The Effects of Student Loans on the Demand for Higher Education: An Econometric Analysis

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Abstract

Since the mid-twentieth century, postsecondary education in the United States has evolved from a niche path taken by a minority of the population into a commodity that many consider essential to a successful career in modern society. This increased demand for higher education was associated with an increase in prices; the average cost of attending postsecondary institutions in the United States has grown dramatically in recent years. However, many people cannot afford these high costs. The Higher Education Act of 1965 initiated federal financial aid, such as Pell Grants and Stafford Loans, to provide low-income households the opportunity to afford education opportunities which might otherwise be unattainable. In exchange for more equitable education opportunities, by 2021, the aggregate student loan balance in the United States swelled to over $1.5 trillion across over 40 million borrowers. Estimates put the federal share of the national loan balance around 90%. Politicians have proposed varying degrees of forgiveness, and a debate about the future of student loan debt has permeated podcasts and social media outlets, among other channels of mass communication. The debate about student loan debt opens a window into a more fundamental question about the structure of society: why is higher education so expensive? The obvious answer is because enough people are willing to pay the price. Since federal student loans increase students' ability to pay, could their availability be driving tuition prices even higher through an increase in demand? The problem is a classic paradox of which came first; did federal student loans help counter high prices, or did high prices result from an increase in demand generated by the availability of student loans? Previous research has investigated both the relationship between financial aid and tuition prices, and the importance of financial aid in prospective students' decision-making process. I build on this research and employ econometric techniques to investigate whether a substantial increase of the annual unsubsidized student loan limit in 2008 caused an increase in the number of applicants to higher education institutions within the United States. This methodology complements existing research by rigorously evaluating the effect of a specific loan policy on the demand for higher education at the national level. The results of this study will provide insight into future decisions regarding student loan policy for both governments and education institutions.

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1 Introduction

1.1 A Brief History of Higher Education in the United States

The main purpose of higher education is to teach people advanced skills and knowledge for the betterment of society; such institutions provide a decentralized mechanism through which individuals can obtain these tools. The typical experience in an emergency room would likely be less enjoyable if doctors were not formally trained in medical school; the same principle applies to nurses and dentists. The typical experience in a courtroom would likely be less pleasant if lawyers were not formally educated in law school. The same can be said of firefighters, police officers, emergency medical technicians, teachers, and so forth; people with advanced skills and knowledge are able to serve society more effectively and efficiently. This increased productivity is reflected in the differences in expected earnings across education levels. Tamborini et al. (2015) estimates the 50-year earnings gap between high school and college graduates is about \$840,000 for men and \$587,000 for women in the United States. Even with an annual discount rate of 4%, the present value of a college education is estimated to be well over \$200,000 for both men and women (Tamborini et al., 2015). Similarly, the U.S. Bureau of Labor Statistics reported a weekly earnings gap of \$524 between high school and college graduates in 2020 (Education Pays, 2021). People with higher educations tend to receive higher wages, at least in part, because they offer skills and knowledge that their less-educated peers are less likely to possess.

The idea of providing members of society with advanced tools dates back to the first higher education institution founded in the United States: Harvard University. Harvard was founded in 1636 with the intention of training clergymen. Not long after, in 1701, Yale University was founded under "An Act for Liberty to Erect a Collegiate School" to educate young people and make them better prepared for public employment (Archives, 2021). Between 1636 and 1819, a total of 49 higher education institutions were founded in the United States. By the turn of the twentieth century, there were over 700 higher education institutions in the United States, the majority of which were private (Goldin & Katz, 1999). Today, there are over 7,000 higher education institutions according to the National Center for Education Statistics databases (U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System). The demand for higher education also increased significantly throughout United States history; in 1890, the number of students enrolled in higher education was less than 5% of the population aged 18 to 24; by 1970, this swelled to nearly 24% (Goldin & Katz, 1999). According to the National Center for Education Statistics, in 2019, about 40% of the population aged 18 to 24 were enrolled in a higher education institution (COE - Undergraduate Enrollment (2021). Although higher education in the United States was originally founded with relatively humble goals, it has since evolved into a highly demanded commodity desired by a near majority of the typical population of consumers. Institutions and attendees alike have proliferated dramatically in the last 300 years.

1.2 Funding Higher Education

The rise and proliferation of higher education institutions in the United States comes with a challenging policy question: who should bear the cost? People who receive training in public-serving fields, such as medicine and law, go on to directly help the rest of society. Doctors and dentists treat patients, lawyers represent innocent people in court, teachers cultivate young minds and inspire the next generation, and so forth. Should society pay for the costs of higher education in exchange for the benefits graduates bring to everyone, or should students bear the cost in exchange for the higher salary and more comfortable jobs they can expect to earn? Millett (1972) sheds an interesting light on this question and argues the proper question to ask is what proportion of which aspects of higher education should be considered a public service. Society typically bears the cost of public services, such as roads, bridges, highways, and public parks, through taxes. If there is an argument to be made that certain aspects of higher education ought to be considered as similar goods, it follows that it might be best for society to bear these costs. However, it is difficult to draw the line between a public service and one that only benefits students. For instance, who would determine how to divide tuition and fees, technology costs, construction of new buildings, etc., between public and private services? Millett (1972) argues for a five-fold classification of higher education expenses: instruction and general, research, public services, auxiliary services, and student aid, and that each area must be individually balanced between societal and student funding. Higher education has a dominant presence in modern society, but its funding sources is a theoretical question of economic system design. In practice, different regions handle higher education funding in different ways. For instance, individual states in the United States have used funding formulas to determine how funds are allocated among higher education institutions. In 1984, 34 states used funding formulas which incorporate factors such as credit hours, head count, and student-to-faculty ratios (McKeown, 1989). One general goal of these formulas is to ensure funds are allocated fairly and equitably among schools and departments.

Another interesting question related to funding higher education institutions is whether or not such financial support should be centrally planned (Barr, 1993). Central planning is one way to structure society in which a central body of power, such as the government, has responsibilities such as setting prices and determining which goods can and cannot be sold. Centrally planned economies are typically associated with extreme communist and socialist nations, such as the Soviet Union, although most modern economies contain some elements of central planning. For instance, the federal minimum wage in the United States can be viewed as a planned policy because the government is making a wage decision instead of leaving it up to the natural forces between consumers and employers. A common argument against centrally planned economies is the presence of the knowledge problem and the power problem (Lavoie, 1985). The knowledge problem refers to the idea that no central body can possibly amass all of the intangible information needed to make granular decisions at such a large scale, while the power problem represents the inability of central bodies to remain unbiased and fair when granted such authority over a nation. Central planning relates to the funding problem at hand in the following way, as noted by Barr (1993): governments can directly subsidize higher education institutions, much like the United States does regarding research grants, or governments can provide funding directly to students to use at a school of their choice. The former structure is farther along the planning spectrum, while the latter leaves more decisions in the hands of consumers and forces institutions to compete directly for students' demand.

Another relevant consideration is performance-based funding, which stems from a core idea in behavioral economics and market design: aligning interests. As a contrived example, consider a state which seeks to improve the employment rate of recent college graduates. One way to pursue this goal is to make some of the funding for local public institutions dependent upon the employment rate of their graduating class each year. This aligns the institutions' interests with the state's, and allows the state to tackle the employment problem without getting directly involved. This environment can be broken down further, as there are interactions between the universities and the state, universities competing with each other, and each university and its students. This environment can be analyzed as an ecology of games, to which performance-based funding policies determine the payoffs (Nisar, 2015). Therefore, policymakers and governments must be careful when designing related funding policies as the strategies and behaviors adopted by institutions and students significantly depend on these rules. Although the United States has largely stayed away from performance-based funding measures until 2015 (Nisar, 2015), other countries have implemented similar policies for much longer. The United Kingdom started the RAE program in 1986, Portugal initiated the Research Unit Evaluation in 1996, Finland has followed a funding formula since 1998, to name a few (Hicks, 2012). Funding is such a critical problem to resolve for higher education institutions because their costs have been growing significantly over time.

1.3 The Cost of Higher Education in the United States

Higher education is a relatively expensive commodity. People who invest in higher education tend to earn more money throughout their careers and unlock barriers to specific fields (e.g., doctors and lawyers). It is no secret that many companies today, at the time of writing, include education qualifications in their job postings. It is an active question whether education is better viewed as investing in human capital or purchasing a signal (Kroch & Sjoblom, 1994) although it is likely a variable combination of the two conditional on individual situations. Regardless, education has become an increasingly desired commodity over the years and its price has risen accordingly. The figure below describes the trend in total estimated costs of attending higher education institutions over time:

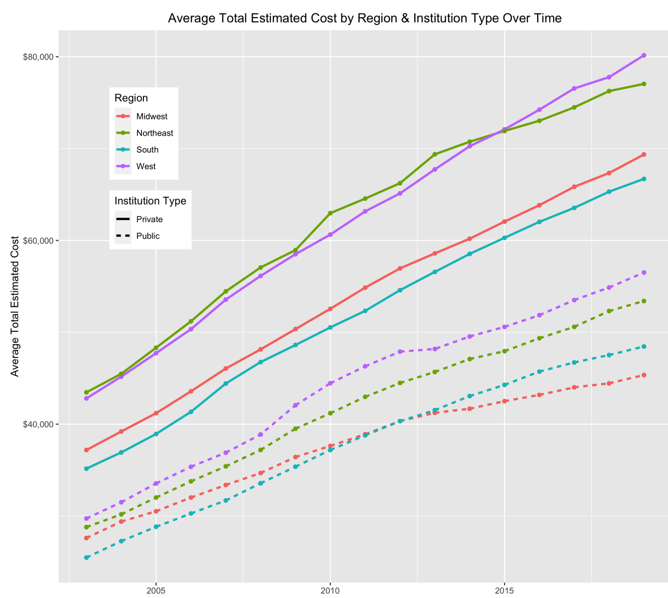

Figure 1: Connected scatter plots of the average total estimated cost over time by region as defined by the U.S. Census. Cost is calculated by taking the average of the total in-state and total out-of-state costs; for private schools, these are identical. Created by author with data used for analysis and further discussed in section 2.

Private institutions tend to be significantly more expensive than their public counterparts. For instance, in the 2000-2001 academic year, private institutions were, on average, more than twice as expensive as public institutions. The average annual cost to attend a four-year private institution in the United States was $31,614. On the contrary, the same cost was only $12,517 for four-year public institutions. In 2018, these costs swelled to $44,662 and $20,598, respectively, and mark significant increases which persist after accounting for inflation (U.S. Department of Education, 2019). Note the costs mentioned here do not correspond to Figure 1 above, which was created with the data used for analysis. For a point of reference, the median income in the United States in 2018 was about $63,000 (U.S. Census Bureau, Current Population Survey, 1992 to 2021). The estimates on the return to higher education suggest the investment is worth it, although perhaps not for the most expensive colleges.

