COLLEGE MAJOR CHOICE: FOR LOVE OR A LIVING?

A Project
Presented to the
Faculty of
California State Polytechnic University, Pomona

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science
In
Economics

By
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2016
SIGNATURE PAGE

PROJECT: COLLEGE MAJOR CHOICE: FOR LOVE OR A LIVING?

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DATE SUBMITTED: Spring 2016

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ACKNOWLEDGMENTS

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ABSTRACT

The percentage of CSU students enrolled in Science, Technology, Engineering and Math (STEM) fields has grown decisively since the Great Recession, from 20.4 percent in 2007, to 26.9 percent in 2014. Those STEM disciplines include Agricultural Sciences, Biological Sciences, Engineering, Health Professions, Information Sciences, Mathematics and Physical Sciences. Previous literature cites perceived probability of success, expected earnings, as well as gender and socioeconomic characteristics as the main driving factors for college major choice. However, the impact of expected earnings has been challenged citing selection bias. Arcidiacono (2004) shows that part of the “ability sorting” which takes place across majors is simply due to students gravitating toward subjects in which they have historically excelled. This paper will analyze STEM and Non-STEM enrollment, in tandem with STEM an Non-STEM unemployment and earnings, by testing Vector Autoregressive models for Granger causality, determining whether or not labor market forces can be used to help to predict college major enrollment. The presence or a lack of Granger causality will offer preliminary evidence for the question: Is college major choice really about love or about making a living?
Chapter 1

Introduction

Choosing a college major can be a daunting task for incoming college students. According to previous literature on the topic, perceived probability of success, expected earnings, and gender all significantly influence college major choice. In addition to these three main factors, family, socioeconomic and demographic characteristics commonly play into the decision of college major choice as well. More advanced models take into consideration the development of a student throughout his or her college years and factor in that obtaining new skills and having more complete information can result in changes of major Arcidiacono (2004). This paper will analyze the impact of the job market on college major choice, offering insight to the following questions: Do industry-specific trends in unemployment and expected earnings result in changes in STEM and Non-STEM enrollment? How does a snapshot of the college population today compare to a snapshot of the college population pre-Great Recession? Finally, what are the policy indications of such changes?
1.1 Background, Significance and Policy Implications

According to a 2012 survey conducted by the consulting firm McKinsey and Co., 45 percent of college graduates in the U.S. report working a job that does not require a 4-year degree and 37 percent of students with 4-year degrees report that they would likely choose a different major if given the opportunity to start over (McKinsey, 2013). This troubling scenario requires further investigation. If nearly half of graduates are performing jobs for which they are overqualified, and over one-third feel as though they did not optimally choose their college major, how can this be corrected? Moreover, if optimally choosing a college major requires that students make their decision with complete information with respect to jobs-skills matching, how can it be ensured that students receive and understand this information?

A healthy jobs market ought not only provide an optimal level of employment, but also, correctly match those skills being sought by employers with those workers who may provide them. Are there any trends in newly-trained labor that might indicate that this is occurring? Is the flow of skilled labor adjusting to better meet the demands of the market? Can we identify potential reasons for non-optimal major choice, a contributing factor to a job-skills mismatch? The issue of students choosing non-optimal majors is two-fold. The immediate economic impact is that a surplus of graduates in any one sector can directly lead to unemployment or underemployment. Following short behind this issue is the inability to pay back student loans, a mounting concern as student loan debt currently stands at over 1.3 trillion dollars (Federal Reserve System, 2016).

One reason why students make sub-optimal major choices is that they are faced with making this decision at a very young age. Students lack not only essential information about each major and the career opportunities they will realistically face, they lack essential information about themselves. This is a tricky obstacle to maneuver, but advocates of
early college preparation and profession-based development believe they have the remedy. In any case, it can be difficult for young adults to know what they want to do with the rest of their lives, with or without early college preparation and profession-driven education.

