Indentured Servitude, Revisited.

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INTRODUCTION

Student loans have become commonplace in the United States. Ever since the passage of the 1944 GI Bill, the United States Federal Government has been in the student loan business.[1] Up until 1993, however, the majority of student loans were provided by private lenders. But following the passage of the 1993 Student Loan Reform Act the federal government, for the first time, began lending directly to borrowers. In 2005, the Higher Education Reconciliation Act further distorted the market, fixing loan fees from 4% to 1%. Later, legislation proposed and passed by the Obama administration made it so that *all* new government loans *must* be direct loans, leaving private firms to pick up the scraps. As a result, while some private lending still exists, federal loans now make up more than more 92% of the student loan market share.[2]

In 1987, six years before the Student Loan Reform Act, Secretary of Education William Bennett argued that increases in financial aid was making tuition hikes possible. Since then, total student loan debt has surpassed one trillion dollars and tuition rates have effectively doubled (see table from in A1).[3] As of 2016, total student loan debt was $1.4 trillion, of which $1.29 trillion was federal.

Particularly noteworthy is the fact that student loan debt is unlike other forms of lending, with more serious long-term ramifications. Loan forgiveness and restructurings are rare, outside of those who seek careers in the public sector, as the federal government will forgive student loan debt for any persons that work in the public sector for 10 years. Otherwise, the student loan remains until it is paid off. Plan to emigrate? Just make sure you keep on with those loan payments.[4] Did your spouse recently pass? Unfortunate, but before you collect that life insurance policy, it's likely that a private student loan lender is entitled to first rights on your spouse's estate.[5] Further, if they do not have an estate, the burden of debt might fall on you. The point is that student loan debt can follow you around until death, and sometimes even after it.

Simply having to pay off the debt is bad enough, but if one were to default on that debt, the situation would likely be considerably worse. A default can absolutely destroy the person's credit.[6] This, presumably, would make it harder to secure a car loan, be granted a mortgage, or to acquire any other meaningful assets. This is a rising concern for much of US population as default rates have been rising across all levels of borrowing.[7]

In *Student Loan Debt and Economic Outcomes (2014)* (referred to from here on as "*SLDEO*"), Daniel Cooper and J. Christina Wang found that students that took out loans during the 1990s were less wealthy as well as less likely to own a home.[8] The fact that it was wealth, and not lifetime earnings, that was adversely affected should be noted. This study compared apples to apples — whether that was college dropouts to college dropouts or college graduates to college graduates. But there has been much talk on how the average lifetime earnings of a college graduate are significantly higher than just a high school graduate. And while that seems almost certainly to be true, there does not seem to be much discussion on whether, or by how much, lingering student loan debt affects a person's ability to accumulate assets.

This paper will explore whether college, along with the unpleasant, but usually necessary accumulation of student loan debt is a good investment. If the conclusions of *SLDEO* are to be believed, and the negative correlation between wealth and debt borrowed during the 1990s is assumed true, then today's trend of rising tuition costs, unprecedented sums of student loan debt, and seemingly stagnant real wages indicate that today's students will likely be worse off in their ability to accumulate wealth.[9] As we will see, there are certain parts of our paper that show this to at least be partly true. For this reason, alternatives such as trade school, apprenticeships, or even a shorter and less expensive associates program may be worthwhile options. However, prior to drawing such conclusions, we first must build on the analysis and findings of *SLDEO* — adding business as well as statistical value to their study.

The analysis done in the first part of this paper, using a Generalized Additive Model, seeks to update the *SLDEO* model from students taking out loans in the 1990s to more recent college graduates in the 21st century, a period in which student loan debt has really ballooned. Additionally, while the *SLDEO* study examined the degree to which borrowing different levels of student loan debt adversely affects wealth for students with similar education and demographic backgrounds, this study will consider the amount of student loan borrowed independent of the level of education or other demographic factors. As a result, our analysis will determine whether it is financially beneficial in the long-run to borrow higher levels of debt if it allows a person to attend a more prestigious college or attain higher levels of education, in a way the *SLDEO* study does not.

Our Clustering analysis is similar to the *SLDEO* study in that it examines a fixed set of students and measures their outcomes following graduation (end of the borrowing period). However, we were only able to obtain data to measure outcomes one year following graduation via a graduate's first year annual income, whereas, the *SLDEO* study was able to obtain a more comprehensive measure of wealth further out from the end of the borrowing period. Still, we were able to improve on the *SLDEO* study by examining students and outcomes over a longer period. Instead of just primarily focusing on the 1990s, we study baccalaureate recipients from 1993, 2000, and 2007. As a result, we can better observe how borrowing levels and resulting wages have changed over time for those who received an undergraduate degree. Also, by using different clustering methods, we employ different machine learning concepts otherwise ignored in *SLDEO*.

Finally, our Granger-Causality test seeks to determine the cause of rising tuition rates. A technique as well as a topic the *SLDEO* study does not explore. We felt that this was a natural way, in the scope of our paper, of testing the Bennett hypothesis empirically, which will complement the analyses in the other sections of our discussion.

In order to get to the point of hypothesis testing, we needed to first compile our data. Unfortunately, our data set is going to have to be significantly different from that which was used in *SLDEO*. A description of what we decided to use is detailed below.

DATA

Model 1 – GAM

Variable Type	Variable Names
Dependent	Asset accumulation – Home Ownership Rate, Average Market Value of Home, Average Number of Vehicles Owned, Average Cost of Vehicle, Average Household Furnishings Value, Average Financial and Mutual Fund Asset Value
Independent	Total Student Loan Debt per Unique Borrower – Total Student Loan Debt and Number of Unique Borrowers
Controls	Inflation, College Graduation Dummy, After-Tax Income, 30-Year Mortgage Interest Rates

Model 2 - CLUSTERING

Variable Type	Variable Names
Dependent	Income One-Year Post College Graduation Per Person
Independent	Total Undergraduate Loans Borrowed Per Person
Controls	Percentage of Students Borrowing

Model 3 – GRANGER CAUSALITY

Variable Type	Variable Names
Dependent	Annual Average Tuition Costs
Independent	Average Federal Loans Borrowed Per Person, Number of Borrowers

For our Generalized Additive Model (from here on referred to as our "GAM"), the dependent variable asset accumulation data was obtained from the Bureau of Labor Statistics (Home Ownership Rate, Average Market Value of Home, Average Number of Vehicles Owned, Average Cost of Vehicle, Average Household Furnishings) and the Investment Company Institute (Average Financial and Mutual Fund Assets) for the years 2004 to 2017. Our dependent asset accumulation variable is comprised of four parts: (i) home ownership percentage multiplied by the average value of a home; (ii) total financial assets; (iii) average value of household furnishings; and (iv) average number of vehicles owned multiplied by the average cost of a vehicle. We estimate total asset accumulation by the sum of these four variables.

The data for the independent variable Student Loan Debt was obtained via the New York Federal Reserve for the years 2004 to 2017.

All data for the dependent and independent variables are based on aggregate figures obtained from survey data seeking to estimate the average asset values and student loan debt for *all* persons in the United States. This data was separated into different age groups. For the asset accumulation data, the age groups were split into five groups: (i) Under Age 35; (ii) Ages 36-45; (iii) Ages 46-55; (iv) Ages 56-64; and (v) Over 65. For the Student Loan Debt data, the age groups were also split into 5 groups: (i) Under Age 30; (ii) Ages 30-39; (iii) Ages 40-49; (iv) Ages 50-59; and (v) Over 60.

Given the differences in the age groups for the asset accumulation data and the student loan debt data, we had to stagger the student loan data by five years so that the age groups matched. As a result, even though we had data from 2004 to 2017 for both asset accumulation and student loan debt, we were only able to analyze trends from 2004 to 2011. We will find that this truncation of our data set affects our analysis and therefore our conclusion.

For the control variables, the data was obtained from the Bureau of Labor Statistics (Inflation, College Graduation, After-Tax Income) and the Federal Reserve Bank of St. Louis (30-Year Mortgage Rates). Similar to the dependent and independent variables, after-tax income, college graduation, inflation, and mortgage rates are based on aggregate figures obtained from survey data seeking to estimate the average values for *all* persons in the United States for the given time period.

The After-Tax Income and College Graduation data are separated into five age groups: (i) Under Age 35; (ii) Ages 36-45; (iii) Ages 46-55; (iv) Ages 56-64; and (v) Over 65.

To test our variables for stationarity, we used both a Phillip Perron's as well as an Augmented Dickey-Fuller test. As one might expect, asset accumulation was found to be nonstationary. Also found to be nonstationary were loans per person and after-tax income (see results in A9). As all three were integrated of order one (or I(1)), we took the first difference, or the *change*, in each variable.

Clearly, it would be better to follow a static set of students who borrow various levels of debt and obtain varying levels of degrees from various institutions and follow their economic outcomes as they age. However, in this scenario, it would be difficult to determine the outcomes of recent graduates, specifically for graduates over the past decade, during which time total student loan debt has ballooned. The only measure of wealth that we were able to obtain for a static set of students borrowing different levels of debt was annual income one year after obtaining an undergraduate degree. The statistics of this data set were descriptive rather than comprehensive, and thus required manipulation.

For the Clustering Model, all dependent, independent and control variables were obtained from the National Center for Education Statistics (NCES). This data was obtained from surveys of those who received a baccalaureate in 1993, 2000, and 2008, with sample sizes of approximately 11,000-12,000 for the years 1993 and 2000, and 17,000 for the year 2008 (see A7 tables). All data was presented in 2009 dollars. We were not able to view the individual survey data, and instead only had access to the average, median, and standard errors of the total amount that was borrowed for undergraduate education and these same figures for the same individuals for their annual income one-year from graduation for each year. We also obtained the percentage of individuals in each sample that borrowed loans in each of those years. This data is separated into quartiles based on the amount borrowed, so we are able to examine the relationship between different levels of borrowing and income one-year after graduation.

For the Granger Causality model, Average Annual Tuition Costs represent the Annual Average Total Tuition, Fees, Room and Board Rates Charged for Students in Degree-Granting Institutions for the years 2007 to 2016. This data was obtained through the NCES. The Average Federal Loans Borrowed per Person and Number of Unique Borrowers was obtained from the Federal Student Loan Aid Office of the US Department of Education and represents quarterly data for the years 2007 to 2016. This was derived from survey data seeking to estimate the total aggregate and average values for all persons in the United States. In order to check each variable for stationarity, we, again, used both Philips Perron and Augmented Dickey-Fuller tests. We found that they were all integrated of order one (or I(1)), and, as a result, took the difference of each variable.

Outside of the NCES data, all figures represent aggregate figures relating to the US' macroeconomy. A symptom of resorting to macro data was the restriction on the number as well as the type of controls that we were able to incorporate into our analysis. With a population as heterogeneous and diverse as is that of the United States, being able to account for different demographics and regions would have been ideal.

Also, for certain variables, we were restricted to using annual figures (tuition costs, student loan debt and number of borrowers from 2013 to 2017, financial and mutual fund assets, home ownership rate, average market value of home, average number of vehicles owned, average cost of vehicle, average household furnishings value, after-tax income, and college graduation rate), while for others we were able to obtain quarterly data (student loan debt, number of borrowers, and mortgage rates). In order to remedy this, we interpolated quarterly figures from our annual data with the help of cubic splines. By simulating quarterly data, we were able to use additional observations in our analysis.

METHODOLOGY

As mentioned in the introduction, this study is split into three parts. The first and third parts both involve inference. In the first we use a standard regression equation (the makeup of which can be seen directly below). In the second part, we run first a simulation and thenperform a clustering analysis. The simulation is used to create a distribution and generate a random subsample, and the clustering analysis is used to examine whether there exist any natural partitions, or clusters, within those subsamples. Lastly, we employ Granger Causality tests to and establish a link between rising tuition costs and the number of people receiving Federal Student Loan Aid and also the average amount of Aid being issued.

Note: the significance level used in all hypothesis testing done here was set at 10%.