1.4 Public Versus Private Higher Education

Different countries have settled into different equilibria regarding the balance of public and private influence in the private sector. Geiger (1988) investigates trends which have emerged around the world and identifies three broad categories. The first is mass private, in which a majority of the higher education sector is dominated by private institutions. These countries include Japan, South Korea, and Brazil. The second category is parallel public and private, in which there is a fairly equal split between public and private. These countries include Chile, Hong Kong, Belgium, and the Netherlands. Finally, there is comprehensive public, in which the higher education sector is dominated by the government. A prime example of this is equilibrium is Sweden (Geiger, 1988).

The price differences between public and private higher education in the United States suggest some disparity between the two classes of institutions. One key difference is that, at least in the United States, tuition tends to make up a larger portion of total revenue for private institutions than their public counterparts (Patton, 1981). The question emerges of why different concentrations of public and private institutions might arise in a nation and what fuels consumer demand for each type. One way in which the literature has sought to answer this question is by analyzing case studies. Bray (1991) explores the development of the higher education sector in two countries which are geographically close to one another: Hong Kong and Macau. Hong Kong has an older higher education sector largely funded by the government, while Macau's infrastructure is younger and started as a private venture. Because the institutions in Hong Kong were largely funded by the government, the budget, and therefore available seats, were severely limited. On the other hand, because the institutions in Macau were privately operated, they had relatively high fees. As a result, students from Hong Kong were going to Macau for higher education opportunities. Since Macau students could not afford to attend the expensive private institutions, they were largely composed of Hong Kong students; in response, the Macau government started subsidizing students by up to 40% to increase domestic attendance (Bray, 1991). So, one reason the higher education sector might shift towards the public end of the spectrum is to encourage domestic students to enroll.

Jamshidi et al. (2012) explores additional case studies in other countries. In Kenya, the government could not afford to subsidize higher education enough to satisfy the demand for seats. Accordingly, in 1985, the Kenyan government founded the Council for Higher Education and allowed for substantial privatization of the higher education sector to meet the excess demand. Indonesia experienced a similar shift; the government could not keep up with demand as the middle class expanded, and they passed laws in the 1950's and 1960's which expanded privatized higher education. These private institutions were largely founded to serve minority groups. Finally, Malaysia passed the Private Higher Educational Institutions Act in 1996 to support competition between private institutions and catalyze innovation (Jamshidi et al., 2012). There are a variety of nuanced reasons privatized higher education might arise in a country, and individual cases must be studied carefully to properly understand how these ecosystems develop over time.

The strength of case studies is supported by the findings reported by Reisz and Stock (2012). In response to an econometric gap in the literature, they conducted a regression analysis to investigate the relationship between the expansion of privatized higher education and the economic development of a country. They report that wealthier nations tend to have a lower proportion of students enrolled in private institutions, but the association between GDP and such enrollment is positive for some countries and negative for others (Reisz & Stock, 2012). Ultimately, their findings suggest a bigger economy does not necessarily lead to more privatized education, and imply a more detailed approach is necessary to understand country-specific trends.

1.5 Demand for Higher Education

There are many factors which go into an individual's decision to attend a higher education institution, and even more which go into the selection process. Using a regression discontinuity approach for a specific higher education institution, van der Klaauw (2002) found that students' attendance decision was more elastic to tuition for those who were offered a financial aid package than for those who were not. This suggests that financial aid plays a significant role in the decision-making process when deciding between higher education institutions. In general, financial aid can encompass loans, grants, and scholarships. Similarly, a 2010 study took advantage of a Danish reform which increased financial aid to students and found that an additional $1,000 in aid is associated with a 1.35% increase in enrollment when controlling for borrowing constraints (Nielsen et al., 2010). Tierney (1980) estimated a logistic regression model using a combined dataset from American College Testing Program, Educational Testing Service, and American Council on Education, and found that a $100 increase in aid is associated with a 6% increase in the likelihood to attend a private school. Hu and Hossler (2000) analyzed survey data from high school students in Indiana and reported two key findings. First, students who are less concerned about tuition are more likely to prefer a private institution. Second, students who are more likely to use financial aid are more likely to prefer a private institution. Turner (2011) estimated a probit model of students' enrollment decisions and found that a $100 increase in tax-based student aid is associated with a 0.3% increase in enrollment. The literature provides ample evidence that financial aid is a significant positive factor in the decision-making process surrounding enrollment in higher education institutions, and suggests this effect might be more significant for private schools.

1.6 Student Loans in the United States

The United States Government provides federal student loans to individuals who wish to attend higher education institutions but cannot afford it themselves. These loans are one measure which ensures equal access to education opportunity across different income backgrounds and familial wealth levels. These loans are accompanied by a plethora of scholarships and grants, which are offered by the Federal Government, state governments, and individual institutions. Without these options for financial support, at current prices, access to higher education would likely be skewed towards wealthier students. The United States Government first implemented student assistance infrastructure in 1965 via The Higher Education Act (Fountain, 2021). This act initiated a wide variety of programs, but the key subsection related to student loans is Title IV. Some of the highlights of Title IV include Pell Grants, the Federal Family Education Loan Program (FFEL), federal work-study programs, and Stafford loans.

Direct subsidized loans are made available to undergraduate students conditional on financial need. They are called direct loans because they are made directly by the Federal Government via the Department of Education, and they are subsidized because students do not pay interest until six months after graduation (Federal Student Aid, 2021). Similarly, direct unsubsidized loans accrue interest at all times and are not conditional upon financial need; they are made available to all students. Direct PLUS loans are available to parents of undergraduate students and independent graduate students; following the vernacular, these can informally be considered unsubsidized loans and are not conditional upon financial need. Prior to 2010, students also had access to indirect loans; in contrast to direct loans, which are made directly by the Government, indirect loans are made by private institutions and guaranteed by the Government. In short, this means the Government picked up the tab of any student who could not make payments on these loans. Indirect loans were abolished, along with the FFEL program, with the passage of the Health Care and Education Reconciliation Act of 2010 (Spratt, 2010).

At the time of writing, the total limit on both subsidized and unsubsidized loans is $31,000 for dependent undergraduate students and $57,500 for their independent counterparts, although this amount has increased over the years. More than half of the student loan debt is owned by graduate students and more than 80% of outstanding loan balances are related to direct loans. One study found that a $1,000 increase in loan limits are associated with a $500 increase in borrowing. (The Volume and Repayment of Federal Student Loans: 1995 to 2017, 2020). The median student loan debt in 2020 was estimated to be between $20,000 and $25,000, while higher education is associated with larger debt balances and less difficulty repaying loans (The Fed, 2021). Student loans are relatively difficult to discharge via bankruptcy and individuals must prove paying back their debt would cause an undue hardship. There are several reasons for this hurdle, which some might find objectionable. First, it would be relatively easy for students to declare bankruptcy upon graduation compared to adults many years into their careers. Second, unlike houses and cars, student loans do not have any collateral; the government cannot repossess an individual's education. Third, if the system is to remain stable for future students, the government must collect as much of the outstanding debt as possible (Lewis, 2018). Despite the strict discharge rules, there are a number of forgiveness options available to teachers, public service workers, disabled individuals, and individuals who were lied to by their school (Federal Student Loan Forgiveness and Discharge, 2020). There are also a variety of repayment plans available which offer modifications such as extensions in the duration of the loan and income-based repayment plans (Repayment Plans | Federal Student Aid, 2021).

Higher education has grown into a near ubiquitous aspect of life in modern society, and its rising costs have been accompanied by piling student loan debt. Evaluating and understanding the consequences of related policies is paramount to maintaining an efficient and financially sound higher education system in the United States.

1.7 The Policy

Although the Higher Education Act was originally passed in 1965, it was re-authorized 8 times since: in 1968, 1972, 1976, 1980, 1986, 1992, 1998, and finally in 2008. At the time of writing, a recent amendment was introduced on October 26, 2021 (Morelle, 2021). In 2008, following the recent recession, the United States Government passed the Ensuring Continued Access to Student Loans Act of 2008 (Miller, 2008) which featured an amendment to the Higher Education Act. This amendment, among other changes, increased the annual limit of direct unsubsidized loans by $2,000. Since unsubsidized loans are not conditional on financial need, they are available to all students. I will take advantage of this policy to investigate whether this increase in student loans had a significant effect on the demand for higher education. If there is a significant effect, I will also test if its magnitude or direction differs between public and private institutions. This is not the first study to take this path; Rose and Sorenson (1991) conducted a regression analysis to investigate the effects of the 1972 Amendment to the Higher Education Act. In section 2, I describe the data, discuss my preprocessing decisions, and provide visualizations and summary statistics for additional background information. In section 3, I discuss my methodology and review the models I built to answer this question. In section 4, I report my results, and in section 5, I conclude.

1.8 The Research Question

Did the $2,000 increase in the annual unsubsidized student loan limit associated with the passage of the Ensuring Continued Access to Student Loans Act of 2008 have a significant effect on the number of applicants to four-year higher education institutions in the United States? If there is an effect, is it significantly different between public and private institutions?

2 Data

I retrieved the data for this analysis from three different sources; all data is publicly available on the web. See section 6.2 for a complete list of data source references. Information about higher education institutions was retrieved from the Integrated Postsecondary Education System (IPEDS) hosted by the National Center for Education Statistics. There were several conditions which an institution had to meet to be included in my analysis:

- Participates in Title IV
- Is located within the United States
- Is a four-year degree-granting institution
- Admits full-time and first-time undergraduate students

These conditions were enforced using filters on the IPEDS database website. This data was supplemented with demographic data retrieved from the Federal Reserve and U.S. Census Bureau. The data is ultimately nested at three levels. First, there is institution-level data, such as the price and number of applicants. Each institution is located within a state, which has its own variables, such as median household income and student loan balance. Finally, each state is nested within the United States, which has variables such as unemployment and education rates. The aggregated dataset contains 17 years of data, from 2003 to 2019. This timespan is the intersection of data availability between the three sources.

2.1 Data Preprocessing

I combined, cleaned, and transformed the data using the R programming language. I did not deem it necessary to identify or treat outliers as part of this analysis. It is likely individual institutions and years are causes of outliers, and removing them from the data would introduce unnecessary bias. The random intercepts in the hierarchical model, which will be discussed in detail in section 3, should help to account for such school- or year-specific outliers. There is no gold standard for identifying or treating outliers, and because I have a relatively large amount of data (e.g., approximately 25,000 data points), I am not concerned that outliers will significantly bias my results. I chose to leave any potential outliers in the data to avoid introducing bias in whichever way I might choose to identify or treat them.

