	20598.95	31748.83	1986	202187
Autism_Count	1320	14.02273	66.65466	0	909
Ratep~100000	1320	24.71559	79.52949	0	638.2397
providerhigh	1320	0.1590909	0.3658995	0	1
timetrend	1320	7	4.322131	0	14
posttime	1320	5.133333	5.657426	0	14

posttimepr~r	1320	1.808333	4.158398	0	14
posttimehigh	1320	0.8166667	2.935965	0	14

Table 5: Mean Autism Rates per 100,000 3-22-year-olds by County Category

Mean Autism Rate	No Providers	Any Providers	# Providers > 1	# Providers ≤ 1
1995	0	0.33381347	0.73915839	0
1996	0	0	0	0
1997	0	0.24385431	0.53996312	0
1998	0	3.0955128	6.8543497	0
1999	0	1.6224485	3.5925646	0
2000	0	4.4128864	9.7713913	0
2001	0	7.7965096	17.2637	0
2002	3.4591276	13.786327	30.526866	2.6644631
2003	13.446728	38.10462	58.82763	15.190809
2004	16.002629	50.371778	92.787183	15.873708
2005	3.6920348	53.29354	98.352388	6.5623283
2006	20.093321	82.005642	152.84554	20.914279
2007	21.496838	116.05959	202.49467	26.868132
2008	28.918623	172.91777	291.73321	39.520913
2009	44.069828	230.38703	366.74065	61.075799

Figure 5: Mean Autism Rates per 100,000 3 to 22-year-olds by County Category

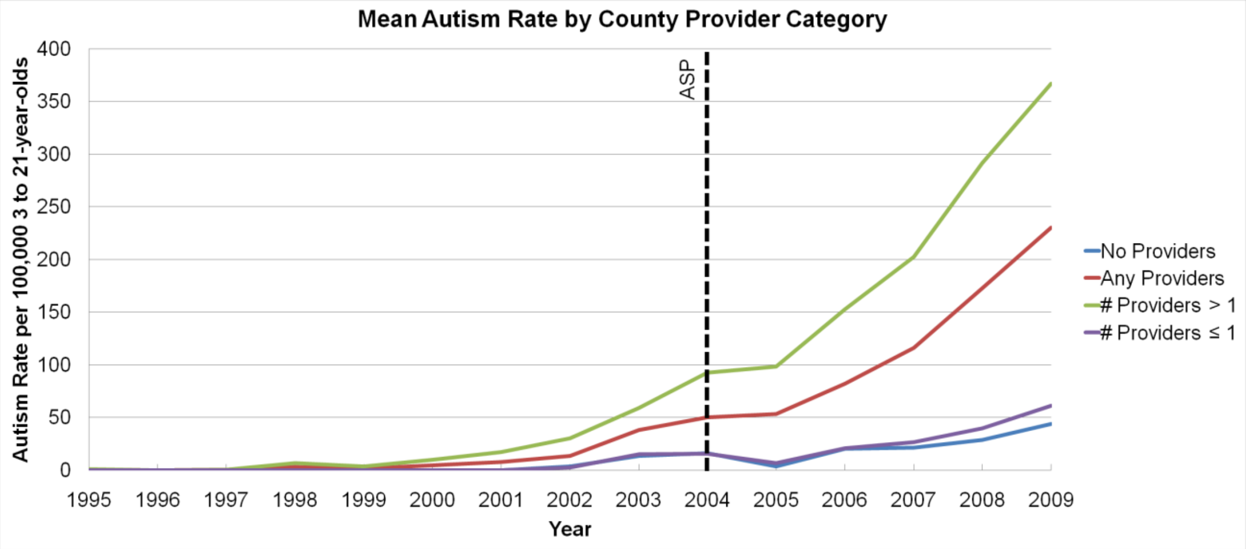
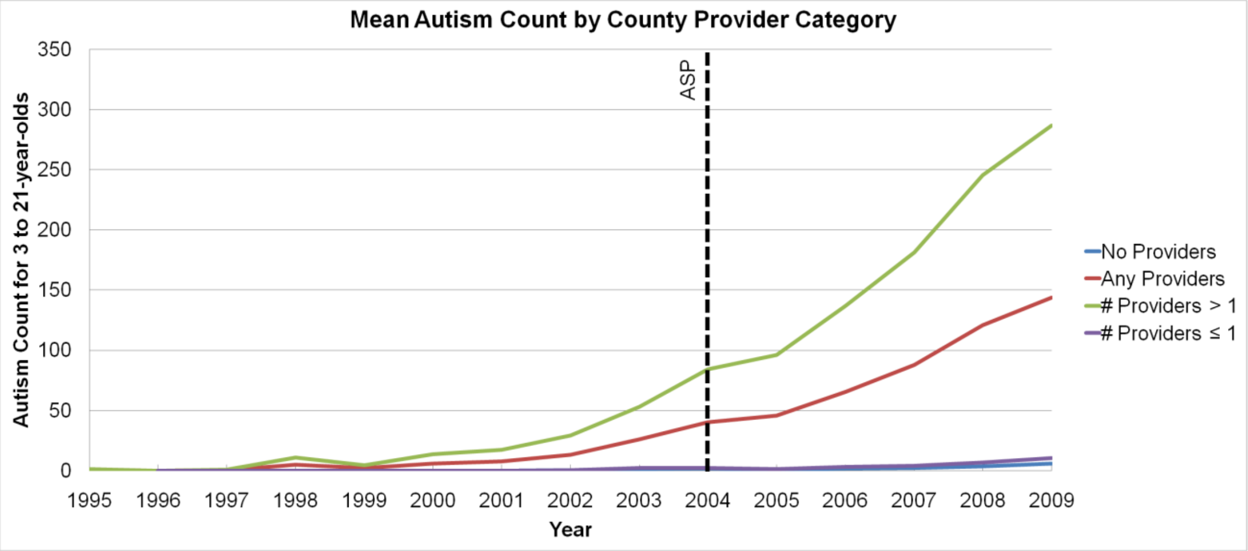