Generalized Additive Model (GAM):

$$\begin{aligned} &\Delta Asset\ Accumulation \\ &\quad = f(\Delta Loans\ Per\ Person) + f(\Delta After\ Tax\ Income) \\ &\quad + \sqrt{College\ Graduation\ Rate} + \Delta 30\ Year\ Mortgage\ Rates \end{aligned}$$

The regression equation used in the first part of our methodology section is very similar to that used in *SLDEO*. However, our dependent variable is asset accumulation, rather than wealth (not including student loan debt) employed by *SLDEO*. Both analyses use student loan debt as the independent variable and both have their fair share of controls.

The decision to use asset accumulation rather than wealth was primarily due to accounting issues. In order to not introduce bias, we would have to make sure we were properly accounting for every asset as well as every liability. Making the primary point of this regression analysis to see what kind of effect student loan debt has on asset accumulation was, in part, to counter that. Aside from that, it builds on the results derived in *SLDEO*, especially the one that suggests borrowers were less likely to be homeowners. Home ownership makes up the most significant portion of our aggregated Asset Accumulation variable, and so it is of implicit interest. In other parts of the paper we will explore different relationships, but here we wish specifically to examine the relationship between student loan debt and the accumulation of assets.

The control variables used in our analysis differ from those used in *SLDEO* as well. As previously mentioned in the data section, data for control variables were hard to obtain, and so, as a result, our analysis has fewer controls. One of the benefits of working with macro data, though, is that you can be sure that the data was collected randomly from all around the country, and so equal amounts of engineers, state school grads and post-graduate students of all different types were mixed in — making such variables less of a necessity.

However, it is still necessary to employ some control variables. The final model controls for after tax income, the square root of proportion of college graduates per age group, and interest rates on a mortgage. Initially, our goal was to load up our equation with control variables and use LASSO regression in order to determine which were meaningful and which were not. As we've already said, though, we were restricted to the number of controls in which we had access.

After tax income was important as periodically higher wages mean a potentially greater accumulation of assets. The fact that it was *after* tax and not pre-taxed income allowed us to sidestep any heterogeneity introduced by the possible changing of tax brackets (new tax policy, i.e.). Additionally, the proportion of college graduates was also important — so much so that we decided to take the square root of it. Since it is a percentage between 0 and 1, this would make the figure more meaningful. Lastly, we control for interest rates on mortgage, as some mortgage policies allow for restructuring, and, in these particular cases, major fluctuations in rates can mean either the financial access to or the restriction of further accumulation of group assets.

SLDEO uses a multiple linear fixed effects regression model. However, linearity seemed too unrealistic an assumption here, and so we decided to adopt a fixed effects Generalized Additive Model (GAM). It is interpretable as well as flexible, and, thus, is capable of fitting our data well. We applied nonlinear functions to both I(1) right hand side variables, change in loans per person and change in after-tax income. And while it is not a metric one should necessarily rely upon, we see that our R^2 showed dramatic improvement after the application of those functions (see output of figures in A10 and A11). Lastly, we chose to maintain a fixed effects model, as we felt that a fixed effects model better accounted for heterogeneity across age groups.

The functions in which we applied to change in loans per person and change in after-tax income took the form of natural splines. They were the *natural* choice, so to speak, as they allowed for us to continue using least squares in the form of fixed/random effects panel estimation. Also, given the small sample size, they were effective estimators of the data's periphery. Smoothing splines and polynomial regression, by comparison, do not deal as well with outlier events as do natural splines. To choose the appropriate number of "knots" in each function, we employed cross-validation. There was a loose constraint as to how many knots there could be. Any more than eight was thought to be excessive as the dataset was relatively small and thus too many could lead to overfitting.

K-Means and Hierarchical Clustering:

The results of our GAM prompted further analysis. Given the lack of meaningful micro data, we decided to try and produce our own. Although this process was somewhat convoluted, the results were quite informative. Most statistics derived from survey data made public are descriptive. Typically, researchers release the sample population's mean, median, and standard error, but rarely do the release the actual data set. This makes reproducing the study or even attempting to resemble it all but an impossible task. In our analysis, however, we used the available statistics in order to "recreate" the data set via a simulation.

That simulation was predicated on the following assumptions: with each sample (and subsample) being in the many thousands, we assumed general normality, save for the kurtosis parameter. The value of each moment was then estimated from the descriptive statistics, with the kurtosis parameter assumed to be proportionally larger than the skewness parameter, as it has a history of being in both income and student loan distributions.[10] To estimate skewness we use Pearson's coefficient of skewness, utilizing the median, mean, and standard deviation (see A13 for its formulation).

This simulation process was two-part, using the NCES survey data sets, which are based on a static set of different college students. In the original data set, student loans and post-graduation income came in the form of different mean and median income based on *how much* the student borrowed. Thus, if the amount a student borrowed up till his graduation in 1993 was in the first quartile (between the 0^{th} and 25^{th} percentile), then the estimated mean was $31,700, the estimated median was $29,000, and the standard error was $1,063; if the amount a student borrowed in 1994 was in the second quartile (between the 25^{th} and 50^{th} percentile), then the estimated mean was $30,800, the estimated median was $28,700, and the standard error was $730, and so on (see sections A2, A3, and A4.2 for further details).

Parameters for *amount borrowed* was then also collected (i.e., the median, mean, and the standard error). Using these figures, we were able to both estimate the distribution's moments as well create quartiles with which the distributions of our *income* could vary. By using moments from all five sets of data, we were able to estimate five unique distributions. We should note, however, that four moments do *not* describe an entire distribution. Our distributions, in other words, are approximations, and are in no way perfect substitutes of the original data.

That being said, we found that each distribution took on, as one might expect, a right tail skew (i.e., where the mean is greater than the median) (see sections A5 and A6). From these distributions, we executed our first step: simulate as many "amount borrowed" observations as there were borrowers for that year based on that year's distribution (see A2 for number of borrowers). In step two, we took a record of those numbers, classified them based on what quartile they fell into, and then generated a random income based on the distribution the quartile followed.

Thus, the process was sequential: first, we simulate loans borrowed; second, we simulate an income based on the quartile distribution the simulated loans borrowed landed in. With this we had our second, simulated dataset and one that was similar to the *SLDEO* data — a micro data set, in other words. This allowed us to make use of both hierarchical and k-means clustering algorithms. The “Elbow Method” was used to pick the number of centroids when using the former method, a dendrogram when using the latter method (see figures in A12.1).

Granger Causality:

Finally, in order to examine whether there existed a “causal” link between tuition costs and the student loans, we used a Granger causality test. Two tests were conducted: the first tested whether change in student loan debt issued by the federal government caused an increase in tuition costs; the second tested whether change in number of persons issued loans caused an increase in tuition costs. In both these tests, we lagged the explanatory variable twice. We chose to use two lags as we felt that, with one, we ran the risk of our test being biased by residual autocorrelation; with three or more, we felt that the additional predictors would make a spurious rejection of the null more likely.

RESULTS

Generalized Additive Model (GAM):

Up to a point, higher levels of student loan debt means higher levels of income, as all coefficients are positive and significant (see section A11). This suggests that, when the sum borrowed is within reason, student loans have a positive effect on asset accumulation. Higher student loan debt resulting in higher income fails to hold in our sixth quantile, where we observe, all else being held equal, that an additional thousand dollars in Student Loans means, on average, $25,849 *less* Assets Accumulated. Thus, only excessive amounts of student loan debt (i.e., the largest borrowers) experience less income as a result of higher borrowing. Noting again that the data used here is overly aggregated as well as from the very short 2005 to 2011 interval, these results make sense. Attending college and obtaining more prestigious or higher levels of education still is likely to be remunerative so long as an individual does not borrow excessive amounts of debt.

Additionally, we observe a larger and larger skew in our student loans simulation data, meaning more and more people were taking out larger and larger loans as time went on. As a result, it should be the highest borrowing quantile (that with the negative coefficient) that is the greatest point of emphasis, as more and more borrowers seem to be heading in that direction.

Another takeaway from the GAM is that after-tax income, though a control variable, is the only other variable of significance. The GAM suggests that the gain in assets of, say, the middle class (in terms of wage) are the only gains that are of statistical significance. It is not surprising that mortgage rates failed to have a significant effect, as they do not typically float, and, even if they did, less debt does not necessarily mean an immediate attainment of new assets. The square root of college graduation rate was found to be insignificant as well, which we believe can be attributed to the dataset's short time interval. If it was significant, though, its positivity, given the general makeup of change in student loans coefficients, would have made sense.

K-Means and Hierarchical Clustering on our Simulation Data:

Taking random subsets (totaling 500 observations each) of each of the five distributions, we run two different kinds of clustering algorithms: k-means++ and hierarchical (or agglomerative). Each method organizes the observations into groups: the "Overly Optimistic" and the "Reasonable." The overly optimistic cluster consists of people that, while expected to make a comparatively lower salary, take out their fair share in loans. They range from borrowing the least and expecting to make the least to borrowing the *most* while also expecting to make the *least* (see figures in A12.2). The reasonable cluster consists of people that, while they *may* take out a lot in loans, they expect to make a somewhat reasonable wage following graduation. They range from borrowing the least to borrowing the most, but also expect to either make the median if not the most relative to their peers.

Looking at each graph, it is apparent that as time goes on, the range/density of both the Reasonable and Overly Optimistic groups starts to evolve (see figures in A12.2). As seen in the charts as well as the histogram, the range for income, in 1994 dollars, stays relatively constant across time (see figures of A6). The difference, primarily, was that fewer and fewer people started off making more than thirty-four to thirty-five thousand dollars a year. This was primarily influenced by the distributions' ever-evolving right tail skew.

The change was made apparent in the income charts. Across all groups, median income shows a decrease, in absolute terms, between 1994 and 2009 (see figures in A4.1). What was interesting, though, is that standard deviation of the distributions began to shrink, suggesting that each distribution began having less of a spread. In a different world, this might be good news. Less variation might mean less income inequality, and less income inequality would certainly not be a bad thing (ceteris paribus). But here, that decline, accompanied by a greater and greater skew as well as a larger and larger amount of kurtosis, means that the spread still exists — just that now that it's in the tails. And so, already noting that with the decrease in the median quite a few people were making less money in 2009, we should also note that quite a few began making significantly more than the rest, as well. This gave us a significant number of outliers.

This growing disparity caused our clusters to take different forms. In terms of student debt in 1994, there was a wide range of observations; the spread, or standard deviation, was large and the kurtosis was small. Most of those carrying lots of debt were seen as "Overly Optimistic," but quite a few were looked at as "Reasonable" as well. However, over time, not only did fewer and fewer Optimists take out big money loans, but the loans, in absolute terms, became relatively larger in size. Ranging between $14,500 and $15,800 in 1994, loans began to range between $22,000 and $24,250 in 2001 and then $24,200 to $26,000 in 2009 (all figures being in 2009 dollars).

As a direct result to the change in these parameters, we see that the Reasonable started to become a smaller, more condensed cohort (see figures of A12.2). They rarely took out big money loans. The Overly Optimistic, by contrast, continued to spread itself thin, tapping into the student loan distributions' fat, newly formed tails. To put this another way, it seems that, as time went on, Reason went out the window for Optimism. Furthermore, it seems that the cause of this was more and more outlier events — or more people borrowing larger and larger sums. Being aware of the Bennett Hypothesis (mentioned earlier in this paper), we aimed to see whether this change in average student loan debt had any effect on the country's average college tuition.

Granger Causality:

In this section, we wanted to examine the relationship between tuition rates and student loan debt per borrower as well as with the number of borrowers. Getting tuition by year and student loan debt per borrower by quarter, we used splines to interpolate from the data of the former. And then, to examine the relationship, we ran a Granger Causality test. To our surprise, there was *not* enough evidence to conclude that the increase in loans per borrower issued by the federal government "caused" higher tuition rates. There was enough evidence, however, to conclude that the increase in the number of new borrowers *did* cause a tuition increase. This is particularly noteworthy, as in the 4th quarter of 2016, the federal government loaned to more *new* borrowers than ever before.