There was a significant amount of missing data in the data downloaded from the IPEDS database. There are generally two ways to handle missing data: imputation and deletion. Imputation is typically desirable, if possible, because it avoids pitfalls of introducing bias by removing incomplete observations which might not have been missing at random. Deletion is a simpler approach but has the potential to produce a biased dataset by removing incomplete observations which might be strongly correlated with a key variable. The core idea behind conducting any analysis is that the dataset should be a random sample from some population. If the dataset is biased (e.g., contains only wealthy individuals) the conclusions cannot be properly extended to the entire population. In this case, hierarchical multiple imputation would be ideal, however, there are significant specification and computational challenges with such an approach. There is the additional avenue for bias in determining if institutions with too few observations ought to be removed (e.g., should an institution which had 90% of its data imputed be considered a legitimate sample?) among other researcher-specific decisions. To avoid these complications, I chose to remove all observations with any missing data, which is often referred to as a complete-case analysis. To support the idea that the sample of complete cases is unbiased and might be considered a proper random sample, I demonstrate the distributions for variables of interest do not change significantly between the incomplete and complete datasets. This approach shows I am not losing any local area of the data (e.g., throwing away all observations in 2003 or all low-income states). See Appendix A for some overlaid kernel density estimates which illustrate this methodology, and Appendix B for the code which generates more of these figures. There are some minor discrepancies, but overall, the results provide evidence that a complete-case analysis does not invite a significant amount of bias. I recognize this does not guarantee my data is not biased around unobserved variables (e.g., average faculty salary), but this presents a difficult problem and is a place for improvement in future work.

2.2 Summary Statistics and Visualizations

The final dataset contains 25,114 observations across 1,588 four-year institutions, all 50 states including the District of Columbia, and 17 years between 2003 and 2019. There are 504 public institutions and 1,084 private institutions. Summary statistics are provided below:

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	Min	Max	Description	Level
year	2,011.152	4.900	2,003	2,019	Calendar year (e.g., 2001)	United States
mean_UNEMP	6.052	1.849	3.683	9.608	Annualized average monthly unemployment rate	United States
medianincome	62,108.490	9,121.810	38,876	96,765	Median household income	State
bachelor_plus	0.326	0.029	0.286	0.389	Percent of adults with at least a bachelor's degree	State
loan_debt	3,699.452	1,598.081	670	13,420	Average student loan balance	State
FGRNT_A	4,466.411	1,083.896	254	19,296	Average amount of federal grant aid per student	Institution
APPLCN	5,441.742	8,293.381	0	113,754	Number of applicants	Institution
CINSON	32,498.340	14,185.420	1,930	81,531	Total estimated cost for in-state students	Institution
COTSON	35,629.220	12,698.760	1,930	81,531	Total estimated cost for out-of-state students	Institution

Visualizations are helpful tools to understand the underlying data and identify interesting trends and patterns before building models and conducting analyses. They can also provide additional insights which are difficult to convey in words. Looking at the number of applicants is a top priority because it will be the dependent variable in my analysis. Looking at the general trend in applicants over time can also provide useful insights. Two visuals of this data are presented below:

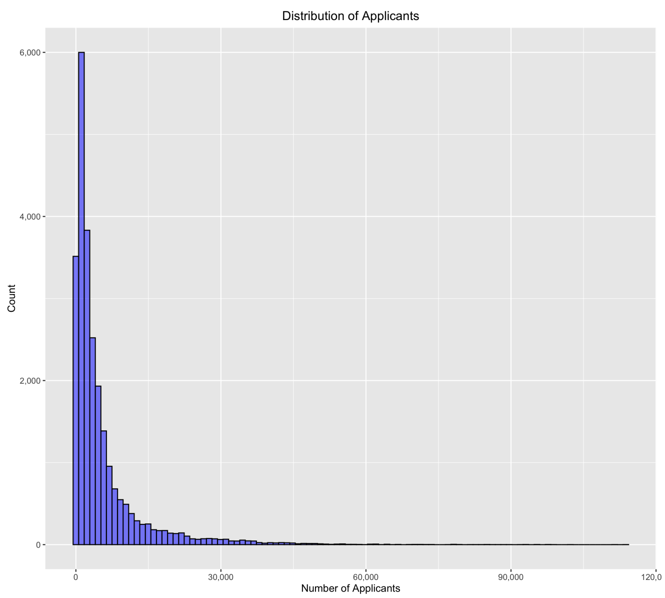

Figure 2: A histogram of the number of applicants to higher education institutions between 2003 and 2019. There are 100 bins for visualization.

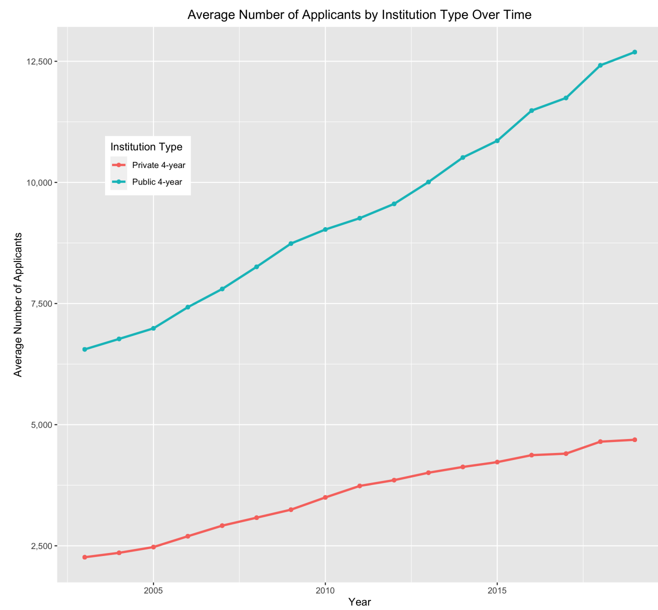

Figure 3: Connected scatter plots of the average number of applicants to each type of institution between 2003 and 2019.

The histogram above highlight the nature of the number of applicants data. First, it is count data and naturally has a physical lower bound at zero. Second, the applicant data is not normally distributed; it looks similar to typical distributions of income and appears to somewhat follow a log-normal distribution. The majority of recorded applicant figures are below 30,000, but there are outliers above 90,000. These characteristics of the applicant data are extremely important to acknowledge and take into account when I build statistical models to answer my research question, since poor assumptions about the underlying data can lead to biased estimates. There are a two key takeaways in the figure on the right. First, it appears the number of applicants to public institutions has increased by a larger margin and at a faster rate than applicants to private institutions. Second, in every year since 2003, four-year public institutions have received, on average, a significantly higher number of applicants than their private counterparts.

Figures 4 and 5 showcase the upwards trend in federal grant aid between 2003 and 2019. The violin plots in Figure 5 emphasize outliers and communicate the overall trend across all institution types. The connected scatter plots in Figure 4 are segmented by institution type; the trend is similar for both public and private four-year institutions, although students at private institutions tend to receive more federal grant aid, on average. However, this observation might be misleading without recognizing that private institutions are typically more expensive than public institutions, as shown in Figure 1.

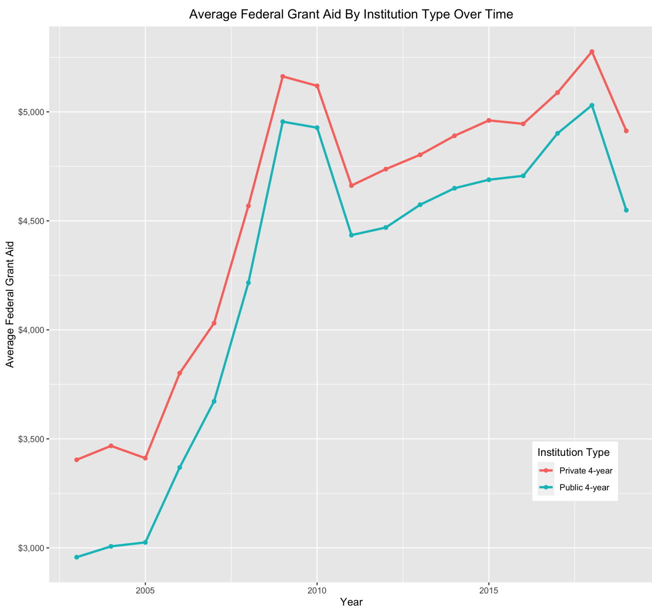

Figure 4: Connected scatter plots of average federal grant aid received per student over time. Federal grant aid includes loans, scholarships, grants, and any other support.

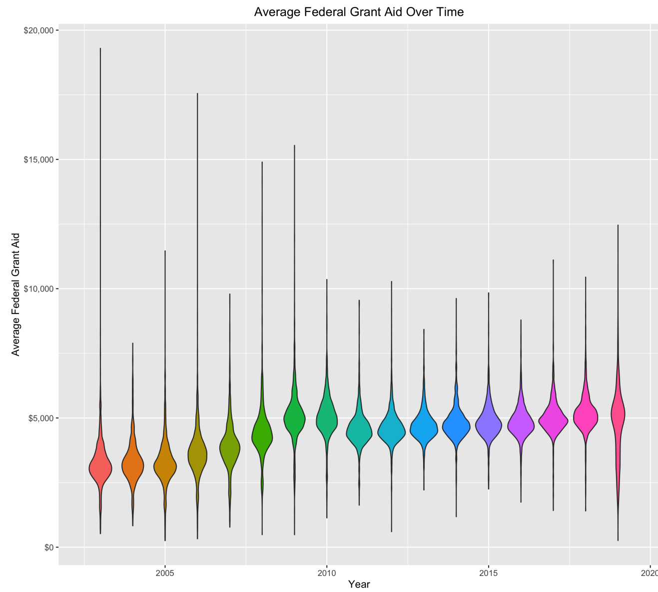

Figure 5: Violin plots of average federal grant aid received per student over time. Colors correspond to the year. Federal grant aid includes loans, scholarships, grants, and any other similar financial support.

Regional variation in cost, and its change over time, is broken down at the state level and compared between years below:

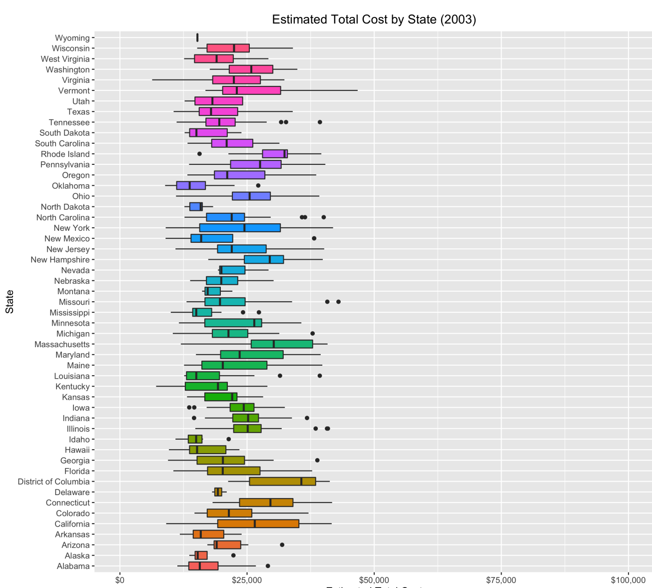

Figure 6: Box plots of the total estimated cost of attending higher education institutions in each state in 2003.