Table 6: Mean Autism Counts for 3 to 22-year-olds by County Category

Mean Autism Count	No Providers	Any Providers	# Providers > 1	# Providers ≤ 1
1995	0	0.516129	1.14286	
1996	0	0	0	0
1997	0	0.387097	0.857143	0
1998	0	4.93548	10.9286	0
1999	0	2	4.42857	0
2000	0	6.09677	13.5	0
2001	0	7.74194	17.1429	0
2002	0.491228	13.129	29.0714	0.378378
2003	1.50877	26.1935	53	2.10811
2004	1.77193	40.1936	84.1429	2.28378
2005	0.421053	45.8064	96.1429	1.32432
2006	1.96491	65.4516	136.857	3.04054
2007	2.21053	87.8387	181.143	4.22973
2008	3.52632	120.677	245.357	6.85135
2009	5.77193	143.645	286.786	10.3649

Figure 6: Mean Autism Counts for 3 to 22-year-olds by County Category



Results

State Analysis:

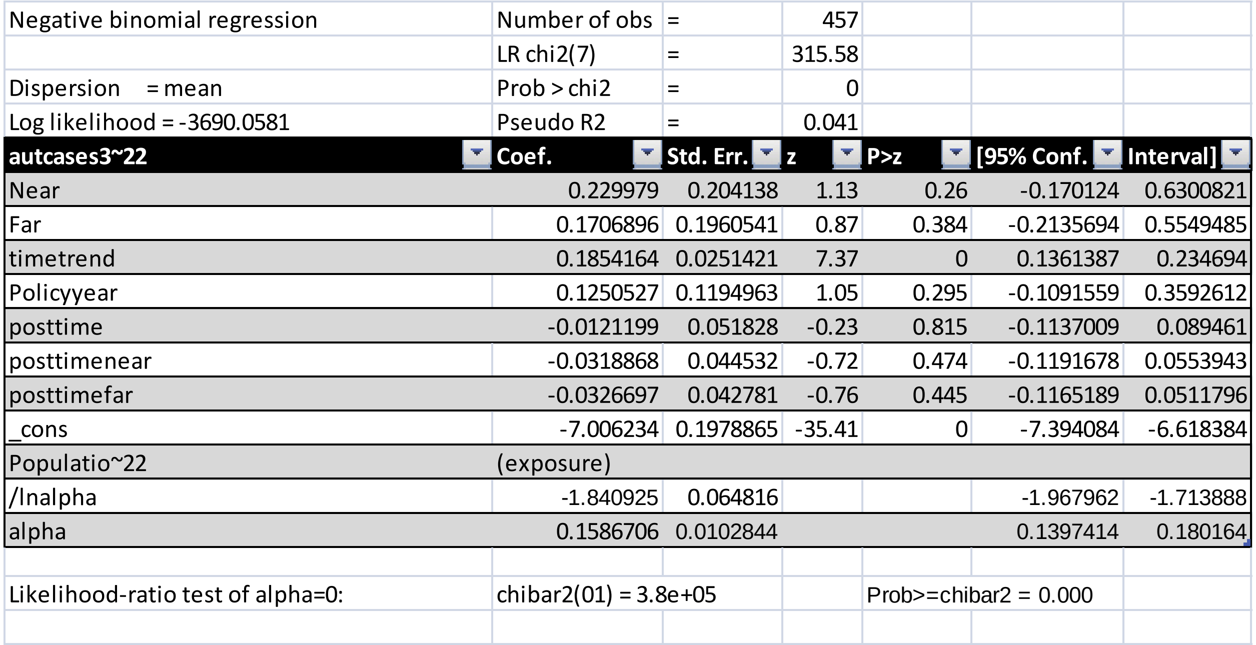
Based on the ordinary least-squares regression technique using the autism rate per 100,000 persons aged 3 to 22 in a state as the dependent variable, the coefficients were negative, consistent with my hypothesis. The coefficient on posttimenear was more negative than the coefficient on posttimefar. Thus, these coefficients show that the autism rate per 100,000 children was less in the near states than in Ohio and even more less in the far states than in Ohio in a given year. Despite all of this, no statistical significance was shown for the variables of interest – posttimenear and posttimefar. Any difference in the autism rates between Ohio, near states, and far states, is therefore due to chance. Table 7. Of note, however, is the statistically significant coefficient . It shows that nationally, on average, the autism rate was increasing by 26.5 cases per 100,000 3 to 22 year olds per year.

Table 7: OLS Regression for State Analysis observing Autism Rates per 100,000 3 to 22-Year Olds

autra~100000	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]
Near	29.71423	51.41008	0.58	0.564	-71.32002	130.7485
Far	21.84146	49.36336	0.44	0.658	-75.17045	118.8534
timetrend	26.54956	6.306163	4.21	0	14.1563	38.94281
Policyyear	-57.0984	29.98972	-1.9	0.058	-116.036	1.839243
posttime	18.94626	13.04678	1.45	0.147	-6.69408	44.5866
posttimenear	-3.48665	11.18904	-0.31	0.755	-25.47604	18.50273
posttimefar	-5.42312	10.74477	-0.5	0.614	-26.5394	15.69316
_cons	83.41767	49.71177	1.68	0.094	-14.27896	181.1143

In the negative binomial regression (Table 8), a likelihood ratio test that alpha equals zero is performed. The chi-squared value obtained was 3.8e+05 with one degree of freedom, indicating the high level of over-dispersion and thus, that the negative binomial model fits the data better than the OLS model. The nbreg regression significantly changed the coefficients on posttimenear and posttimefar from what they were in the OLS regression. Both coefficients were less negative (nearly 0) and statistically insignificant. This means that the average number of autism cases in near and far states were less than (but to a lesser extent than the OLS regression depicted) the rates in Ohio.

Table 8: Negative Binomial Regression for State Analysis Observing the Number of Autism Cases among 3-22 Year-Olds