This particular statistic, while significant, should not come as a surprise. Requirements for getting a loan are not particularly strict.[11] So long as one has a high school diploma, maintains a 2.0 GPA, and is in good financial standing with the federal government, it is most likely that they will be approved for a student loan. The results of this test, however, suggest that such low standards may not be in the long-term interest of the borrower. If increased access to student loans means more students receiving loans, and if an increase in students receiving loans means an increase in tuition costs, then the value of a college education has effectively lowered, holding expected future income constant (a not so lofty assumption, as we've seen). The degree to which a college education has lost value will require further research.

Still, it is clear that the government — in their effort to make higher education more accessible to the masses — has essentially subsidized the higher education system. That subsidy is at the expense of the borrower. In a time where college degrees seem to be the new high school diploma, it feels as if the former has become an absolute must. By the federal government guaranteeing its payment — a good with, one should think, an extremely inelastic demand — they have flooded the market with new buyers. It should come as no surprise that in this seller's market there has been an increase in prices.

ROOM FOR IMPROVEMENT

This paper was lacking in a few areas. The original dataset, as we've already mentioned, was both small in size and overly aggregated (only about 140 observations, all told) (see figure A14). Larger data sets would have allowed for us to use different, more complex forecasting techniques — an LSTM, for example — and, in the process, manage a more in-depth analysis. If our data was in the form of micro panel data, as we'd originally planned, we would have been able to control for factors such as college major, gender, ethnicity, university attended, exact age, etc. when running our GAM. It would have closely mirrored the analysis done in *SLDEO*, but, given what we felt were superior techniques, would have been a bit more accurate. And while, in a way, this was one of our paper's strengths (with regard to our use of control variables, we were allowed to take liberties that the authors of *SLDEO* could not by using macro data), had we had access to a comprehensive micro data set, we could have been more detailed in our conclusion.

Complementing, or perhaps compounding, the issue of having to deal with a small data set is the time period (or perhaps lack thereof) in which our data was observed. It is ideal, when trying to establish a causal relationship, to have a large data set that is rich in controls and spans plenty of time. Without panel data spanning the periods discussed in the paper's other sections, it's hard to relate the results of our Granger Causality section to that of our clustering analysis and the results of either to that of our GAM's without being imprecise.

One last thing of note was our inability to use lagged variables in our regression equation. The general expectation, it would seem, is that yesterday's actions are going to be the main influencers of today. Whether that means getting locked in to a comparatively higher mortgage rate or landing a job with relatively better pay, it isn't so radical to think that the outcomes of past quarters influence our dependent variable more than the reality of the present. Given our relatively small panel dataset, though, every lag applied would have meant five observations lost.

Even if we did choose to endure a smaller sample size, it is not clear what kind of effect the imposition of the lags would have had on the model's accuracy. Our panel data was collected on a group by group basis. Ages in these groups ranged anywhere from ten to thirty years. Lagging a variable would have meant lagging the entire group, and it is not clear that the past of a group so large in scope would mean as much as, say, the past of the individual.

And while this paper does raise its fair share of questions, it manages to answer quite a few as well. For that reason, it was overall a success.

CONCLUSION

Our analysis has allowed us to develop multiple conclusions. First is that while higher levels of student loan debt generally translate to higher asset accumulation, excessive amounts of student loan debt mean lower amounts of asset accumulation. Second is that more and more students are taking out, by today's standards, excessive amounts of student loans. Third is that, given current trends, there will only be more of them in the future, and not just more outliers, either — more borrowers. Given our Granger-Causality model results, more borrowers at least partly contribute to higher tuition rates. Finally, we see that although tuition rates and borrowing per person is increasing over time, resulting wages are largely stagnant.

Taking all that into consideration, we can conclude that while over the past 30 years the initial value of a four-year degree has remained about the same, the cost has roughly doubled. Thus, education alternatives should at least bear some consideration. However, while the value of a college education over time has diminished, it remains a relatively better option for today's crop of prospective baccalaureate recipients, so long as the borrower is not taking an excessive amount of debt. It seems, however, that such debt levels is starting to become the norm.

A scenario in which the average principal becomes so large that at some point the borrower can no more than pay off the loan's interest let alone touch the principal is not so hard to envision. Not only would it inhibit the borrower from acquiring any meaningful assets — it would make for a sort of modern day indentured servitude. The only difference here being that the "indenturee" wouldn't have some fixed-term contract. They would need to work so long as the debt was outstanding — a sentence that is as variable as it is daunting. This makes the question we posed at the beginning of this paper all the more relevant. If tuition rates continue to go up, and wages continue to remain stagnant or are not able to keep pace, you really ought to ask yourself: is college going to continue to be worth it?

GENERAL APPENDIX

A1. The "All Institutions" section of the table from https://nces.ed.gov/fastfacts/display.asp?id=76

Average total tuition, fees, room and board rates charged for full-time undergraduate students in degree-granting institutions, by level and control of institution: Selected years, 1984–85 to 2014–15

Year and control of institution	Constant 2014–15 dollars[1]			Current dollars		
	All institutions	4-year institutions	2-year institutions	All institutions	4-year institutions	2-year institutions
All institutions						
1984–85	$10,210	$11,548	$7,115	$4,563	$5,160	$3,179
1994–95	13,069	15,308	7,291	8,306	9,728	4,633
2000–01	14,625	17,468	7,389	10,820	12,922	5,466
2001–02	15,115	18,116	7,595	11,380	13,639	5,718
2002–03	15,613	18,766	8,126	12,014	14,439	6,252
2003–04	16,475	19,720	8,528	12,953	15,505	6,705
2004–05	17,030	20,384	8,760	13,793	16,510	7,095
2005–06	17,405	20,756	8,606	14,634	17,451	7,236
2006–07	17,951	21,415	8,656	15,483	18,471	7,466
2007–08	18,146	21,647	8,538	16,231	19,363	7,637
2008–09	18,845	22,502	9,083	17,092	20,409	8,238
2009–10	19,274	23,070	9,327	17,650	21,126	8,541
2010–11	19,778	23,630	9,493	18,475	22,074	8,868
2011–12	20,178	23,932	9,721	19,401	23,011	9,347
2012–13	20,699	24,420	9,794	20,233	23,871	9,573
2013–14	21,148	24,878	9,959	20,995	24,699	9,887
2014–15	21,728	25,409	10,153	21,728	25,409	10,153

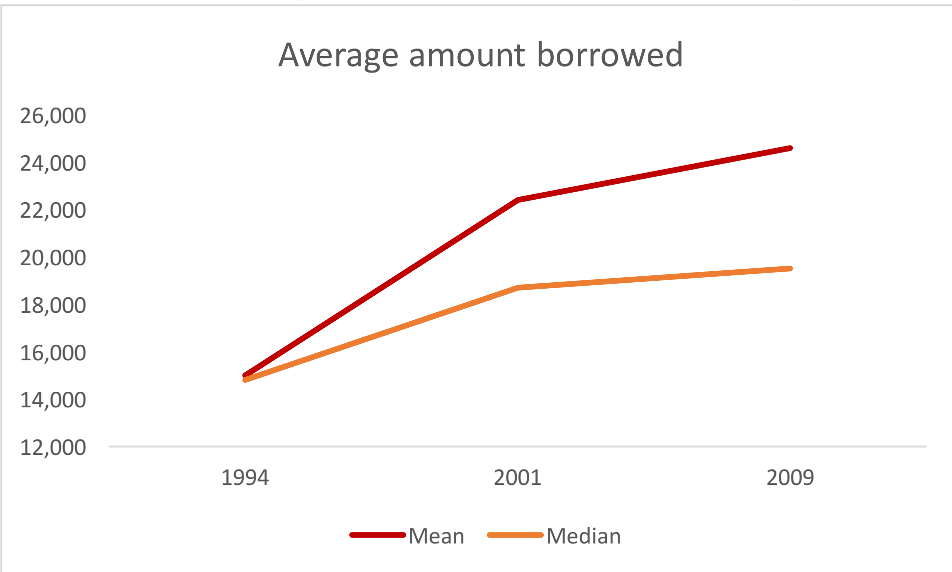
SOURCE: U.S. Department of Education, National Center for Education Statistics. (2016). *Digest of Education Statistics, 2015* (NCES 2016-014), Chapter 3.

A2. Federal loans and tuition rates over time

Fiscal Year	Dollars Outstanding	Unduplicated Recipients	Debt per person	Tuition Rates
2007 Q1	516.00	28.30	18233.22	17951.00
2007 Q2	530.30	28.66	18501.62	17963.13
2007 Q3	544.98	29.04	18766.67	17989.90
2007 Q4	560.42	29.45	19031.28	18045.98
2008 Q1	577.00	29.90	19297.66	18146.00
2008 Q2	595.01	30.41	19568.27	18297.85
2008 Q3	614.43	30.96	19848.89	18482.29
2008 Q4	635.13	31.53	20146.26	18673.34
2009 Q1	657.00	32.10	20467.29	18845.00
2009 Q2	679.87	32.66	20814.70	18978.40
2009 Q3	703.29	33.21	21174.23	19083.18
2009 Q4	726.77	33.76	21528.24	19176.13
2010 Q1	749.80	34.30	21860.06	19274.00
2010 Q2	772.21	34.84	22163.32	19389.32
2010 Q3	795.11	35.39	22469.06	19517.60
2010 Q4	819.96	35.94	22815.49	19650.08
2011 Q1	848.20	36.50	23238.36	19778.00
2011 Q2	880.09	37.06	23745.05	19894.32
2011 Q3	911.17	37.59	24240.97	19998.79
2011 Q4	935.76	38.02	24613.81	20092.87
2012 Q1	948.20	38.30	24757.18	20178.00
2012 Q2	945.94	38.41	24627.23	20255.80
2012 Q3	938.84	38.44	24425.59	20328.51
2012 Q4	939.84	38.49	24414.87	20398.49
2013 Q1	961.90	38.70	24855.30	20468.15
2013 Q2	998.60	38.90	25670.95	20539.87
2013 Q3	1006.80	38.70	26015.50	20616.02
2013 Q4	1040.20	39.60	26267.68	20699.00
2014 Q1	1051.80	40.00	26295.00	20791.21
2014 Q2	1087.00	40.00	27175.00	20895.12
2014 Q3	1096.50	39.90	27481.20	21013.22
2014 Q4	1129.80	40.70	27759.21	21148.00
2015 Q1	1140.10	41.10	27739.66	21299.20
2015 Q2	1174.40	41.00	28643.90	21455.59

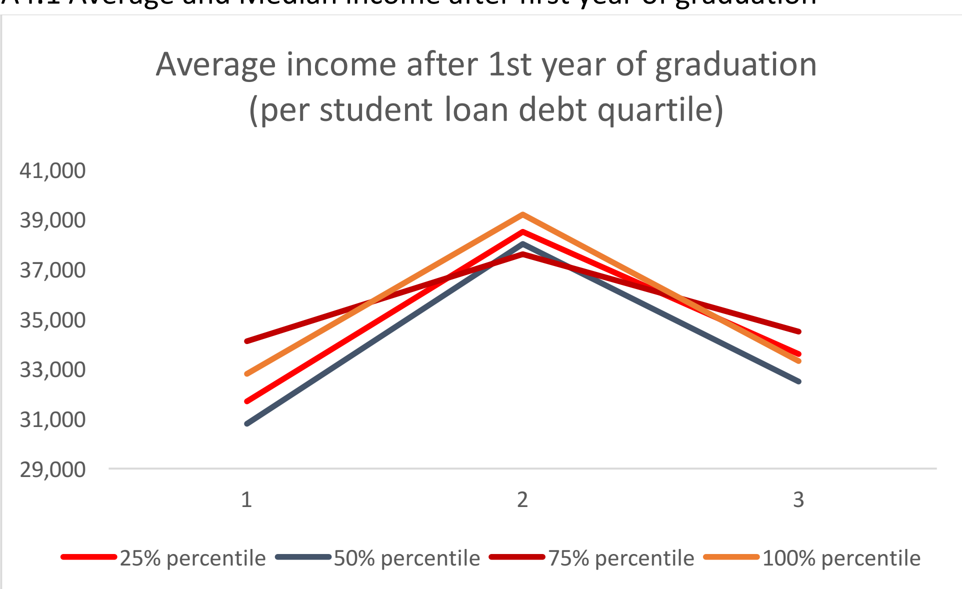
2015 Q3	1182.10	40.80	28973.04	21603.19
2015 Q4	1212.40	41.60	29144.23	21728.00
2016 Q1	1220.30	41.80	29193.78	21819.92
2016 Q2	1254.90	41.70	30093.53	21884.26
2016 Q3	1262.20	41.50	30414.46	21930.23
2016 Q4	1292.20	42.30	30548.46	21967.00