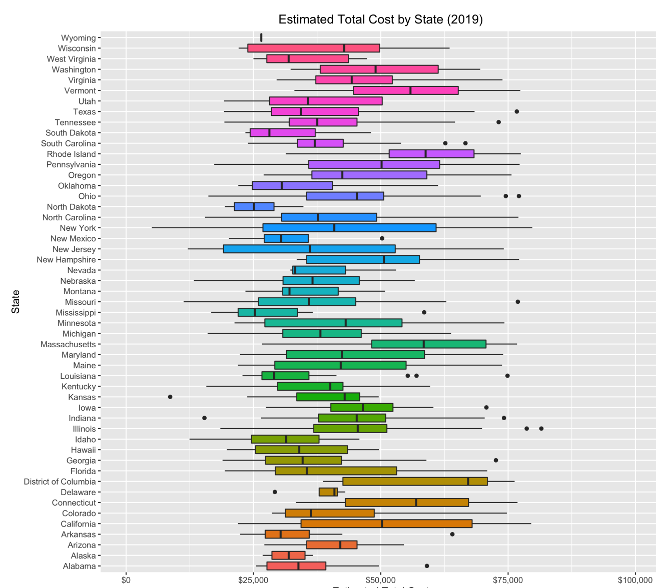

Figure 7: Box plots of the total estimated cost of attending higher education institutions in each state in 2019.

There are two important takeaways from the pair of figures above. First, the cost of attending higher education institutions has increased in every state between 2003 and 2019. This is not especially surprising given the general upward trend in purchasing power and inflation throughout the United States' history, however, this is still worth noting. Second, the within-state variance of costs has increased over time as well. The box plots representing 2019 costs in each state are generally wider than those which represent 2003 data, which suggests the cost of attending different institutions has changed according to institution-specific factors.

3 Methods

3.1 Directed Acyclic Graph

It can be difficult to determine which variables should be included in a regression model; to this end, directed acyclic graphs are an excellent tool. They can be used to visualize causal relationships between variables within a system and utilized to determine which variables should be included in a regression model to estimate the causal influence of a particular predictor on an outcome. I developed the following directed acyclic graph for my analysis:

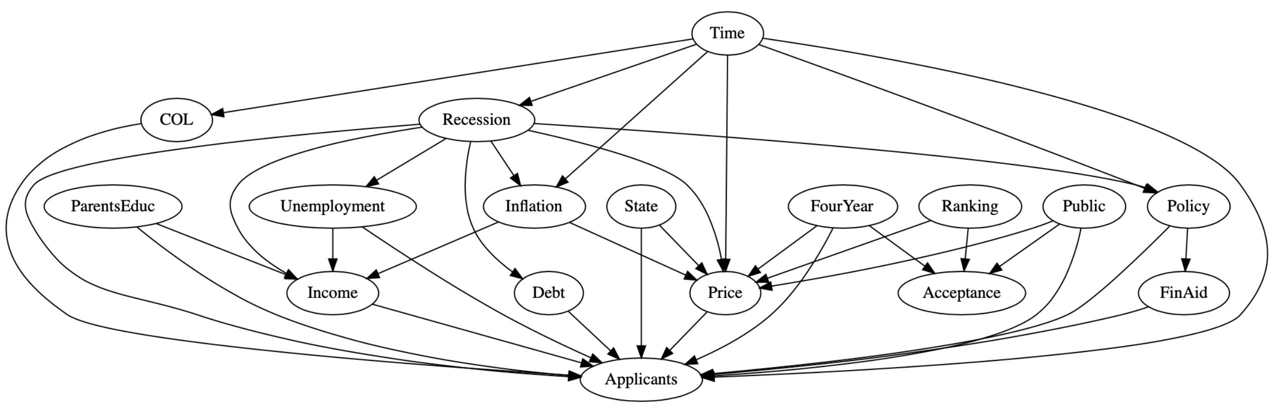

Figure 8: Directed acyclic graph I developed to choose variables for my regression models. The direct causal effect of interest is from the Policy node on the far right to the Applicants node at the bottom center.

There are 4,112 unique sets of variables which can be specified in the model to properly estimate the total causal impact of the policy, given that the graph is correct. There is only one set of variables which coincides with the data I collected for analysis. Conditioning on this set of variables, given the graph is correct, will ensure my estimate of the policy's effect is unbiased and represents the total causal impact it has on the number of applicants. This works by ensuring all back-door paths are closed and that information cannot flow into the estimate from confounds and bias the result. The direct causal impact of the policy can be estimated by additionally conditioning on the average federal aid awarded per student. The variables which must be conditioned on are provided in the following section within the regression model specification.

3.2 Regression Models

I constructed a hierarchical model with random intercepts at the state, year, and institution level pursuant to the directed acyclic graph above. It is not necessary to condition on the individual institution, however, there are likely significant differences between schools and including this as random intercept should help provide more precise parameter estimates. The model is specified as follows:

$$
\begin{aligned}
y_{ijk} = \beta_0 + \mu_i + \mu_j + \mu_k + \beta_1 L_{jk} + \beta_2 F_{ik} + \beta_3 PO_{ik} * \delta_i + \beta_4 PI_{ik} + \beta_5 R_k \\
+ \beta_6 Inc_{jk} + \beta_7 UE_k + \beta_8 Educ_{jk} + \beta_9 \delta_i + \beta_{10} P_k + \beta_{11} P_k \delta_i + e_{ijk}
\end{aligned}
$$

where each element in the model is specified in Table 2:

Table 2: Model Term Definitions

Term	Description
μ_i	random intercept for each institution
μ_j	random intercept for each state
μ_k	random intercept for each year
L_{jk}	the average per-capita student loan balance in state j in year k
F_{ik}	the average federal grant aid received by each student at institution i in year k
PO_{ik}	the estimated total cost for out-of-state students at institution i in year k
δ_i	dummy variable equal to one if the institution is public
PI_{ik}	the total estimated cost for in-state students at institution i in year k
R_k	a dummy variable equal to one if the recession was happening in year k
Inc_{jk}	the median household income in state j in year k
UE_{jk}	the average unemployment rate in year k
$Educ_{jk}$	the proportion of the population with at least a bachelor's degree in state j in year k
P_k	a dummy variable equal to one if the policy had been passed in year k

I estimated the model with three different assumptions about the underlying data as a measure of robustness. The first model, a standard linear regression, assumes the outcome data, number of applicants, is a continuous variable which can be approximated by a gaussian distribution. This is a poor assumption because the outcome data is count data. This means the linear model will assume the number of applicants can be non-integer values and extend below zero; this is not true. The second model, a poisson regression, corrects this inaccurate assumption and assumes the outcome data are counts and can be approximated by a poisson distribution. This is a better assumption because the poisson model will restrict the number of applicants to non-negative integer values. One possible limitation of a poisson regression is that it assumes the mean is equal to the variance. This is not overly restrictive in practice, but I also estimated a negative binomial model to test if relaxing this assumption yields a better fit to the data. The negative binomial model maintains the assumption regarding count data, but allows for an additional dispersion parameter which allows the variance to differ from the mean.

Note that all continuous variables in the model were standardized to improve parameter estimates and avoid scaling issues.

3.3 Robustness Checks

I performed two robustness checks to test how sensitive the results are to different specifications and researcher preferences. It is exciting to find significant results, but it is equally important to ensure those findings are robust to various specifications and choices made during the research process. If a significant result vanishes with small adjustments to the methodology, it should be further investigated and interpreted with more caution. On the other hand, if a significant result is robust to a variety of methodological tweaks, there exists more convincing evidence the result is meaningful and not an artifact of individual preference. First, the starting year of the policy was varied between 2004 and 2018. This tests if any significant effects on the policy coefficient are simply capturing noise present at various times, or if a significant result is actually detecting something meaningful about the real cutoff year. For instance, if the policy coefficient is significant when the start year is set to 2014, that is evidence the significant result with a real start year of 2008 is simply noise. However, if the coefficient is only significant in close proximity to the real start year, that is evidence it is detecting a real effect. I expect there to be some lagged effects of the policy, so it would make sense to see significant results up to a few years after the real start year. Second, the analyses was conducted with three different assumptions about the underlying data. It is important to test different models to investigate which assumptions best reflect the data and to prevent model misspecification from biasing results. For instance, the linear model is likely a poor specification because it does not properly reflect the count data, and significant results from a linear model should be taken with caution. This is especially true if more appropriate models, such as the poisson and negative binomial, do not find the same significant results.

4 Results

I only provide and discuss visuals for the linear and poisson models. The results from the poisson and negative binomial models are quite similar and it would be redundant to fully comment on both in this paper. Estimates from all three models will be reported and code to reproduce the models and corresponding visuals can be found in the supplementary materials (see Appendix B).

4.1 Model Diagnostics

One useful diagnostic tool when evaluating model performance is examining the residuals. It is generally desirable for the residuals to be normally distributed when fitting regression models, although it is not a serious concern if this condition is violated. Model misspecification is likely a more serious issue. First, I looked at the distribution of residuals for both models in Figures 9 and 10.

Looking at Figures 9 and 10 below, the distributions of residuals for both models look reasonably normal. Note that the residuals for the Poisson model are not the working residuals, i.e., the differences in the expected value and actual value. This is because such residuals are less relevant for generalized linear models. Instead, the residuals used for the poisson model are deviance residuals, which are more useful when evaluating generalized linear models. While looking at the distribution of residuals for a model is a good first step, it can be misleading and should not only be the only diagnostic tool. Quantile-Quantile plots are an additional visual aid which can be used to evaluate the normality of residuals for a regression model.

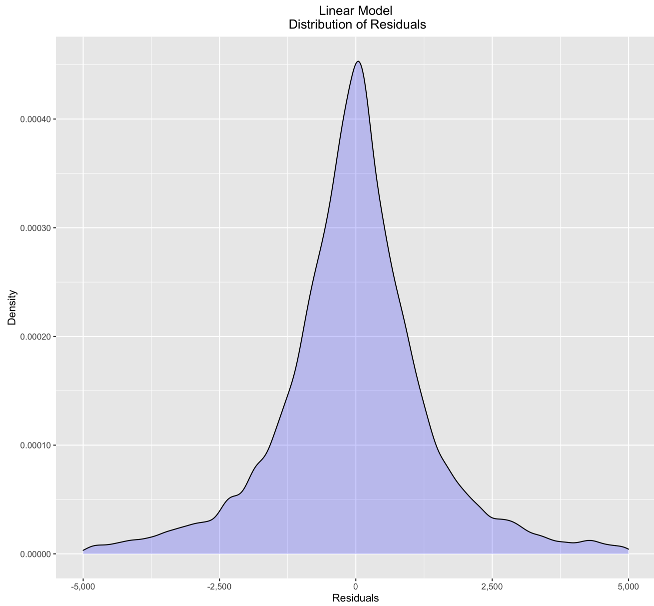

Figure 9: Distribution of working residuals from linear model using a kernel density estimate. The plot is symmetrically truncated for visualization purposes.