Another issue, as posed by U.S. Senator Ron Wyden in Senate Bill 1195 “The Student Right to Know Before You Go Act of 2015,” is that students are not currently provided with sufficient data on career expectations as they pertain to each campus and academic program. The goal of SB 1195, introduced in Senate last May, is to require educational institutions receiving Federal spending to provide “Earning metrics...that shall include - (i) median annual earnings and employment metrics, disaggregated by - (I) educational program... (II) credential received... (III) educational institution; and (IV) State of employment... for each of the following time periods: (I) 2 years after educational program completion. (II) 6 years after educational program completion. (III) 15 years after educational program completion,” (Wyden, 2016). This type of reporting would directly associate degree type and level of education with earning expectations. Currently, there are a wide variety of studies on the returns to higher education, but institutions are not required to provide this type of information to students. Therefore, it is more difficult for students to make fully informed decisions about which major to choose.

Ultimately, education is an investment. Clearly presenting students with the earning metrics of their older peers would allow students to make more informed decisions than they are currently able to make. If it is determined that a predictive relationship exists between labor market forces and enrollment, this discovery would support the argument for expedited action on The Student Right to Know Before You Go Act of 2015. SB 1195 was introduced in the Senate on May 5th, 2015. No further action has taken place (Wyden, 2016).
1.2 Theory

While, college is an investment, the process of choosing a college major is far more complex than a student simply seeking to maximize return on investment. A variety of other factors, seen and unseen, fall into consideration. Those factors include but are not limited to enjoying a particular field of study, enjoying the community or networking opportunities which accompany a particular major, wanting to follow in family tradition, having a history of success in a particular area of study, having a history of non-success in a particular area of study and so on. As all economic agents do, students seek to maximize utility. With so many factors dependent on internal preference, this topic begs the question- how much of college major choice is predetermined and how much of it is choice to begin with?

As previously mentioned, 37-percent of college graduates would choose a different major if given the opportunity McKinsey (2013). This also means that 63-percent of college graduates would choose the same major or are unsure. These are very distinct groups of students with varying degrees of preferences for a wide variety of subject matter. Some have a strong preference for their field of study. Others may have a weak preference for their field of study or even a preference against their field of study. Students with a strong preference for a particular field of study are less likely to be influenced by changes in labor market forces. However, those students with weaker preferences are more likely to act on the margin. College major selection for these students is adjustable. They consider the various upsides of a wider range of majors, whereas major selection is more closed for those students with strong preferences.
1.3 Preliminary Analysis

As a cursory analysis of student enrollment, three clear pieces of information can be observed. First, STEM disciplines experienced a declining trend in enrollment up until the Great Recession, after which STEM enrollment consistently increased. Second, non-STEM disciplines experienced the opposite; an increasing trend in enrollment leading up to the Great Recession, after which non-STEM enrollment decreased. Third, while nearly all observed changes in enrollment for STEM majors were positive since the recession, observed changes in enrollment for non-STEM majors were not all consistently negative. Moreover, some non-STEM majors, namely Education and Psychology, have consistently increased since the recession. These trends can be observed in Figures 1.1 and 1.2 below.

Figure 1.1: STEM Majors (CSU, 2016)

(a) Biology Majors

(b) Engineering Majors

(c) Information Science Majors

(d) STEM Majors
Figure 1.1 includes 3 examples of STEM enrollment: Biology, Engineering, Information Sciences and all of STEM combined. Engineering and Information Sciences demonstrate a more typical pattern of enrollment observed among STEM majors, whereas enrollment in Biology has persistently increased over time. Trends in Non-STEM enrollment generally look the opposite of those observed in STEM, as shown below.

Figure 1.2: Non-STEM Majors (CSU, 2016)

(a) Letters Majors
(b) Psychology Majors

(c) Fine Arts Majors
(d) Non-STEM Majors

Figure 1.2 demonstrates that although Non-STEM enrollment, as a percentage of the CSU population, has decreased since the 2007-2009 recession, enrollment in Psychology has persistently increased during that time. Enrollment in Education (not shown), has similarly increased. Between 2008 and 2014, enrollment in Psychology and Education combined increased from 11.5 percent to 13.7 percent of the total CSU population. This may indicate that there has been some shuffling around among students in Non-STEM
majors. Enrollment in all of Business, Communications, Fine Arts, Letters and Social Science exhibit general upward trends pre-recession and downward trends post recession. How can these trends be accounted for?