A3. Student loan debt (mean and median amounts borrowed)

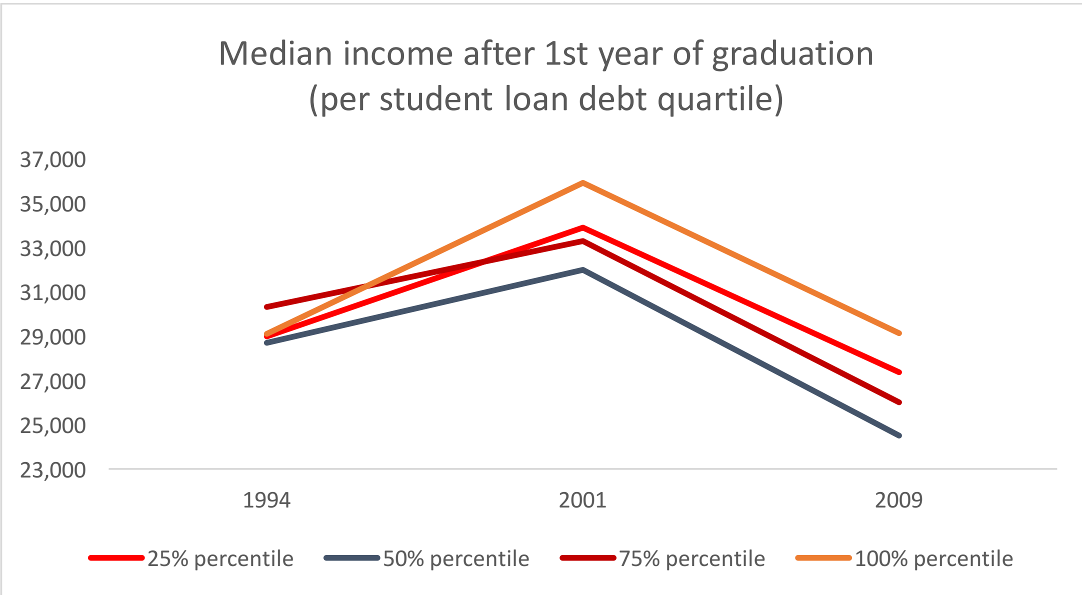


A4. Income after first year of graduation

A4.1 Average and Median income after first year of graduation

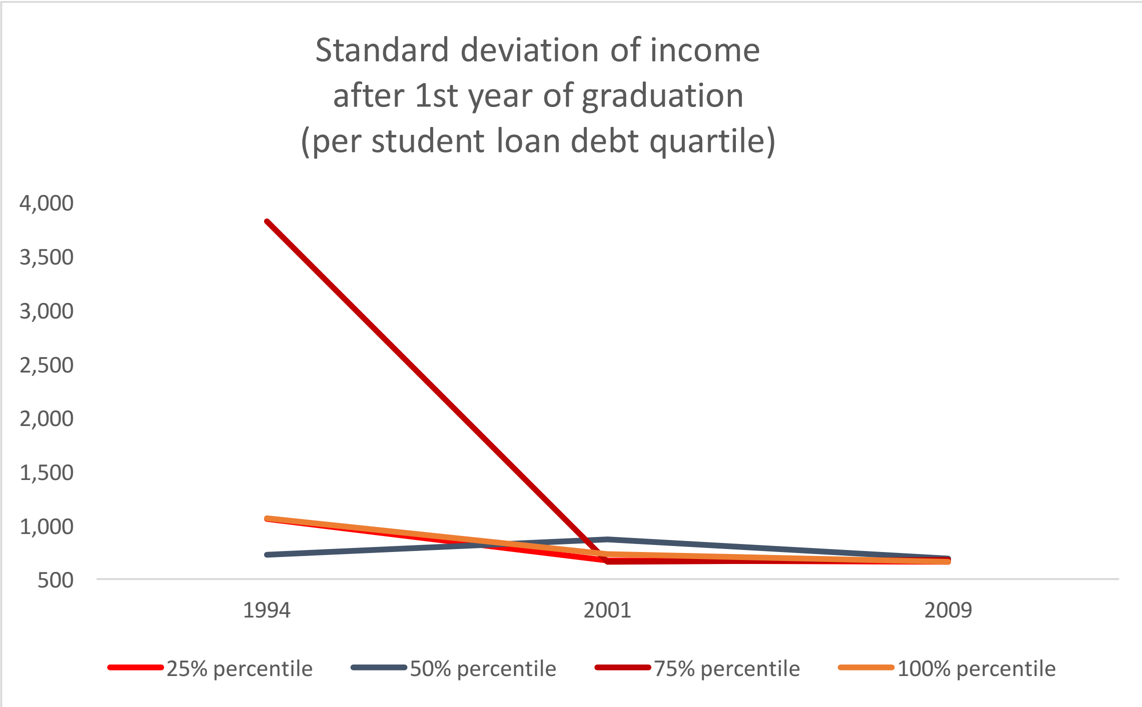


Mean	1994	2001	2009
Did Not Borrow	33,400	33,400	33,400
25% percentile	31,700	38,500	33,600
50% percentile	30,800	38,000	32,500
75% percentile	34,100	37,600	34,500
100% percentile	32,800	39,200	33,300



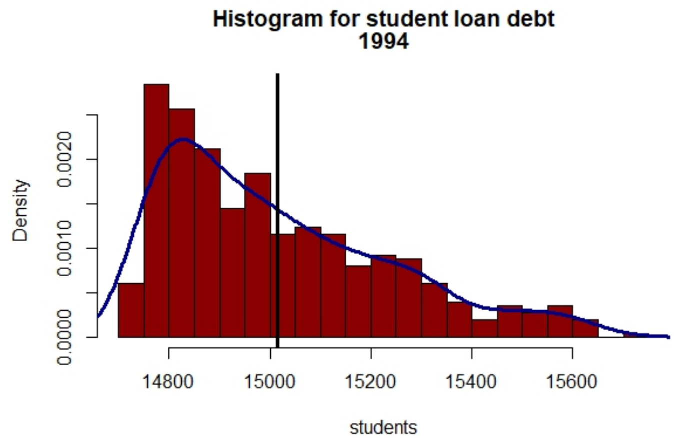
Median	1994	2001	2009
Did Not Borrow	30,100.00	33,900.00	28,210.00
25% percentile	29,000.00	33,900.00	27,360.00
50% percentile	28,700.00	32000	24500
75% percentile	30300	33300	26,000.00
100% percentile	29,100.00	35,900.00	29,120.00

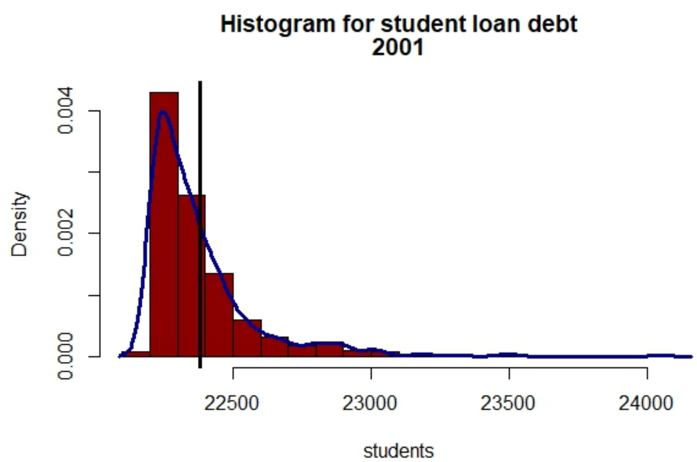
A4.2 Standard deviation of income after first year of graduation

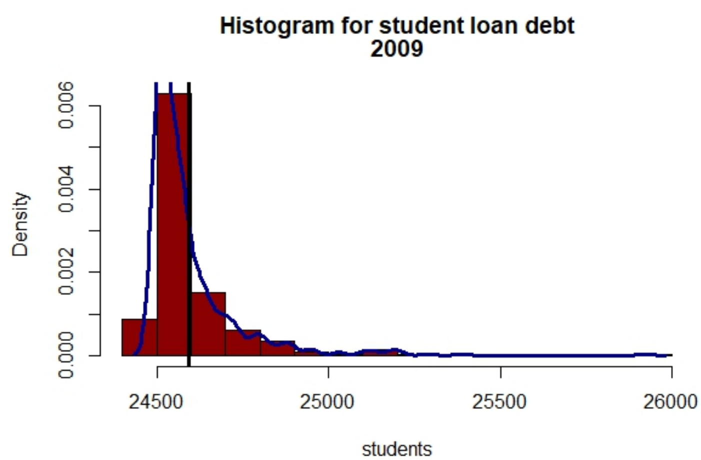


Standard Deviations	**1994**	**2001**	**2009**
Never borrowed	1,214	782	801
Lowest 25 percent	1,063	674	662
Lower middle 25 percent	730	868	693
Upper middle 25 percent	3,821	664	680
Highest 25 percent	1,065	731	662

A5. Histograms for student loan debt (1994, 2001 and 2009)