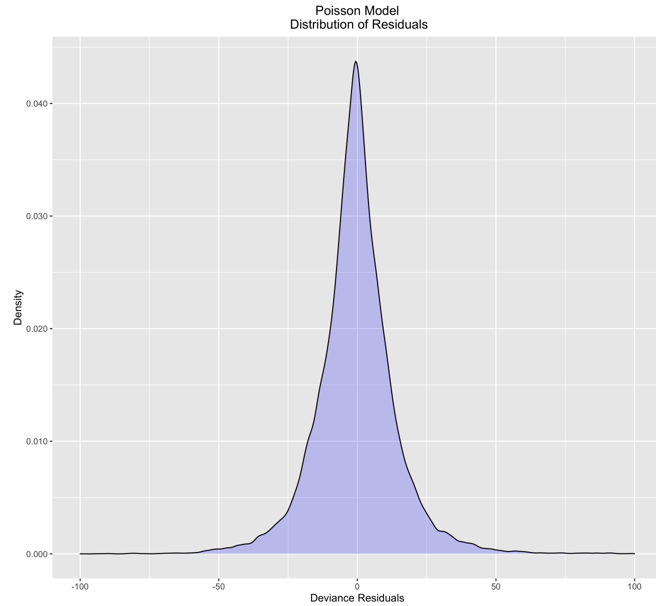

Figure 10: Distribution of deviance residuals from poisson model using a kernel density estimate. The plot is symmetrically truncated for visualization purposes.

Quantile-Quantile plots for both models are shown in Figures 11 and 12 below:

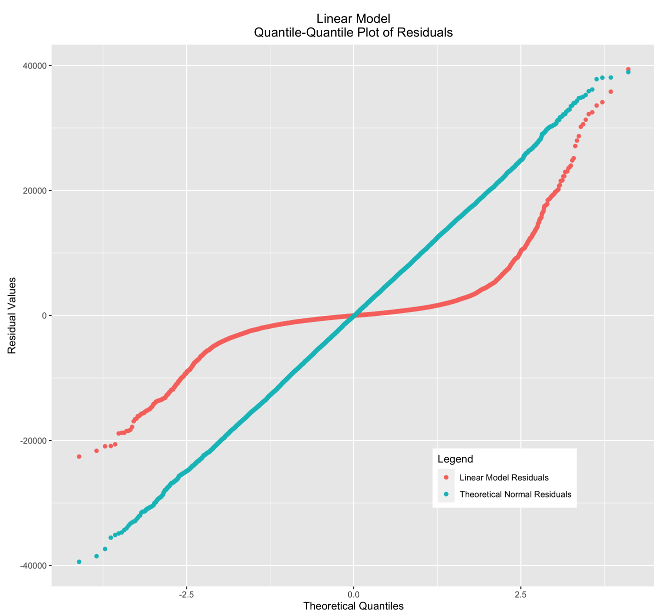

Figure 11: Quantile-Quantile plot of working residuals from linear model.

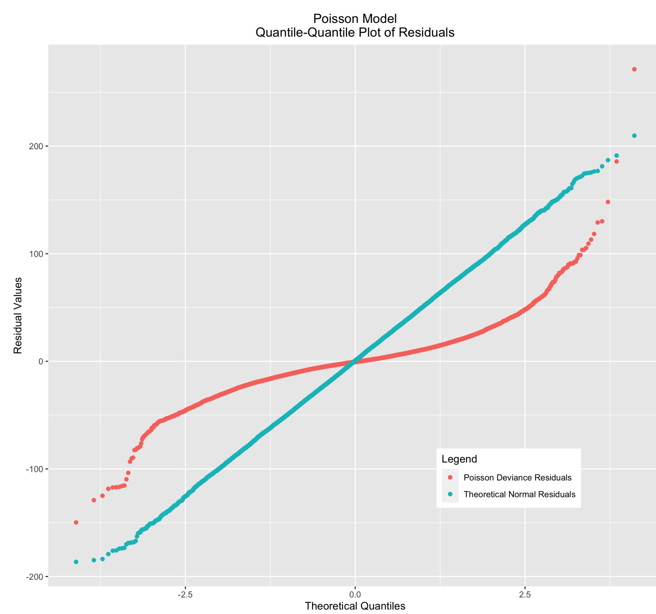

Figure 12: Quantile-Quantile plot of deviance residuals from poisson model.

A theoretically normal plot would look quite similar to a straight line that runs somewhat diagonal from the bottom left corner to the top right. Although neither set of residuals matches to the theoretical plot extremely well, it is clear the residuals from the poisson model are more normally distributed than the residuals from the linear model. This is evidence that the poisson model fits the data better than the linear model and makes better assumptions about the underlying structure and processes. A third model diagnostic is to test for the presence of heteroskedasticity. This can be done visually by looking at plots of the fitted values against the residuals, and investigating whether there is a relationship between them. In the absence of heteroskedasticity, there should be no relationship between the fitted values and their residuals; the model should be expected to miss evenly across all observations. These plots are below for both models:

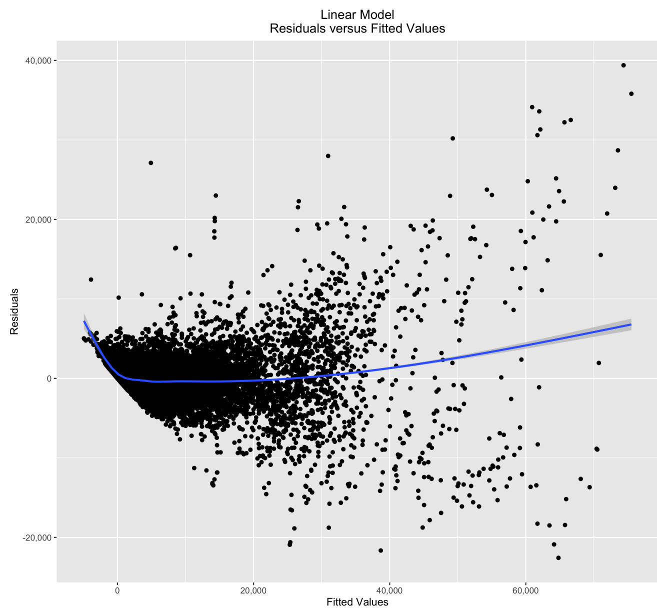

Figure 13: Scatter plot of the working residuals from the linear model against the fitted values. The best fit curve is estimated using generalized additive mode smoothing.

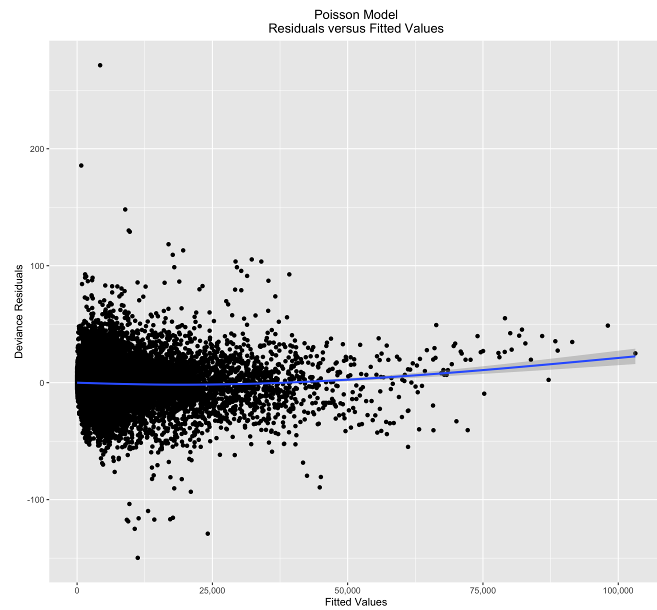

Figure 14: Scatter plot of the deviance residuals from the poisson model against the fitted values. The best fit curve is estimated using generalized additive mode smoothing.

The two figures above provide additional evidence that the poisson model makes more accurate assumptions about the underlying data and is a better specification than the linear model. There is clear heteroskedasticity in the linear model because the residuals are much wider for higher numbers of applicants; that is, the linear model is less accurate for higher numbers of applicants than lower numbers of applicants. This is not a terrible feature of the model, but it suggests some underlying specification issues and the presence of significant heteroskedasticity. The figure on the right suggests the poisson model significantly corrects these issues, as the best fit curve is closer to a straight line with a y-intercept of zero and the residuals do not display the same upward trend as the number of applicants increases. The poisson model does appear to overshoot more than undershoot for high numbers of applicants, but the plots suggest the issue is less severe than in the linear model. While not a formal statistical test, and although the poisson residuals appear to be a bit wider for lower counts, these plots suggest the poisson model deals with much of the heteroskedasticity present in the linear model and is a better specification given the data.

These model diagnostics generally suggest the poisson model might be preferred over the linear model in this case. This is important to note when comparing and interpreting the results of each model.

4.2 Model Comparisons

Beyond model diagnostics, the model fits can be directly compared by investigating how well the distribution of predicted values match the distribution of actual data. It would be ideal to use a statistical criterion, such as R^2 or the Akaike information criterion, however, these statistics are not valid when comparing generalized linear models with different function families (e.g., linear, poisson, and negative binomial). Alternatively, visualizations can be used to obtain some inference. For instance, if the model is predicting many values far higher than were observed in the data, this is an indicator of misspecification or other problems. Two plots illustrating model fits for the linear and poisson models are below:

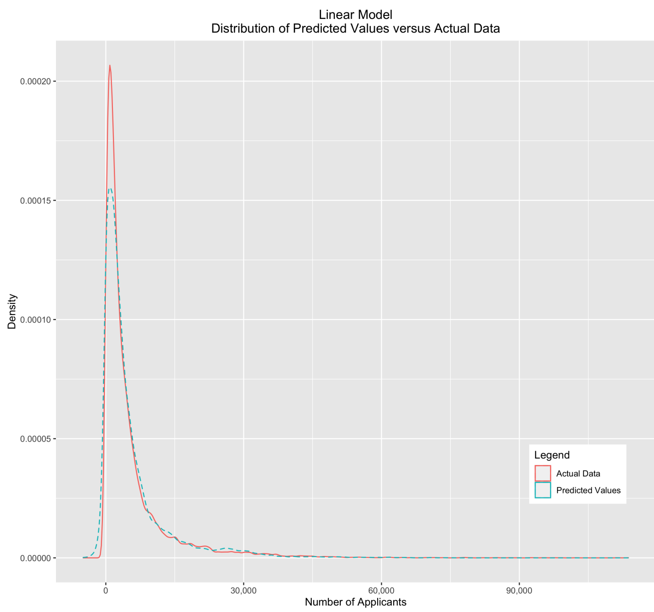

Figure 15: Distributions of the actual data versus predicted values using kernel density estimates for the linear model.