The data collected to perform the analysis in this paper include yearly observations ranging from 1995-2015. Inclusion of more observations provides for better testing. Observations of new student STEM and Non-STEM Enrollment alongside changes in Unemployment and Income from Salary or Wages can be found below:

Figure 1.3: Enrollment, Unemployment, & Income (IPUMS-CPS, 2016)

(a) STEM Enrollment & Non-STEM Unemployment
(b) STEM Enrollment & Income
(c) Non-STEM Enrollment & STEM Unemployment
(d) Non-STEM Enrollment & Income
There appear to be some loose relationships between the variables in question. For example, while STEM Enrollment is far less erratic than Non-STEM Unemployment, in Figure 1.3(a), there is a possible positive relationship between these two variables over time. Is it possible that rising Non-STEM Unemployment feeds into higher enrollment numbers in STEM? Similarly, is it possible that decreasing STEM Unemployment detracts from students enrolling in Non-STEM disciplines, as in Figure 1.3(c)? There is also a possible long-run positive relationship between STEM Enrollment and STEM Income, in Figure 1.3(b). This relationship is not apparent with Non-STEM Enrollment and Non-STEM Income, in Figure 1.3(d). Do any of these variables Granger-cause another? Visually, Figure 1.3(c) Non-STEM Enrollment and STEM Unemployment appear to be the leading candidate.

Lastly, in order to better understand the value of STEM and Non-STEM degrees, it is helpful to observe the unemployment and earnings of each one together over time. The graphs below offer their histories side-by-side. These results include workers who have obtained a Bachelor’s degree only:

Figure 1.4: STEM Versus Non-STEM Unemployment and Income (IPUMS-CPS, 2016)

(a) STEM and Non-STEM Unemployment    (b) STEM and Non-STEM Income

Since 1995, Figure 1.4(a) indicates that, with the exception of the years 2003-2005,
STEM unemployment rates have outperformed Non-STEM unemployment rates. Figure 1.4(b) indicates steady earnings premiums for STEM degree holders versus Non-STEM degree holders for the entire duration of time being observed. Over the past 20 years, STEM degree holders have earned, on average, 14.5-percent more annually than Non-STEM degree holders.
Chapter 2

Literature Review

2.1 Literature of Primary Importance

According to the literature, perceived probability of success, expected earnings, gender, and various socioeconomic characteristics are the variables considered most critical in determining college major choice. Although alternate methods will be used to test the predictive nature of labor market forces on college major choice in this paper, a complete understanding of the topic necessitates review of the primary findings of previous research.

Those variables considered most pertinent to the decision of college major choice come from a variety of sources. Plentiful literature exists on the demand of higher education, especially with respect to differences in gender and socioeconomic backgrounds. Duru-Bellat (1979) reports findings that college major choice is influenced by the presence of a balance between economic return and the risk of failure in each major. Bamberger (1987) and Arcidiacono (2004) contribute to the aforementioned ideas by developing dynamically structured models reflecting a students ability to change educational
decisions over time, depending on the students stage in college-age life. Montmarquette, Cannings and Mahseredjian (2002) attempt to include each one of the previous ideas into their research, for a comprehensive approach.

Of particular interest to this paper is the student enrollment response to the rising job availability for careers in STEM. Langdon et al. (2011) recently produced a report specifically with regard to the growth in demand for STEM workers. STEM jobs have far outpaced non-STEM jobs in recent years and projections strongly indicate that this trend will continue. The authors not only highlight the importance of competent workers for these positions, but also the importance of STEM as an area of study which innovates and creates new industries. Two standout figures from Langdon et al. (2011) is that (1) “STEM occupations are projected to grow by 17 percent from 2008-2018, compared to 9.8 percent growth for non-STEM occupations” and (2) “STEM workers command higher wages, earning 26-percent more than their non-STEM counterparts.”