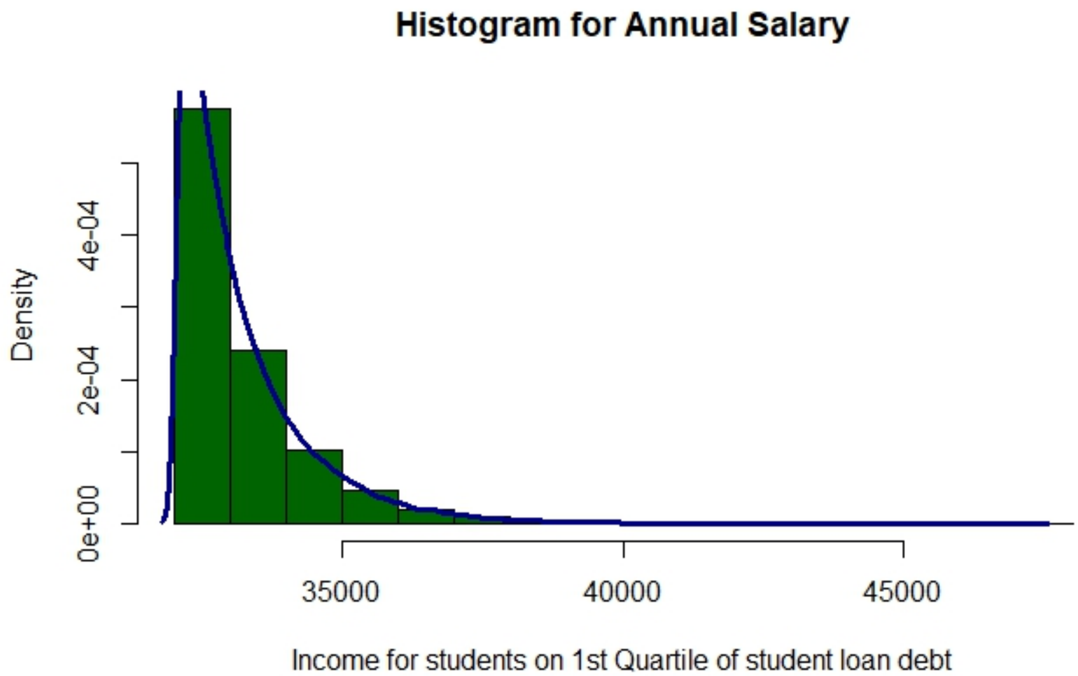


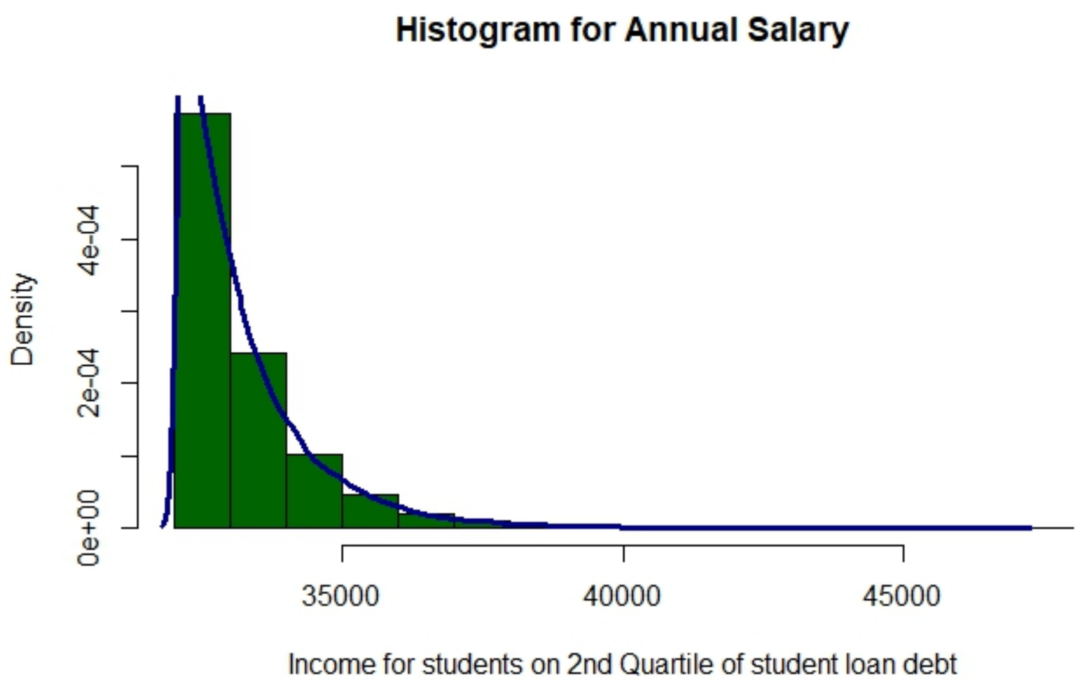


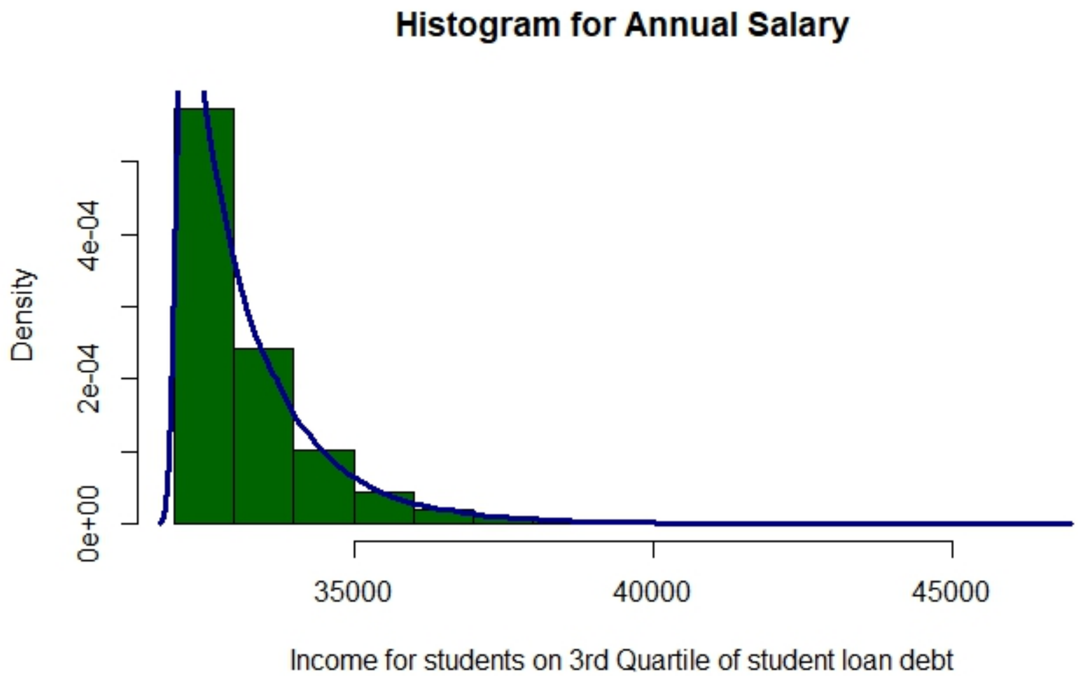


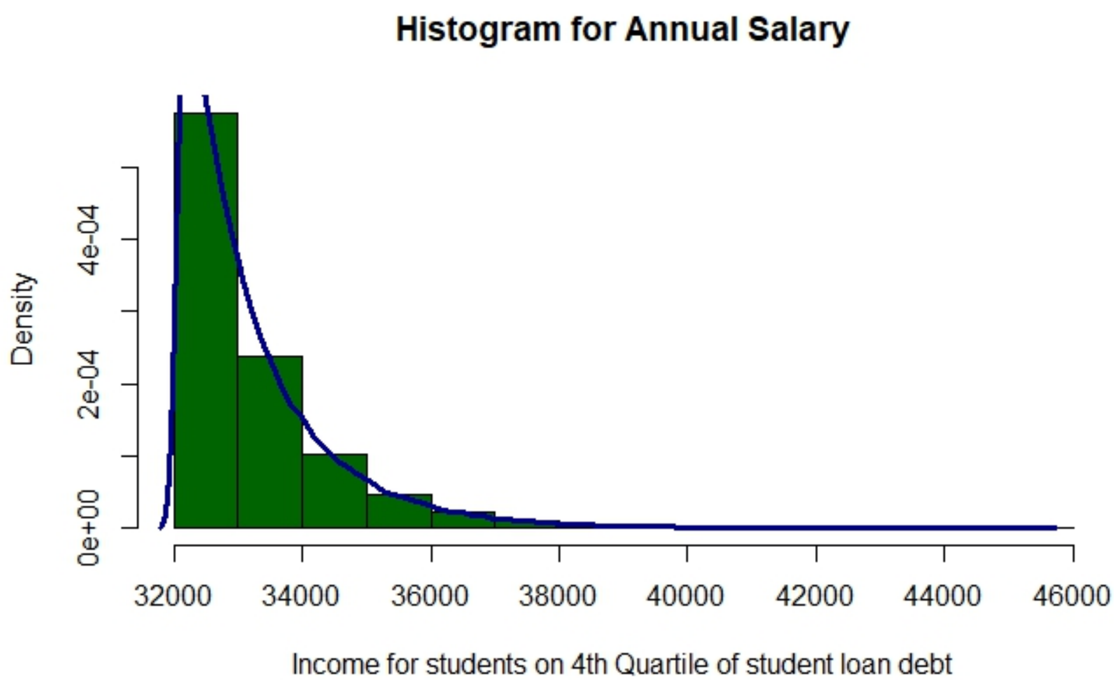
A6. Histograms for income after first year of graduation per quartile of student loan debt (1994, 2001 and 2009)