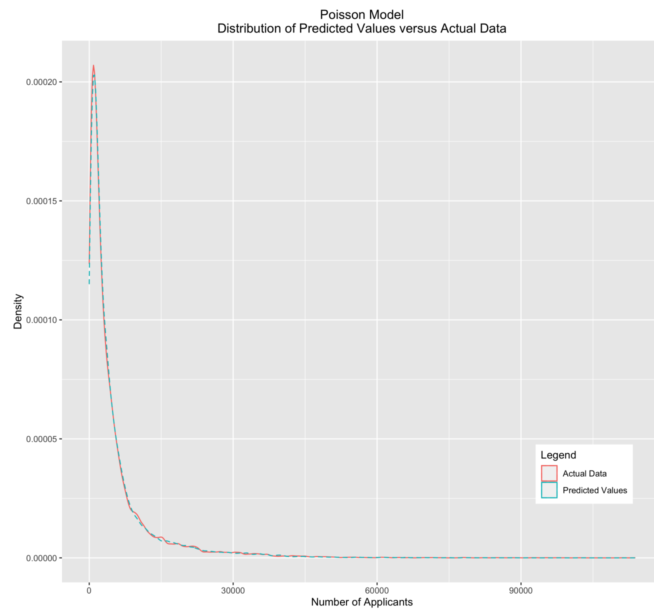

Figure 16: Distributions of the actual data versus predicted values using kernel density estimates for the poisson model.

It is apparent from the figures above that the poisson model fits the data much better than the linear model. There are two key takeaways here. First, the linear model underestimates the likelihood of observing a small number of applicants, indicated by the shorter peak. The poisson model does a much better job in this regard. Second, the linear model allows for negative predictions while the poisson model does not make this error. A second way to visually compare models is by plotting the predicted values against the actual values for each model. The slope of the best fit line for such a plot would be equal to one for a model which fits the data perfectly. Therefore, such a line can be used as a heuristic for visually comparing models. This plot for all three models is provided in Figure 17.

The visualization in Figure 17 echoes a similar general conclusion as the other comparisons and model diagnostics. The linear model generally misses the data by a wider margin than the poisson and negative binomial models. This is especially apparent for high numbers of applicants, as it consistently undershoots the actual data beyond roughly 65,000 applicants. The poisson and negative binomial models are quite similar, except the poisson tends to be a bit more accurate for high numbers of applicants; this can be seen by close inspection of the points in the upper right quadrant. This is an unexpected result, as the negative binomial relaxes an assumption made by the poisson and includes an additional parameter, which I would expect to improve the fit to the data. Further diagnosing model fits between the poisson and negative binomial is beyond the scope of this paper, but would be interesting for future work.

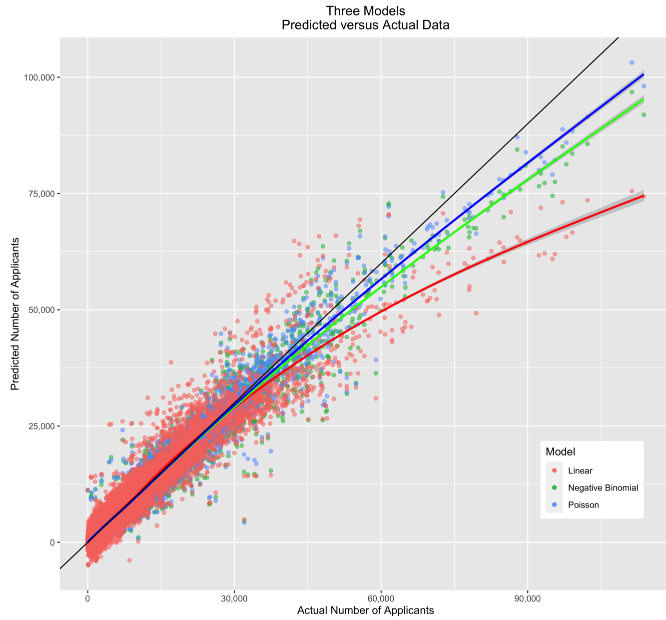

Figure 17: Predicted versus fitted values for all three models. All three best fit curves are estimated using generalized additive smoothing. The black line represents y = x, or a perfectly predictive model.

These comparisons suggest results from the poisson and/or negative binomial are more more trustworthy than results from the linear model. This is in line with my prior expectations because the linear model makes incorrect assumptions about the underlying data, while the poisson and negative binomial models do not suffer from the same lack of constraints.

4.3 Estimated Effects

It is only after thorough model diagnostics and comparisons that it is appropriate to comment on the parameter estimates from each model. Results for the institution-level random intercepts for each model are illustrated in Figures 18 and 19. The random intercepts for both models yield the same overarching conclusion. There are a cluster of institutions which receive a significantly higher than average number of applicants, a group of institutions which receive a significantly lower than average number of applicants, and a majority of the institutions hover around the average. Each model identifies a small handful of outliers which receive far more then the average, although the identities of these institutions differs between models. While these discrepancies are likely due to the nature of the log link function in the poisson model, diagnosing the reasons behind these differences are beyond the scope of this study.

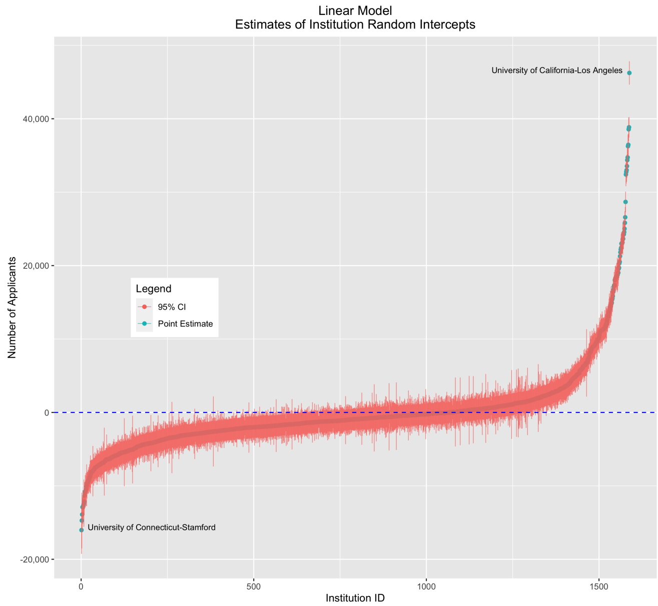

Figure 18: Scatter plot of the point estimates and their 95% confidence intervals for the institution-level random intercepts in the linear model. The dotted line represents no significant difference from the average.

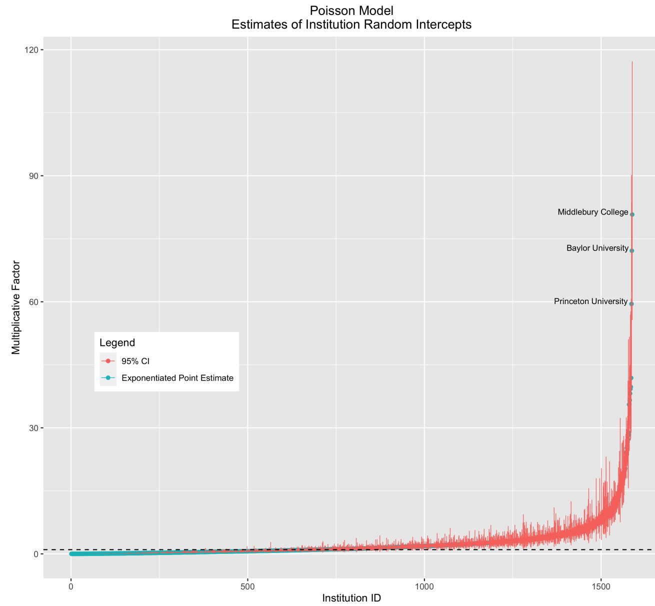

Figure 19: Scatter plot of the point estimates and their 95% confidence intervals for the institution-level random intercepts in the poisson model. The dotted line represents no significant difference from the average.

Results for the state-level random intercepts for each model are illustrated in Figures 20 and 21:

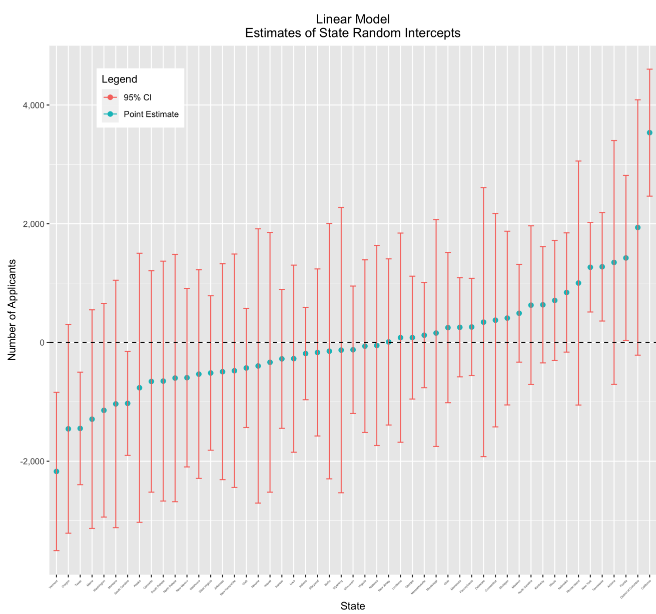

Figure 20: Scatter plot of the point estimates and their 95% confidence intervals for the state-level random intercepts in the linear model. The dotted line represents no significant difference from the average.