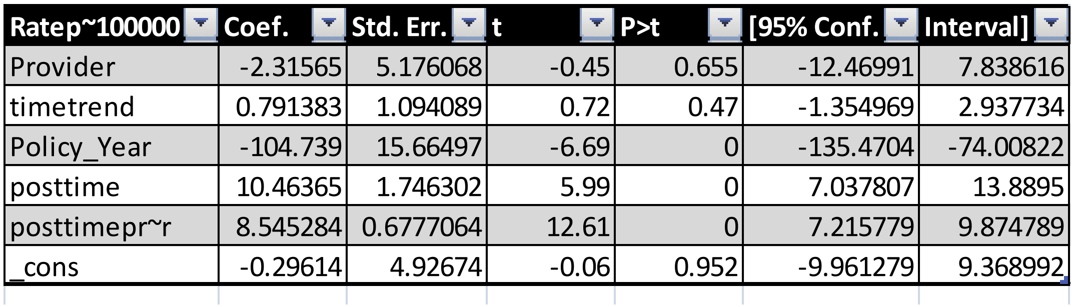


Negative binomial regression	Number of obs	=	457			
	LR chi2(7)	=	315.58			
Dispersion = mean	Prob > chi2	=	0			
Log likelihood = -3690.0581	Pseudo R2	=	0.041			
autcases3~22	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
Near	0.229979	0.204138	1.13	0.26	-0.170124	0.6300821
Far	0.1706896	0.1960541	0.87	0.384	-0.2135694	0.5549485
timetrend	0.1854164	0.0251421	7.37	0	0.1361387	0.234694
Policyyear	0.1250527	0.1194963	1.05	0.295	-0.1091559	0.3592612
posttime	-0.0121199	0.051828	-0.23	0.815	-0.1137009	0.089461
posttimenear	-0.0318868	0.044532	-0.72	0.474	-0.1191678	0.0553943
posttimefar	-0.0326697	0.042781	-0.76	0.445	-0.1165189	0.0511796
_cons	-7.006234	0.1978865	-35.41	0	-7.394084	-6.618384
Populatio~22	(exposure)					
/lnalpha	-1.840925	0.064816			-1.967962	-1.713888
alpha	0.1586706	0.0102844			0.1397414	0.180164
Likelihood-ratio test of alpha=0:	chibar2(01) = 3.8e+05			Prob>=chibar2 = 0.000		

County Analysis:

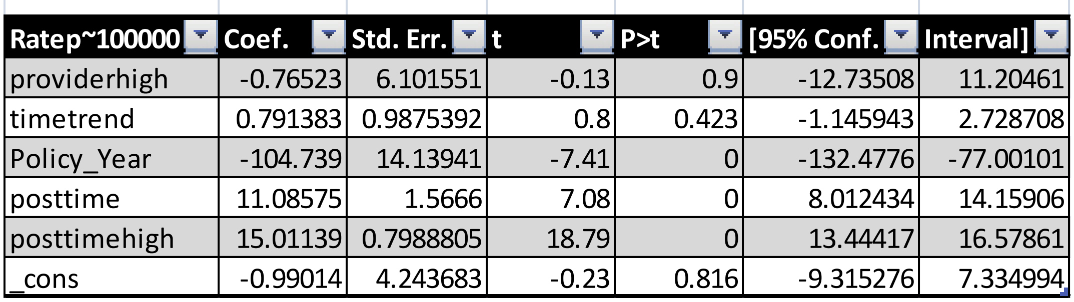
Based on an OLS regression technique observing the autism rate per 100,000 students in a given year in a given county, the coefficients derived from conducting two regressions (Tables 9 and 10) were positive and statistically significant, consistent with my hypothesis. The coefficient on posttimeprovider, the variable concerned with demonstrating the effect of provider status on autism rates in counties, was lower and less statistically significant than the coefficient on the variable posttimehigh, the variable concerned with demonstrating the effect of provider status on autism rates in counties more than 1 provider (a “high” number of providers). This means that counties with providers experienced a significantly greater growth rate in autism rates than counties without providers and “high” provider counties had significantly greater autism rates than low or no provider counties. This sort of observed “dose response” was correctly predicted in my hypothesis.

Table 9: OLS Regression for County Analysis Observing Autism Rate per 100,000 3-21-Year-Olds Using Provider Counties as Comparison Group



Ratep~100000	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Provider	-2.31565	5.176068	-0.45	0.655	-12.46991	7.838616
timetrend	0.791383	1.094089	0.72	0.47	-1.354969	2.937734
Policy_Year	-104.739	15.66497	-6.69	0	-135.4704	-74.00822
posttime	10.46365	1.746302	5.99	0	7.037807	13.8895
posttimepr~r	8.545284	0.6777064	12.61	0	7.215779	9.874789
_cons	-0.29614	4.92674	-0.06	0.952	-9.961279	9.368992

Table 10: OLS Regression for County Analysis Observing Autism Rate per 100,000 3-21-Year-Olds Using High Provider Counties as Comparison Group