A6.1 Histograms of the distribution of income per quartile in 1994

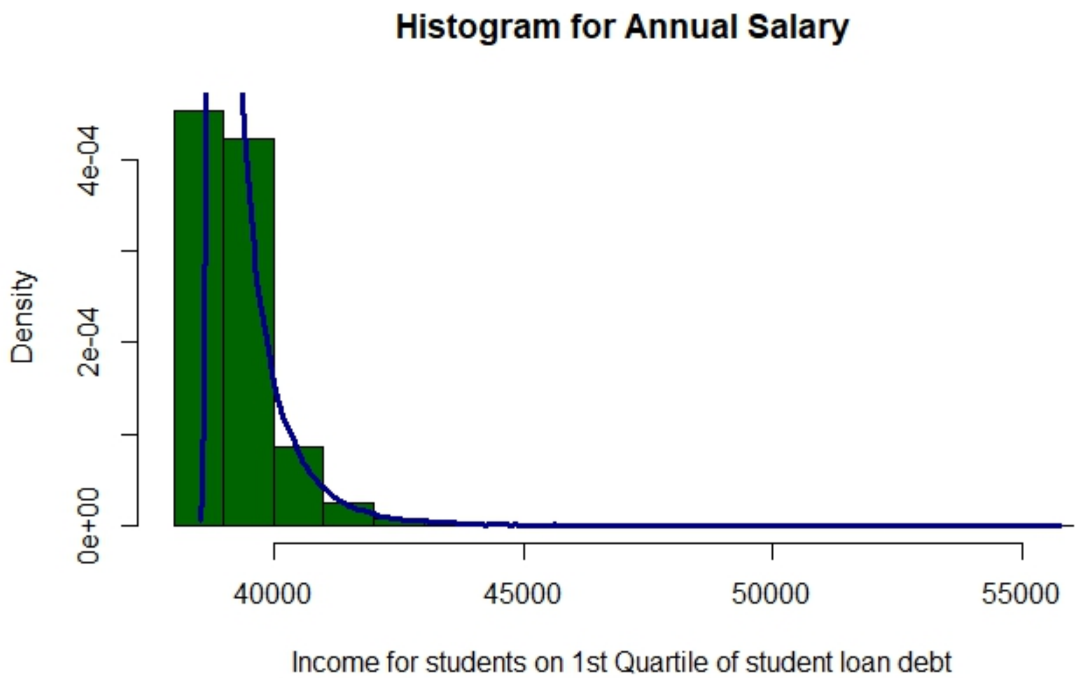


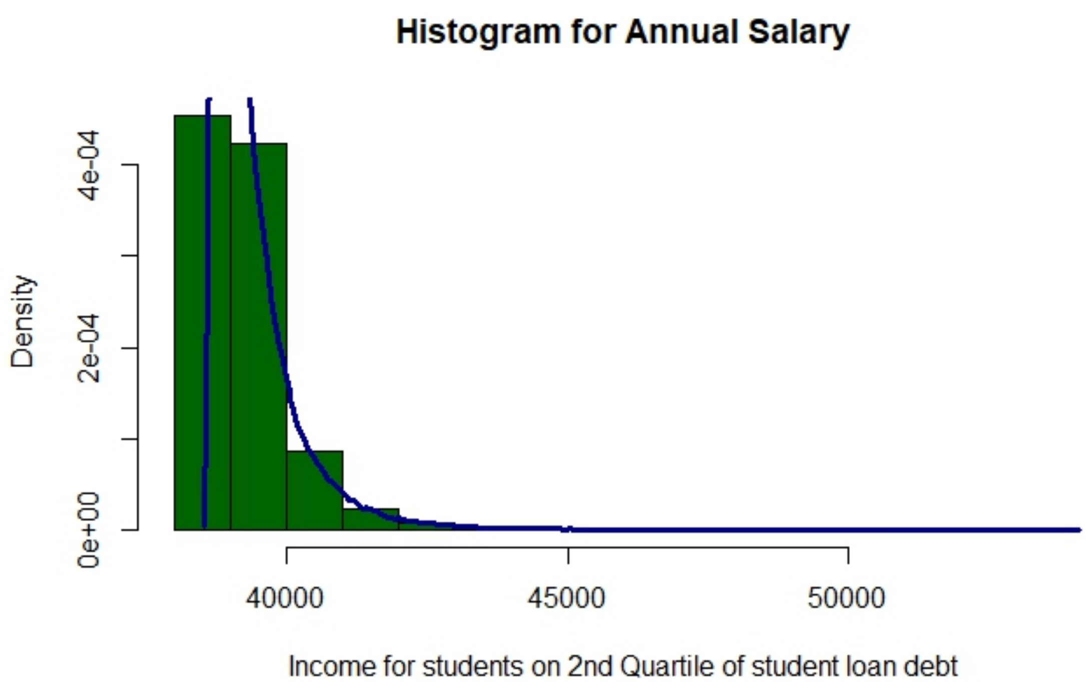


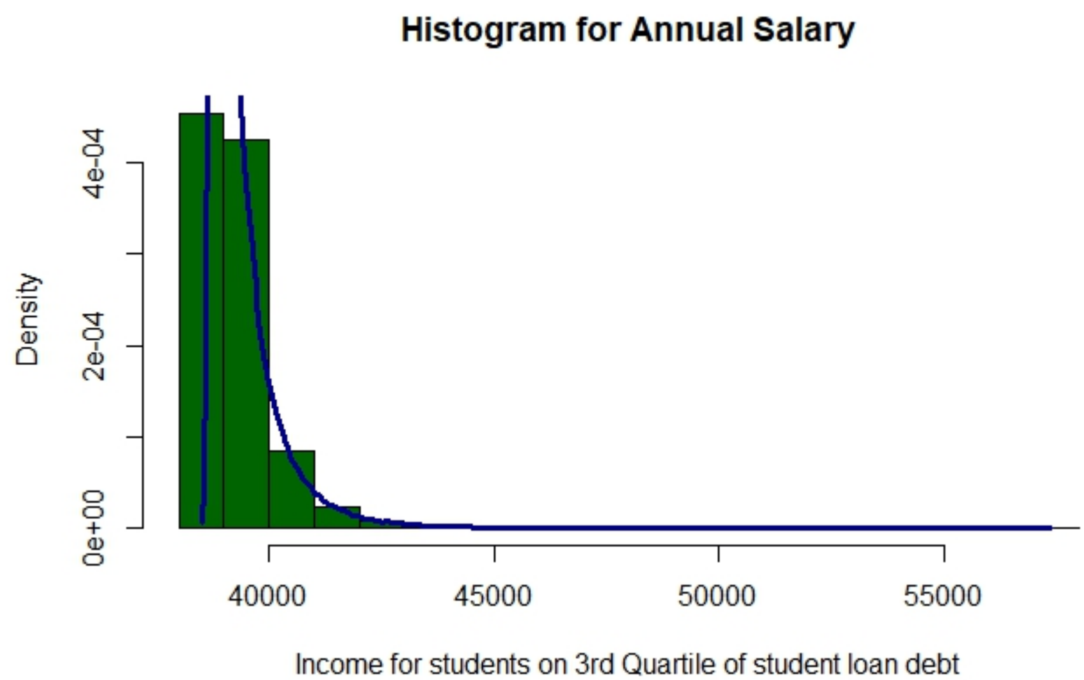

Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
35000
40000
45000
Income for students on 3rd Quartile of student loan debt

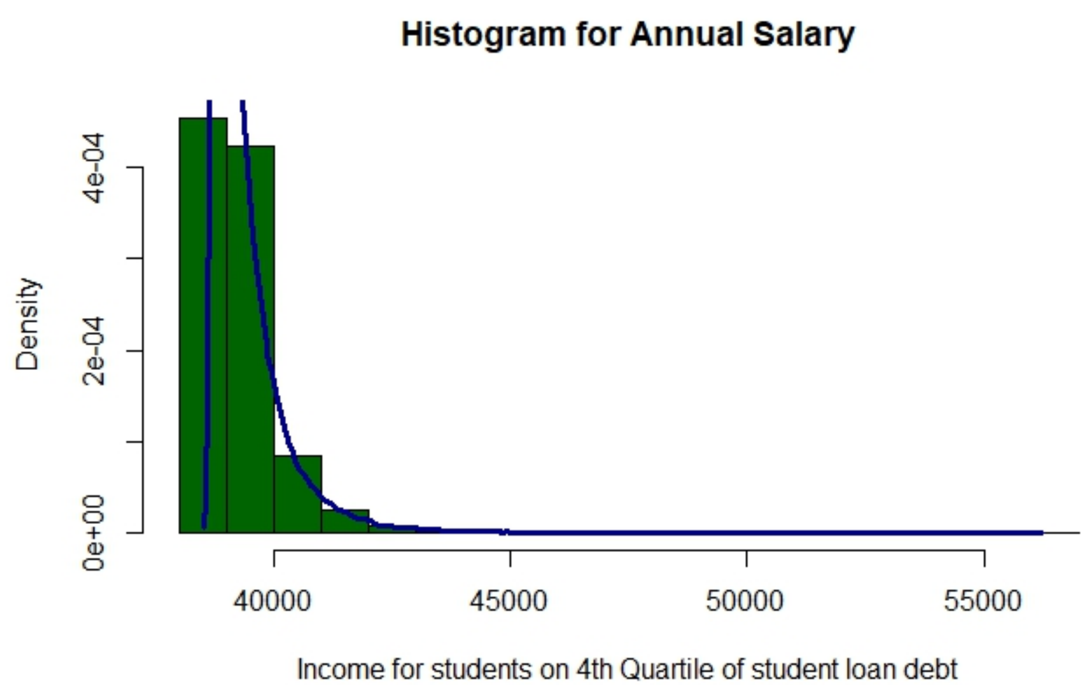

Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
32000
34000
36000
38000
40000
42000
44000
46000
Income for students on 4th Quartile of student loan debt

A6.2 Histograms of the distribution of income per quartile in 2001

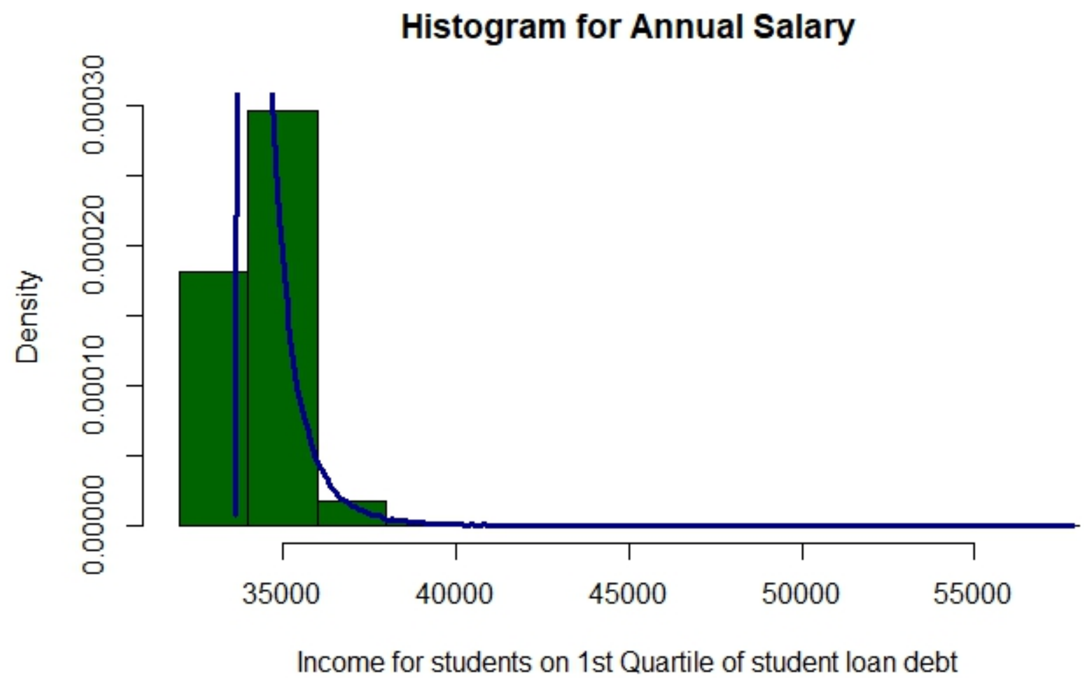


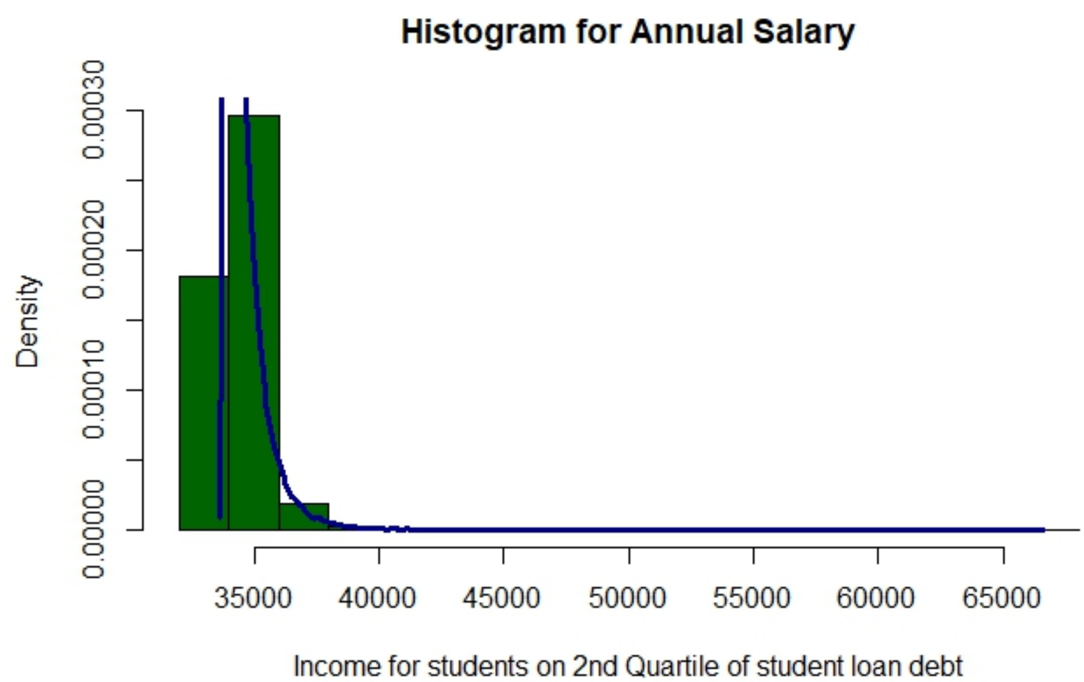


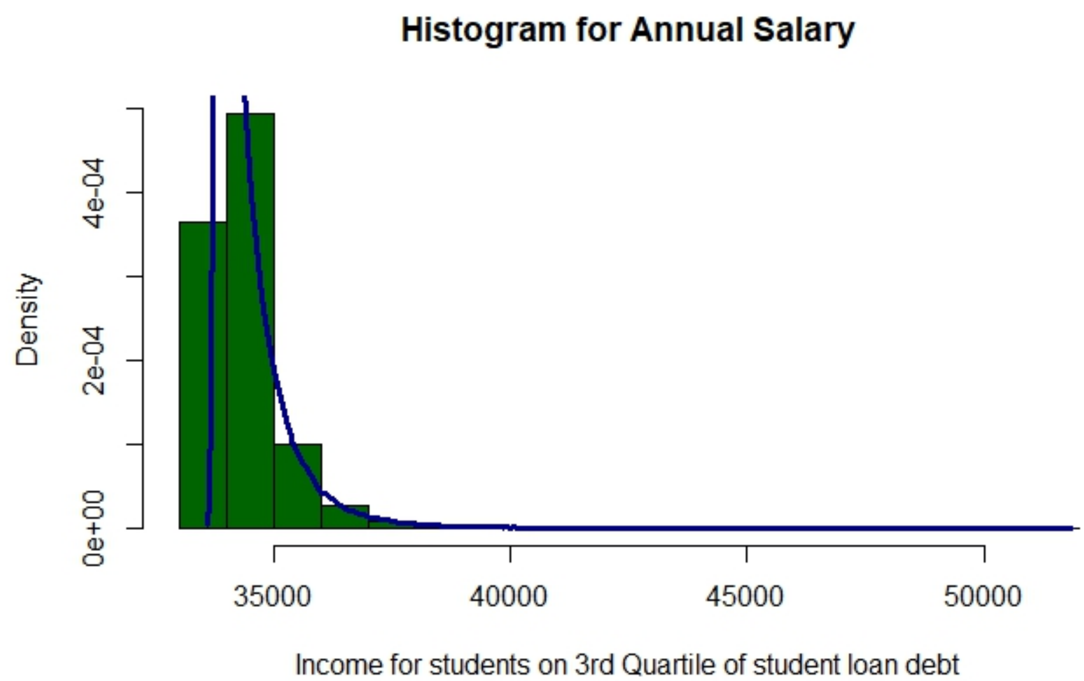

Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
40000
45000
50000
55000
Income for students on 3rd Quartile of student loan debt