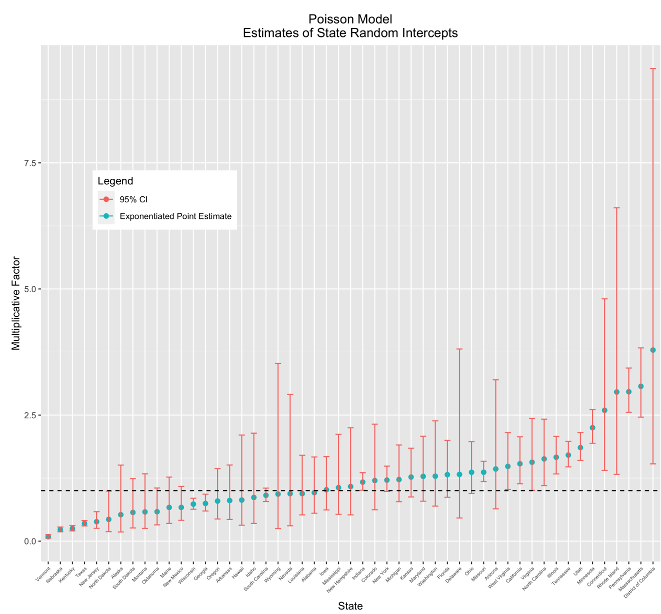

Figure 21: Scatter plot of the point estimates and their 95% confidence intervals for the state-level random intercepts in the poisson model. The dotted line represents no significant difference from the average.

The state-level random intercepts for both models follow a similar pattern as their institution-level counterparts. It is worth noting that both models estimate institutions in Vermont receive a significantly below-average number of applicants while institutions in California receive a significantly above-average number of applicants. Results for the fixed effects for all three models are presented in Table 2:

Table 2: Fixed Effects Estimates

	Linear Model			Poisson Model			Negative Binomial Model		
Predictors	*Estimates*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*
(Intercept)	5681.08	5077.36 – 6284.80	**<0.001**	770.37	594.88 – 997.63	**<0.001**	919.15	734.25 – 1150.62	**<0.001**
loan debt	-656.04	-827.46 – -484.61	**<0.001**	0.87	0.87 – 0.87	**<0.001**	0.91	0.89 – 0.93	**<0.001**
recession	-17.25	-208.96 – 174.47	0.860	0.87	0.80 – 0.95	**0.003**	0.94	0.89 – 0.99	**0.026**
FGRNT A	-81.60	-133.45 – -29.75	**0.002**	0.99	0.99 – 0.99	**<0.001**	0.99	0.98 – 0.99	**<0.001**
COTSON public	5862.53	5632.15 – 6092.92	**<0.001**	1.10	1.10 – 1.10	**<0.001**	1.13	1.09 – 1.16	**<0.001**
CINSON	2489.24	2339.95 – 2638.52	**<0.001**	1.06	1.06 – 1.06	**<0.001**	1.23	1.21 – 1.26	**<0.001**
medianincome	111.17	1.45 – 220.89	**0.047**	1.00	1.00 – 1.00	**<0.001**	0.98	0.97 – 0.99	**0.001**
mean UNEMP	11.31	-74.18 – 96.79	0.795	0.98	0.94 – 1.02	0.315	1.00	0.97 – 1.02	0.826
bachelor plus	128.26	-36.03 – 292.56	0.126	1.19	1.11 – 1.27	**<0.001**	1.13	1.09 – 1.18	**<0.001**
type	-2424.26	-3177.48 – -1671.04	**<0.001**	5.00	4.23 – 5.91	**<0.001**	5.17	4.40 – 6.08	**<0.001**
policy type	-783.71	-1004.46 – -562.96	**<0.001**	0.88	0.88 – 0.88	**<0.001**	0.96	0.93 – 0.98	**0.001**
Policy	327.83	-29.48 – 685.14	0.072	1.55	1.34 – 1.80	**<0.001**	1.22	1.12 – 1.34	**<0.001**
Random Effects									
ICC	0.86			1.00			0.97		
N	51 $_{state}$			51 $_{state}$			51 $_{state}$		
	1588 $_{instnm}$			1588 $_{instnm}$			1588 $_{instnm}$		
	17 $_{year}$			17 $_{year}$			17 $_{year}$		
Observations	25114			25114			25114		
Marginal R^2 / Conditional R^2	0.261 / 0.894			0.180 / 1.000			0.191 / 0.975		

There are a number of important takeaways here. First, note the bottom two variables (called predictors in the table) which are policy type and policy, respectively. These are the variables of interest. The coefficient on the policy variable represents the effect of the policy on the number of applicants to a private institution while the coefficient on the policy type variable represents the difference in the effects of the policy between private and public institutions; their sum represents the total effect of the policy on a public institution. The linear model suggests the policy does not have a significant effect on the number of applicants to private institutions, however, the previous visualizations and model diagnostics suggest the linear model can be better specified and its estimates might be biased. Both the poisson and negative binomial models estimate a significant effect of the policy on both private and public institutions, as well as a significantly different effect between public and private institutions. These results generally suggest there is a non-zero effect of the policy on the number of applicants to higher education institutions, however, there are some additional model diagnostic issues to recognize at this stage.

The intra-class correlation coefficients are high for all three models. This suggests a hierarchical model accurately represents the underlying data and it would be inappropriate to use a one-level model. The marginal R-squared values for all three models are within reason for modeling a behavioral process, but the conditional R-squared values are extremely high. The marginal R-squared is calculated using the fixed effects, while the conditional R-squared incorporates the random effects. The disparity between the marginal and conditional R-squared values suggests there are significant variations within institutions, states, and years, which are poorly explained by the variables specified as fixed effects. The extremely high conditional R-squared values might cause additional concern because of the large number of parameters specified in each model. There are 1,668 parameters in each model and only 25,114 data points. Although this allows for about 15 data points per parameter, which is reasonable, these diagnostics should be recognized when interpreting the model results.

4.4 Robustness Check

I employed an additional robustness check by varying the start year of the policy to test if that has an effect on the significance of its regression coefficient. This robustness check was only performed with the poisson model for brevity. The results are illustrated below:

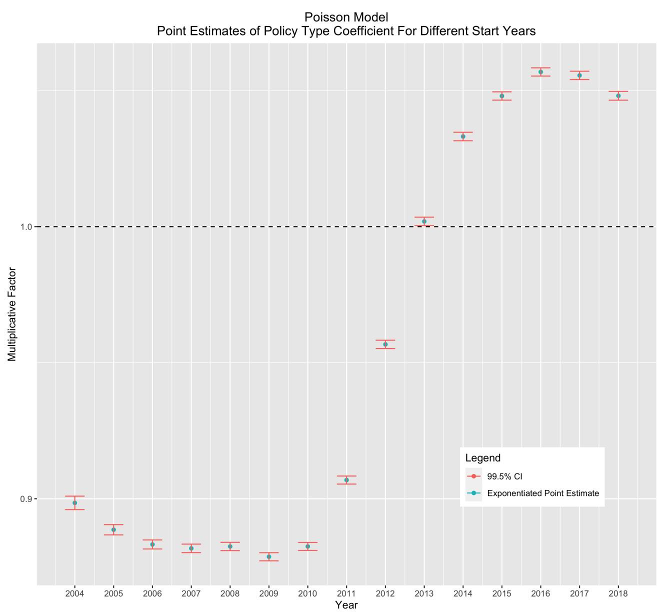

Figure 22: Scatter plot of the point estimates and 99.5% confidence intervals for the policy type coefficient in the poisson model. The dotted line represents no significant effect.

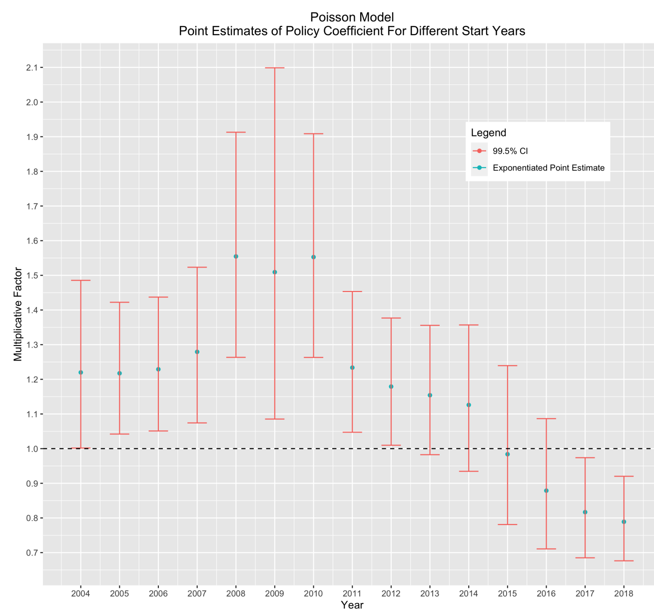

Figure 23: Scatter plot of the point estimates and 99.5% confidence intervals for the policy coefficient in the poisson model. The dotted line represents no significant effect.

It is clear the policy type coefficient did not pass the robustness check. The figure on the left suggests, while the poisson and negative binomial models estimated a significantly different effect between public and private institutions, this should be interpreted with extreme caution and perhaps disregarded given the volatility of the estimate with respect to the specification of the start year. The cyclical nature of the estimate is interesting and might be worth exploring in future work. The policy coefficient did not fail the robustness check as spectacularly, but did not perform well either. The poisson model estimated significant positive effects of the policy for start years in 2008, 2009, 2010, 2011, and 2012. This alone might be plausible given that the policy could have a delayed effect on potential applicants, as mentioned earlier. However, the effects were also significant when the start year was specified as 2004, 2005, 2006, and 2007, which suggests the significant effects estimated in the original models were most likely noise. This robustness check provides evidence that the significant effects on the policy coefficients in the poisson and negative binomial models should be taken with caution, and further research is needed to detect a significant effect, if one exists.

5 Discussion

I find weak evidence that the passage of the Ensuring Continued Access to Student Loans Act of 2008 is associated with a significant positive increase in the number of applicants to private and public four-year institutions in the United States. This result does not withstand a robustness check which varies the start year of the policy, and additional drawbacks in the model diagnostics should be acknowledged when discussing this result. Although I initially found evidence that this effect significantly differs between public and private institutions, this finding evaporates under the same robustness check and I cannot report evidence of a substantial effect difference between institution types. The effect of the policy remains significant after controlling for a variety of demographic and institutional factors, although it also evaporates under the same robustness check.

How do these results connect back to the real world? First, if a local or federal government wants to increase the level of education, perhaps it is worthwhile to experiment with increasing student loan limits to increase the number of prospective students. Second, individual higher education institutions might benefit from these results for a similar reason. If an individual institution is struggling with its applicant rate and wants to increase demand, it might be beneficial to initialize or expand a private student loan policy for its students. Previous studies have already commented on the positive relationship between financial aid and the decision to attend college (Nielsen et al., 2010; Tierney, 1980; Turner, 2011) and this finding weakly supports those conclusions. Furthermore, these results suggest governments and institutions do not necessarily need to offer grants and scholarships to increase attendance, and loans might be sufficient to provide equitable access to higher education across the wealth distribution. It is likely financially advantageous for entities to distribute loans instead of grants, since loans are expected to be repaid while grants are not. Future work might seek to investigate whether student loans and grants have different impacts on the demand for higher education.