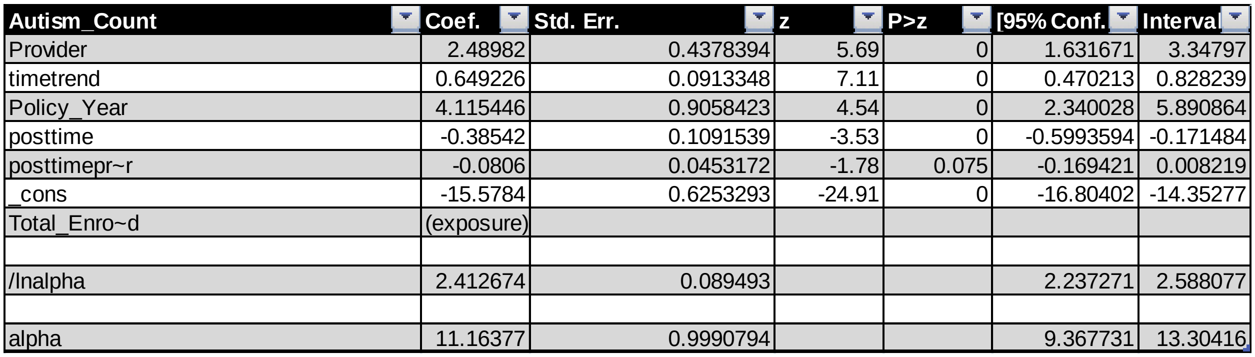


Ratep~100000	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
providerhigh	-0.76523	6.101551	-0.13	0.9	-12.73508	11.20461
timetrend	0.791383	0.9875392	0.8	0.423	-1.145943	2.728708
Policy_Year	-104.739	14.13941	-7.41	0	-132.4776	-77.00101
posttime	11.08575	1.5666	7.08	0	8.012434	14.15906
posttimehigh	15.01139	0.7988805	18.79	0	13.44417	16.57861
_cons	-0.99014	4.243683	-0.23	0.816	-9.315276	7.334994

However, in the negative binomial regression using autism counts the dependent variable controlling for total enrollment independently, both coefficients on the any number of provider and high provider counties were negative (see Tables 11 and 12). The coefficient for any number of provider counties was close to 0 (-0.08). The coefficient for high provider counties was negative but almost 0 (-0.16). Both the coefficients on posttimeprovider and posttimehigh were significant. The results of this regression set seem to directly contradict the previous OLS results and suggest that there are fewer autism cases in provider counties relative to no provider counties. Thus, an inverse dose response appears here and contradicts the hypothesis. These two nbreg models nevertheless show that there was a statistically significant increase in autism cases occurring statewide in Ohio by an average 0.65-0.77cases per year. Because the chi-squared values (1.30e+04, and 9990.86, for the provider regression and the high provider regression, respectively) indicate that the nbreg model takes into account the over-dispersion of the count data and is stronger than the OLS model, these results might take precedence.

Table 11: Negative Binomial Regression for County Analysis Observing Autism Count Using Any Number of Provider Counties as Comparison Group

Negative binomial regression
Number of obs = 1320
LR chi2(5) = 256.05
Dispersion = mean
Prob> chi2 = 0
Log likelihood = -1488.2455
Pseudo R2 = 0.0792



Autism_Count	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval
Provider	2.48982	0.4378394	5.69	0	1.631671	3.34797
timetrend	0.649226	0.0913348	7.11	0	0.470213	0.828239
Policy_Year	4.115446	0.9058423	4.54	0	2.340028	5.890864
posttime	-0.38542	0.1091539	-3.53	0	-0.5993594	-0.171484
posttimepr~r	-0.0806	0.0453172	-1.78	0.075	-0.169421	0.008219
_cons	-15.5784	0.6253293	-24.91	0	-16.80402	-14.35277
Total_Enro~d	(exposure)					
/lnalpha	2.412674	0.089493			2.237271	2.588077
alpha	11.16377	0.9990794			9.367731	13.30416

Likelihood-ratio	test	of	alpha=0:	chibar2(01	=	1.30E+04	Prob>=chibar2	=	0

Table 12: Negative Binomial Regression for County Analysis Observing Autism Count Using High Provider Counties as Comparison Group

Negative binomial regression	Number of obs	=	1320
	LR chi2(5)	=	304.02
Dispersion = mean	Prob > chi2	=	0
Log likelihood = -1464.2616	Pseudo R2	=	0.094