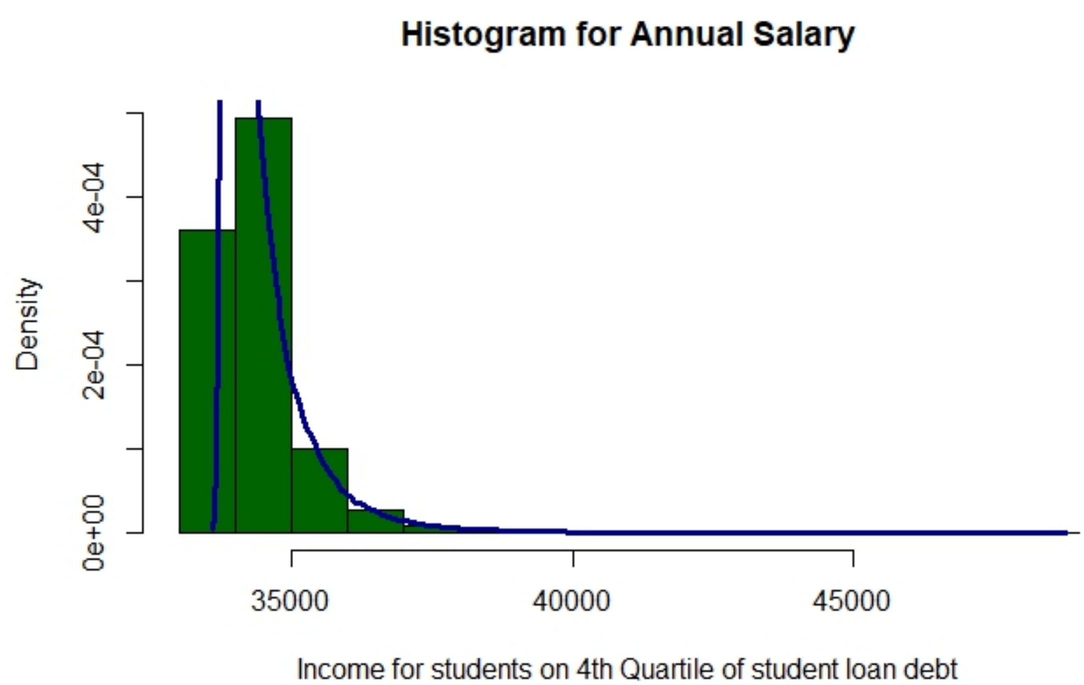

Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
40000
45000
50000
55000
Income for students on 4th Quartile of student loan debt

A6.3 Histograms of the distribution of income per quartile in 2009






Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
35000
40000
45000
50000
Income for students on 3rd Quartile of student loan debt


Histogram for Annual Salary
Density
0e+00
2e-04
4e-04
35000
40000
45000
Income for students on 4th Quartile of student loan debt

A7. Summary statistics for student loan debt (1994, 2001, 2009)

Percentage who borrowed		
1994	**2001**	**2009**
49.3	63.5	65.6
Total Numbers of People		
11,192	11,630	17,160
Total Numbers of Borrowers		
5518	7385	11257

Borrowing Parameters			
	1994	2001	2009
Mean	15,000	22,400	24,600
Standard	222	255	270
Variance	49284	65025	19,500
Skewness	2.702703	43.52941	56.66667
Kurtosis	3.24	52.24	68.00

MEDIAN AMOUNT BORROWED		
11,192	11,630	17,160
In 2009 dollars		
1994	**2001**	**2009**
14,800	18,700	19,500

A8. Summary statistics for income after first year of graduation per quartile of student loan debt.

Never Borrowed — Parameters			
	1994	**2001**	**2009**
Mean	33,400	33,400	33,400
Standard Deviati	1,063	674	662
Variance	1129969	454276	438244
Skewness	9.313264346	-2.22552	23.51964
Kurtosis	11.17591722	-2.67062	28.22356

Income of Lowest 25 percent — Parameters			
	1994	2001	2009
Mean	31,700	38,500	33,600
Standard Deviati	1,063	674	662
Variance	1129969	454276	438244
Skewness	7.619943556	20.47478	28.27795
Kurtosis	9.143932267	24.56973	33.93353

Income of Lower middle 25 percent — Parameters			
	1994	2001	2009
Mean	30,800	38,000	32,500
Standard Deviati	730	868	693
Variance	532900	753424	480249
Skewness	8.630136986	20.73733	34.63203
Kurtosis	10.35616438	24.88479	41.55844

Income of Upper middle 25 percent — Parameters			
	1994	2001	2009
Mean	34,100	37,600	34,500
Standard Deviati	3821	664	680
Variance	14600041	440896	462400
Skewness	2.98351217	19.42771	37.5
Kurtosis	3.580214604	23.31325	45

Income of Highest 25 percent — Parameters			
	1994	2001	2009
Mean	32,800	39,200	33,300
Standard Deviati	1065	731	662
Variance	1134225	534361	438244
Skewness	10.42253521	13.54309	18.9426
Kurtosis	12.50704225	16.25171	22.73112

A9. Stationarity test

Levin-Lin-Chu Unit-Root Test (ex. var.: None)

Data	Z	p-value	Stationarity
Asset accum per split	4.1977	1	No
Loan per split	5.5242	1	No
Imcome after split	2.1557	0.9844	No
HS grad split	-7.7428	4.86E-15	Yes
Coll grad split	9.105	1	No

alternative hypothesis: stationarity

A10. Fixed effects results

Fixed Effects
Oneway (individual) effect Within Model

Call:
plm(formula=D_Asset_Accum~D_Loans_per+D_Income_After+
sqrt(Coll_Grad)+D_Mort_Rate,data=paneldata,model=within,
index=c("Age_Group",Time))

UnbalancedPanel:n=5,T=24-29,N=140

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-35530.79	-4786.59	-143.81	5692.05	24670.21

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
D_Loans_per	-2.44E+03	2.23E+04	-0.1091	0.9133
D_Income_After	-3.22E-02	9.72E-01	-0.0331	0.9736
sqrt(Coll_Grad)	-1.01E+05	8.10E+04	-1.2433	0.216
D_Mort_Rate	8.80E+02	2.59E+03	0.3392	0.735

Total Sum of Squares: 1.80E+10
ResidualSumofSquares: 1.77E+10
R-Squared: 0.014853
Adj. R-Squared: -0.045309
F-statistic: 0.493754 on 4 and 131 DF,p-value:0.74033

A11. GAM results

GAM Fixed Effects
Oneway (individual) effect Within Model
plm(formula=D_Asset_Accum~ns(D_Loans_per,df=6)+ns(D_Income_After, df=6)+sqrt(Coll_Grad)+D_Mort_Rate,data=paneldata, model=within,index=c("Age_Group",Time))
Unbalanced Panel: n=5, T= 24-29, N=140
Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-19790.68	-6530.44	-135.77	5307.81	26926.8

Coefficients:	Estimate	Std. Error	t-value	Pr(>|t|)	
ns(D_Loans_per,d	29659.69	7857.95	3.7745	0.0002498	***
ns(D_Loans_per,d	31644.78	9575.6	3.3047	0.0012511	**
ns(D_Loans_per,d	38475	9923.72	3.8771	0.0001723	***
ns(D_Loans_per,d	28663.85	8594.96	3.335	0.001133	**
ns(D_Loans_per,d	67444.58	18480.74	3.6495	0.0003892	***
ns(D_Loans_per,d	-25848.68	8919.19	-2.8981	0.0044584	**
ns(D_Income_Afte	646.61	5742.33	0.1126	0.9105317	
ns(D_Income_Afte	12991.71	7341.71	1.7696	0.0793168	.
ns(D_Income_Afte	15750.06	6947.34	2.2671	0.0251616	*
ns(D_Income_Afte	-3401.41	6006.04	-0.5663	0.5722172	
ns(D_Income_Afte	14942.65	14616.28	1.0223	0.3086648	
ns(D_Income_Afte	-6622.07	7193.42	-0.9206	0.3591054	
sqrt(Coll_Grad)	49497.55	89978.25	0.5501	0.5832609	
D_Mort_Rate	-278.8	2264.54	-0.1231	0.9022194	

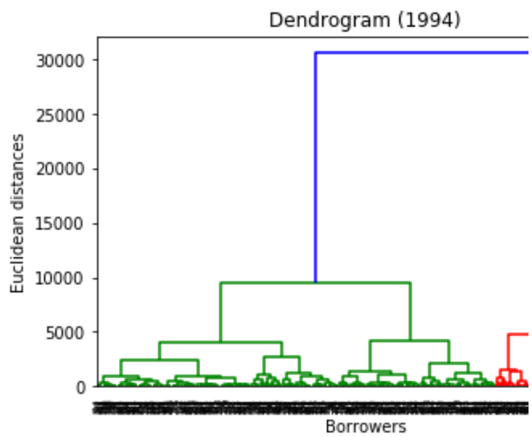
Signif.codes: 0‘***’ 0.001‘**’ 0.01‘*’ 0.05‘.’0.1

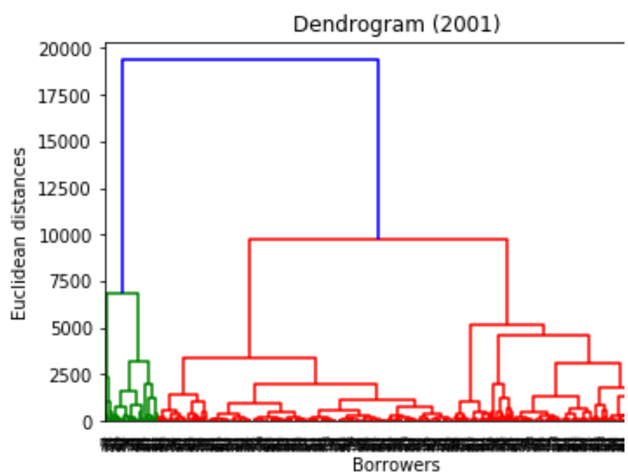
Total Sum of Squares:	1.80E+10
ResidualSumofSquares:	1.17E+10
R-Squared:	0.34972
Adj. R-Squared:	0.25298

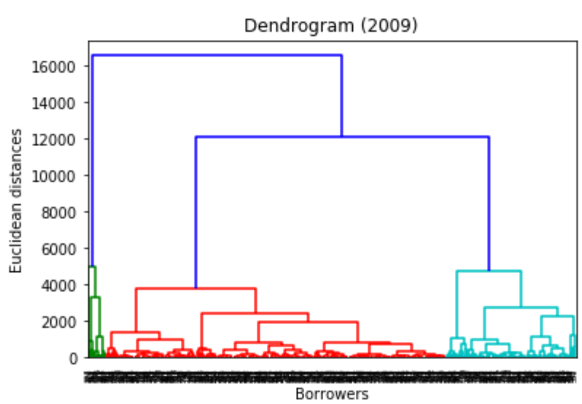
F-statistic: 4.64805 on 14 and 121 DF, p-value:0.0000010406

A12.1 Graphs used in Cluster Number Selection.