5.1 Limitations and Future Research

This study faced a number of limitations. First, there are a variety of data-related shortcomings which can be reconciled in future work. The data collection process was constrained to freely available sources, some of which might have been subject to self-reporting bias. It is possible the IPEDS database itself is biased and certain sectors of institutions (e.g., certain political affiliations, religious slants, extreme student:faculty ratios, etc.) do not report to the NCES. Future work in this area might look towards web-scraping techniques to extract institution-level information from public-facing websites. An alternative avenue for collecting better institution-level data might be to work with the Department of Education to develop a representative sample of institutions and work with each institution individually to collect data. The data I did pull from IPEDS suffered significantly from missing data problems. I chose to conduct a complete-case analysis, but it is generally difficult to detect biases which exist outside of the data (e.g., institutions with male provosts have more missing data). Future research might employ more advanced hierarchical imputation techniques or work with individual institutions to acquire and fill in missing data. Alternatively, the missing data might be modeled within a bayesian framework. I did not include two-year institutions in this analysis to maintain a narrow research question, but it would be interesting to conduct a broader analysis and test if the effects of the policy differ between two-year and four-year schools. The data I analyzed only went back to 2003; it would be insightful if future work collected data over a longer time period (e.g., since 1960) and modeled the short-term and long-term effects of different financial aid policies. Increasing the amount of data used would also help alleviate any concerns about over-fitting the models, as the ratio of parameters to observations should decrease with time.

Second, there are a number of model-related choices which might be modified in future research endeavors. I chose to develop my models according to the frequentist paradigm instead of following bayesian methods. This increases the risk of over-fitting as a bayesian approach would allow for regularizing priors to guard against over-fitting concerns. I chose to specify the recession as a dummy variable only active in 2008 and 2009, but this decision might be at odds with other researchers' preferences. Future work might seek to better model the recession, perhaps as a consequence of other variables within a bayesian framework or as a log-normal distributed variable with diminishing effects over time. The number of applicants to a given institution could have also been modeled as an ARIMAX process and included auto-regressive effects (i.e., the number of applicants for that institution in the previous year). The directed acyclic graph is a likely source of debate, as different researchers might develop different causal maps given the same problem. Since the directed acyclic graph directly informs model specification, it would be of interest to future researchers to improve this part of the methodology and test different sets of causal pathways.

There are several core improvements and ideas I would encourage other researchers to explore to properly answer this question. First, I think obtaining more data is a simple yet critical step to improving the work done here. This should be a combination of going farther back in time and taking additional steps to fill in missing data, whether that involves hierarchical imputation techniques, web-scraping, or cooperation from individual institutions. Second, I think an interesting approach would be to gather data going back into the mid-twentieth century such that several federal aid policies are encompassed. The number of applicants can be modeled over time and researchers can test for the existence of decaying perturbations following each policy. If the effects exist, this would lead to a nice visual representation of the impact these policies have on the demand for higher education. My final two suggestions are to utilize bayesian methodologies and expand the directed acyclic graph.

5.2 Conclusion

Higher education has become commonplace in the United States, and with it, increasing student loan debt and debate about the cost and funding of higher education institutions. A core investigation in the literature, and one central to this issue, is to better understand which factors drive the demand for higher education. Since private institutions tend to be more expensive than their public counterparts, this question can be narrowed down to studying the demand for privatized higher education. I contributed to the existing literature and investigated the effects of a $2,000 increase in the annual unsubsidized student loan limit associated with the passage of the Ensuring Continued Access to Student Loans Act of 2008 on the number of applicants to four-year institutions in the United States. I collected data from the Integrated Post-

Secondary Education Data System, hosted by the National Center for Education Statistics, the U.S. Census Bureau, and the Federal Reserve, and built a regression model supported by a directed acyclic graph. I estimated the regression model with three different assumptions about the underlying data, via a linear model, poisson model, and negative binomial model. I found weak evidence that the policy had a positive effect on the number of applicants to four-year institutions, when controlling for time, location, institution, and a variety of demographic factors. This effect should be taken with caution because it did not hold up well against a robustness check which varied the start year of the policy. Future research should build on this study, improve the data collection process, and test more complex models.

6 References

6.1 Works Cited

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7 Appendix A - Complete-Case Distributions

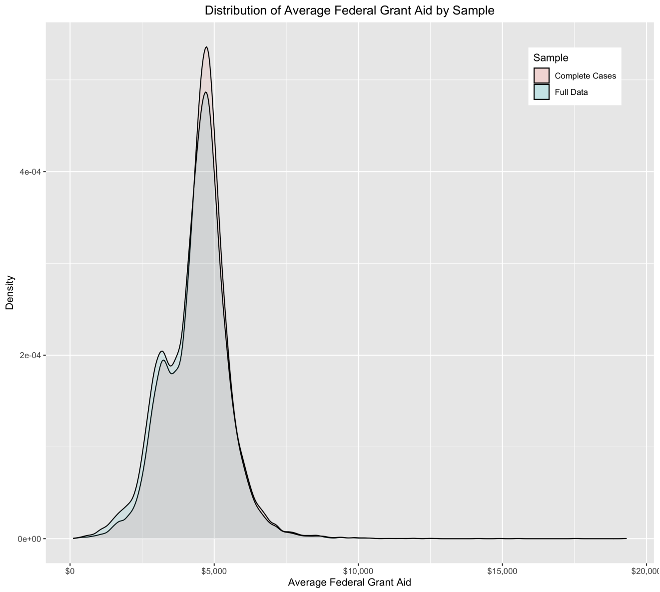

Figure 24: Kernel density estimates of the average federal grant aid for the complete case sample and the full dataset.

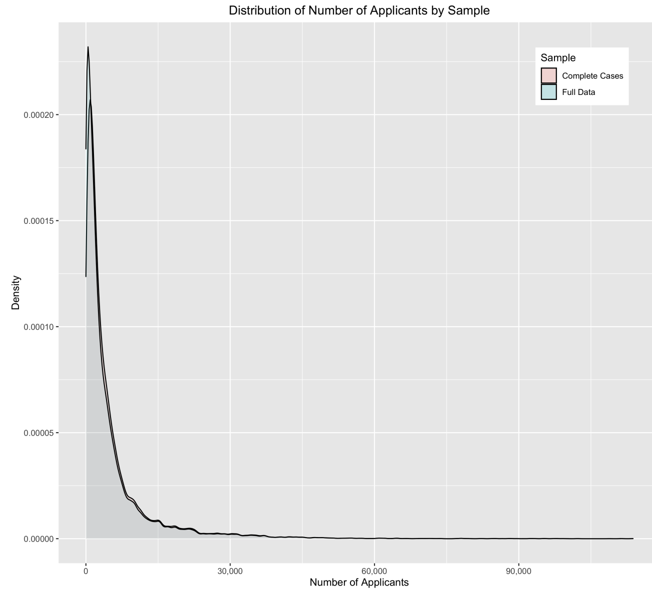

Figure 25: Kernel density estimates of the number of applicants for the complete case sample and the full dataset.

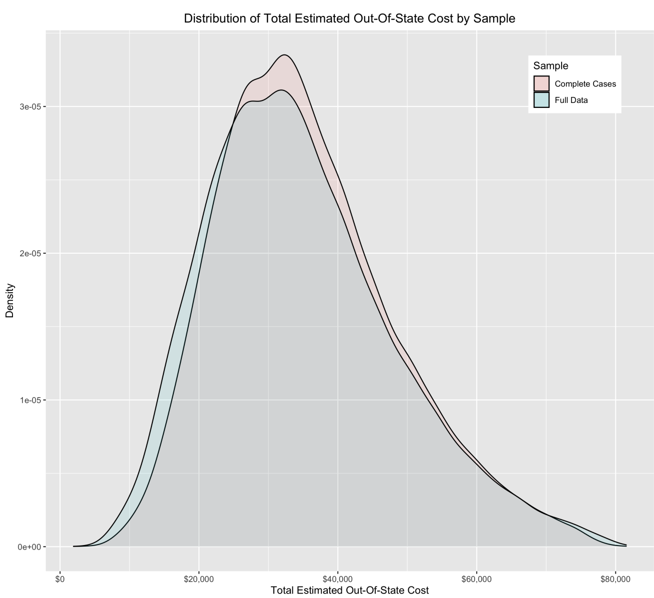

Figure 26: Kernel density estimates of the total estimated out of state cost for the complete case sample and the full dataset.

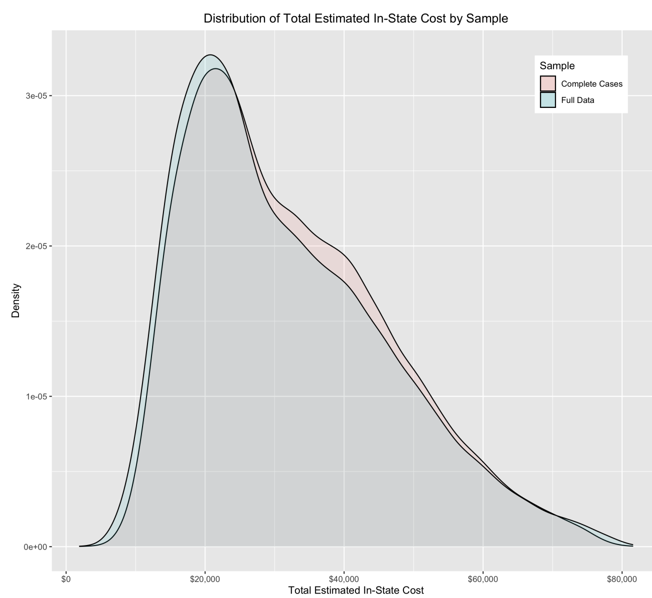

Figure 27: Kernel density estimates of the total estimated in-state cost for the complete case sample and the full dataset.

8 Appendix B - Supplemental Materials

The following supplemental materials are provided in an attached folder for completeness:

- models.R - this file reads in the cleaned data and runs the three primary models including those needed for the robustness checks. This file also creates all visuals in the results section.
- dataCleaning.R - this file reads in all the raw data from various sources, cleans and compiles it, and outputs the data file used for analysis.
- dataVisualizations.R - this file reads in the cleaned data and produces all visualizations seen in the data section.
- DAG.ipynb - this python notebook generates the directed acyclic graph and solves for the set of variables which should be conditioned on.
- ultimateData.csv - this is the cleaned dataset used for analysis.
- institutionData.csv - this is the institution-level data downloaded from the IPEDS database.
- valueLabels.csv - this file is used to fill in the state and institution type values in the institution-level data.
- unemployment.xls - this file contains unemployment data from the Federal Reserve Bank of St. Louis.
- debt.xls - this file contains per-capita student loan balance data.
- education.xlsx - this file contains education information by state.
- medianHouseholdIncome.xlsx - this file contains income information by state.
- policy.xlsx - this file contains contrived policy enactment data by year.