Autism_Count	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval
providerhigh	3.818563	0.5490005	6.96	0	2.742542	4.894585
timetrend	0.772515	0.1144596	6.75	0	0.5481784	0.996852
Policy_Year	5.23764	0.9800643	5.34	0	3.316749	7.158531
posttime	-0.49688	0.1265204	-3.93	0	-0.7448561	-0.248905
posttimehigh	-0.16435	0.0549714	-2.99	0.003	-0.2720963	-0.056612
_cons	-16.6361	0.7586911	-21.93	0	-18.12311	-15.1491
Total_Enro~d	(exposure)					
/lnalpha	2.278508	0.0903779			2.10137	2.455645
alpha	9.762103	0.8822789			8.177368	11.65395

Likelihood-ratio	test	of	alpha=0:	chibar2(01	=	9990.86	Prob>=chibar2	=	0

Conclusions

The state analysis was done to show whether the ASP had an impact on autism rates and my results show that it did not. These results were to be used in tandem with the county analysis to confirm an effect of the ASP on autism rates. While the OLS regressions show that the ASP might have had a positive impact on increasing autism rates in provider counties, the nbreg regression shows also with significance that a reduction in autism rates results from the presence of a provider in a county. These contradictory county analysis results, combined with non-confirmational state analysis results, overall lead to a rejection of the hypothesis that programs which offer financial incentives for autism diagnoses increase autism rates. At best, even if we give precedence to the OLS results for the county analysis, we cannot make any statement about the impact of the ASP on autism rates. Perhaps through these results, we can observe confirmation in the ability for markets to respond to changes in demand. This is to say that the opposing mechanism could be observed: providers observed that there was a need for services and that if they did not provide services, the existing autism-affected community would be underserved. Yet, because the autism count data was heavily over-dispersed, it is more likely that once county student population size is taken into account, there are actually reductions in autism counts among provider counties. One of the major limitations to this analysis that pre-policy provider counts were not able to be measured or observed in any way and the best indication of post-providers that we have is the number of providers in a county in 2006, even though the policy was active in 2004. In looking at post-2006 provider lists, we do know that the number of providers does change from year to year and can mean the difference between a county having a "high" level of providers (2 providers) and no providers. While all of this can be interpreted to mean that the Ohio Autism Scholarship program is not causing an increase in autism cases and, thus, avoids a potential misallocation of resources to children who are not truly autistic, this conclusion should be made cautiously. Several additional, and perhaps more important, limitations in this analysis prevent strong conclusions from being drawn. First, because data on the actual number of students using the scholarship in each county was not available, the measure of autism cases in counties is a crude proxy at best and does not directly measure the number of autism cases related to the policy. This analysis only assumes that the scholarship program might incentivize autism diagnoses but does not actually show that this happens by linking autism diagnoses with actual usage of the scholarship. Second, because the scholarship can be used anywhere in Ohio, the location where child lives (although the county where his/her autism case is documented) does not, in fact, entirely restrict provider usage. Although it was for this reason that the state analysis was also performed, this logistical issue does present problems in the analysis. I only have assumed that if no providers exist in an autistic child's home county, there is more difficulty in utilizing the ASP and thus less incentive to obtain an autism diagnosis in order to use it. We have no measure of parent's willingness levels to gain access to autism services and perception of what is and is not worth the incentive. Perhaps parents in non-provider counties would be willing to drive 1 or 2 hours to a provider county to access the policy. Unfortunately, a randomized quasi-experimental setup is not possible here. Nevertheless, this novel study makes an important contribution to the literature as it proposes a method for quantitatively evaluating the impact of financial incentive-diagnosis linked policies on autism diagnoses, or diagnoses for another condition, for that matter. Departments of Education responsible for overseeing such enacted policies should collect more complete data and make it accessible to researchers in order to perform better impact assessments and ensure that disability resources are being spent in an ethical and reasonable way. The ideal data set would contain the number of autism-diagnosed children in a county using the Ohio ASP. It would show on a person-by-person level where these children were living as well as where they were using the scholarship funding in order to show how influential the role provider proximity plays to program usage. It would also be interesting to know how much money each student is claiming from the scholarship each year and the composition of care they are using. An interesting question to explore would be whether the amount of care is affected by scholarship program usage. Are those receiving the financial incentives using more care than those not on the program or the same amount, just paying less? It might also be helpful to know about alternative forms of financial support utilized by the autistic child's family, such as Medicaid or private health insurance. As this analysis shows, there is a great degree of over-dispersion in the autism count and rate data. Clearly there is a need for more explanatory variables to be included that might explain the great deal of variance among autism counts and rates in the various state and county groups.

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