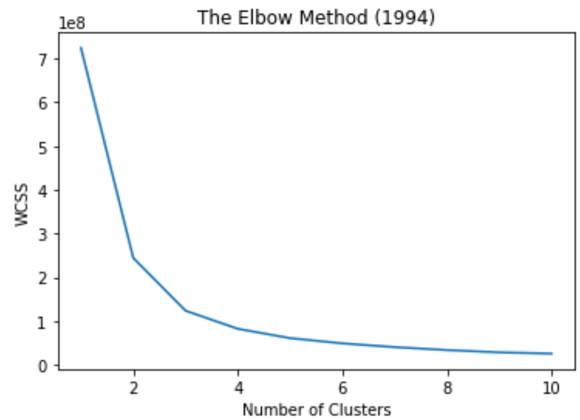
Hierarchical Clustering

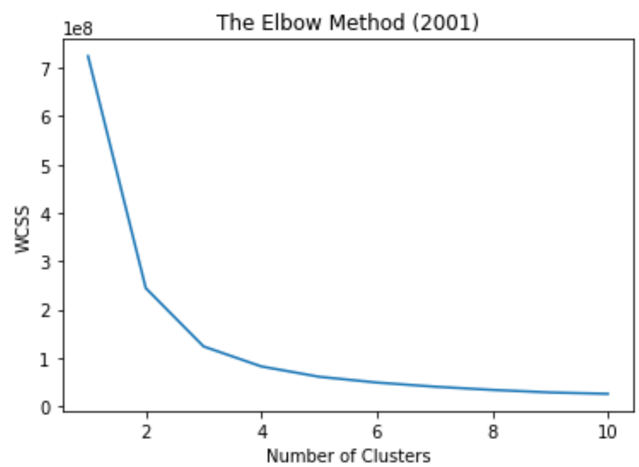


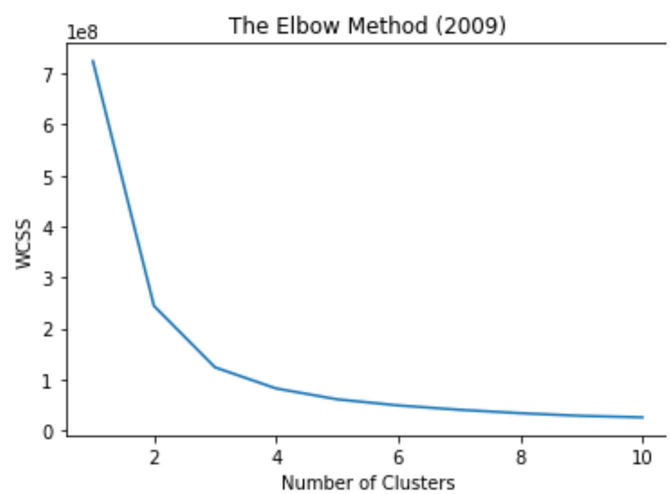




K-Means Clustering

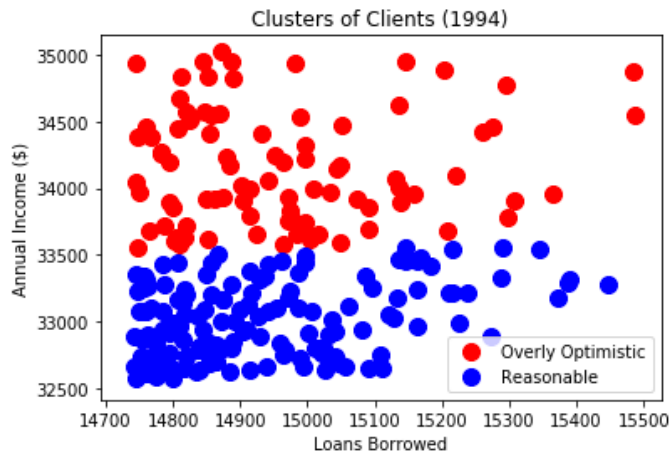


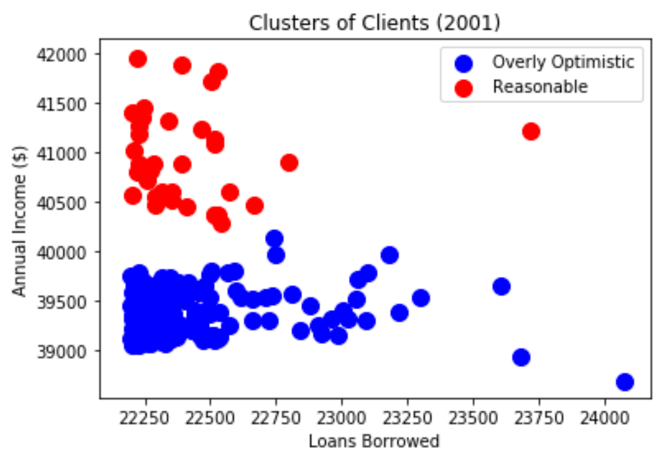


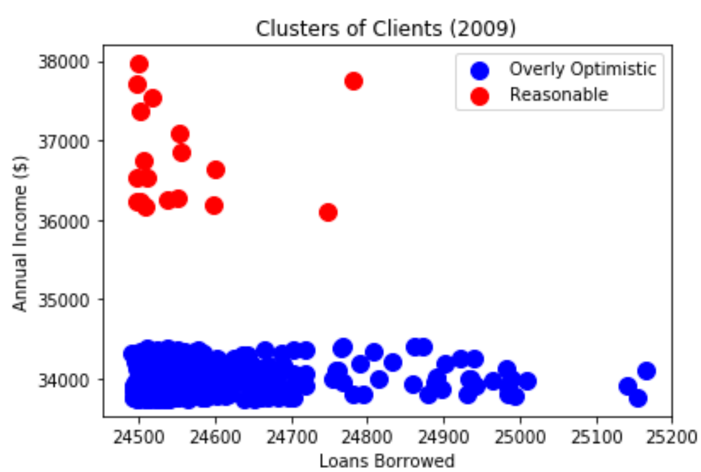


A12.2 Graphs of Clusters.

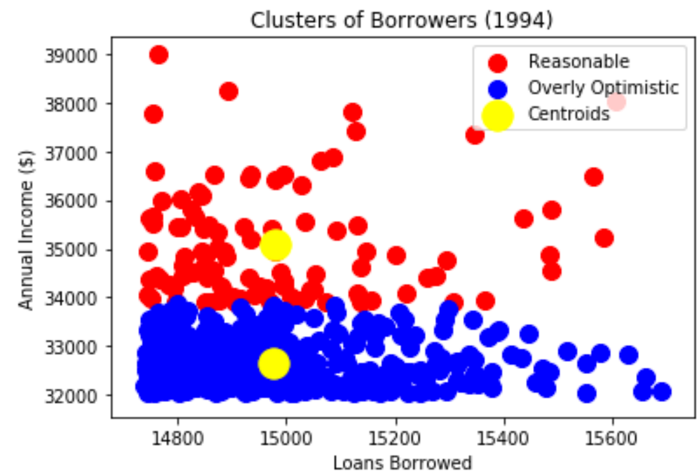
Hierarchichal Clustering

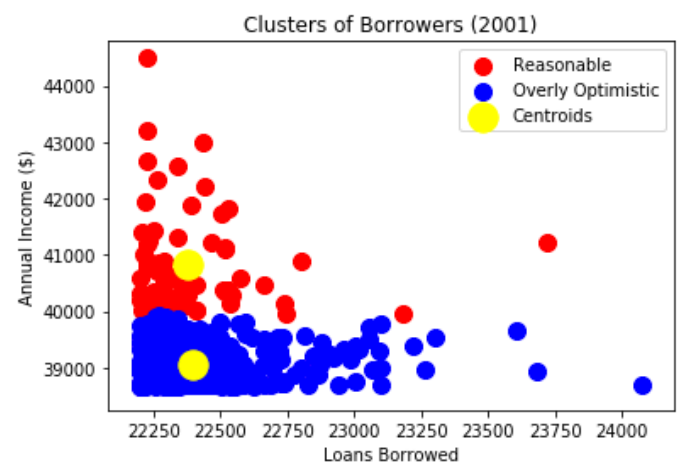


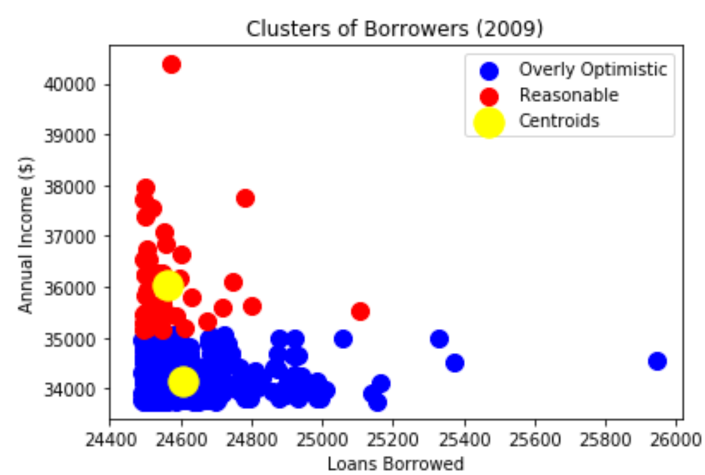




K-Means Clustering







A13. Pearson's skewness Coefficient:

$$Sk_2 = \frac{3(\bar{X} - Md)}{s}$$

Where $\overline{X}$ = the mean, Mo = the mode and s = the standard deviation for the sample.

It is generally used when you don't know the mode.

A14. Panel Data Summary:

Variable	Obs.	Mean	Std. Dev.	Min	Max
Δ Asset accum.	140	6098.076	12109.06	-35497.57	35989.2
Δ Loans per	140	0.30945	0.0628932	0.18	0.481
Δ After-tax Income	140	154.85	1058.631	-3295.587	2459.406
College Grad. Rate	140	0.6282713	0.0667167	0.45	0.7201593
Δ Mort. Rate	140	0.0664286	0.388691	-0.99	0.6

WORKS CITED

1. Gitlen, Jeff. “A Look Into the History of Student Loans.” LendEDU, 15 Aug. 2016, lendedu.com/blog/history-of-student-loans.
2. Nykiel, Teddy. “2018 Student Loan Debt Statistics.” NerdWallet, 22 Sept. 2017, www.nerdwallet.com/blog/loans/student-loans/student-loan-debt/.
3. Kena, G. “Tuition Costs of Colleges and Universities.” National Center for Education Statistics, U.S. Department of Education, 26 May 2016, nces.ed.gov/fastfacts/display.asp?id=76.
4. Sisolak, Paul. “Can You Really Get Rid of Student Loans by Leaving the Country?” Student Loan Hero, 6 Apr. 2016, studentloanhero.com/featured/how-to-get-out-of-student-loan-debt-leave-country/.
5. Templeton, Deanna. “What Happens to Student Loans When You Die?” ABC News, Credit.com, 23 June 2013, abcnews.go.com/Business/student-loans-die/story?id=19460467.
6. Carter, Shawn M. “Here's What Happens If You Default on Your Student Loans-and How to Get Back on Track.” CNBC, The Definitive Guide to Student Loans, 9 Oct. 2017, www.cnbc.com/2017/10/09/what-happens-and-what-to-do-if-you-default-on-a-student-loan.html.
7. Simone, Sean A. *Repayment of Student Loans as of 2015 Among 1995–96 and 2003–04 First-Time Beginning Students*, 2017.

8. Cooper, Daniel J. and Wang, J. Christina *Student Loan Debt and Economic Outcomes*, 2014.
9. Donovan, Sarah A. and Bradley, David H. *Real Wage Trends, 1979 to 2017*, 2018.
10. McDonald, James B.; Sorensen, Jeff; and Turley, Patrick A. *Skewness and kurtosis properties of income distribution models*, 2011.
11. Kumok, Zina. "What Are The Requirements To Get A Student Loan?" The College Investor, 7 Nov. 2017, thecollegeinvestor.com/18701/requirements-get-student-loan/.
12. Woo, Jennie H. *Degrees of Debt Student Borrowing and Loan Repayment of Bachelor's Degree Recipients 1 Year After Graduating: 1994, 2001, and 2009. National Center for Education Statistics*, 2013