Montmarquette, Cannings and Mahseredjian (2002)’s research, as well as Arcidiacono (2004)’s research would seem to suggest that the recent surge in STEM occupations would result in more STEM students. Montmarquette, Cannings and Mahseredjian (2002)’s research demonstrates the positive influence of earning potential on major choice and Arcidiacono demonstrates the ability of students to find the major most advantageous for them, considering their educational performance. Therefore, a marginal student, majoring in Social Science might instead major in a STEM field if they are proficient in mathematics and wish to enjoy a higher earning potential. Arcidiacono (2004) frames major choice differently than Montmarquette, Cannings and Mahseredjian (2002). Monetary returns are more a description resulting from ability differences, than they are an explanation for a particular major choice, something he alternatively refers to as ‘ability sorting.’ Given that a student is capable, he or she may move to
a more economically advantageous major. However, ‘ability sorting’ does not suggest that a choice took place to begin with, rather that the student followed a natural path to declaring a major based upon their previous ability (Arcidiacono, 2004). Arcidiacono (2004) discovered that math ability, as measured by student SAT scores, was particularly influential to college major choice or ‘ability sorting’ and ultimately on earnings. Arcidiacono (2004) also notes that students receive feedback on ability in the form of grades and may adjust preferences on college majors over time based on new experience. Montmarquette, Cannings and Mahseredjian (2002)’s research reveals more decisive results that expected earnings influence college major choice.

2.2 Literature of Secondary Importance

With respect to return on investment, James et al. (1989) studied the impact of college quality on future earnings and found that major choice, especially in combination with GPA, is a more impactful indicator of potential earnings than university quality and specifically references the reader to the premium earned by holders of engineering degrees at public universities. Given that the enrollment information generated for this paper will come from the California State University Analytic Studies data set, this will be something to look for. Additionally, Kahn (2010) assesses the long-run impact on wages for workers who graduate college during a recession. This study serves to provide useful supplemental information on this topic. It includes typical labor market characteristics and their impact on recent college graduates. Kahn (2010)’s findings suggest that a significant amount of students end up waiting to enter the labor market during recessions due to the decrease in earnings and job prospects. Perhaps they re-evaluate their major choices as well.
Chapter 3

Methodology

3.1 Overview

The testing procedure used in this paper is composed of three steps. First, accurate calculations of STEM and Non-STEM Enrollment ($STEMEnl$, $NonSTEMEnl$), Unemployment ($STEMUnemp$, $NonSTEMUnemp$) and Salary from Wages or Income ($STEMInc$, $NonSTEMInc$) are calculated. Second, time series models for these variables are constructed. Third, a series of Granger-causality tests are performed.

3.2 Calculating Enrollment, Unemployment and Salary from Income or Wages

It is critical that any testing occur based on accurate estimations of enrollment, unemployment and earnings. If accurate estimations cannot be made, any test for correlation between these variables over time cannot reliably be produced.

Determining enrollment is a very straightforward process. Precise calculations of the
proportion of students enrolled in STEM and Non-STEM disciplines are obtained from data provided by the California State University Division of Analytic Studies (CSU, 2016). These numbers are well-documented. The researcher need only add together total enrollment for all of STEM or Non-STEM students and divide by CSU system-wide enrollment. For the purpose of this research, only new student enrollment is used. This determination is made based on the assumption that students normally don’t re-choose their major every year. The more coursework a student completes in any given field of study, the less likely they are of changing majors due to the ongoing commitment of completing a degree. Therefore, capturing only those students who made college major choices within the current year would provide a more telling picture of the feedback between labor market forces and the decision of college major choice.

Average STEM and Non-STEM Salary from Income or Wages and Unemployment are estimations obtained using Current Population Survey (CPS) microdata (IPUMS-CPS, 2016). It is not stated which discipline any particular worker studied during their undergraduate career but rather it is inferred based on occupational classification. This is the same methodology employed by the Department of Commerce in Langdon et al. (2011)’s report. STEM and Non-STEM workers are determined by classifying each occupational code into STEM and Non-STEM categories. Non-specialized labor is excluded. Any occupation which does not explicitly indicate a background in STEM or Non-STEM is also excluded. For example, Civil Engineers (OCC 1360) belong to STEM, whereas Accountants and Auditors (OCC 0800) belong to business (Non-STEM). A Secondary School Teacher (OCC 2320) is an example of an occupation which cannot be determined to be STEM or Non-STEM and is excluded. Cases are further filtered to include only those individuals with Bachelors degrees.

Although there is nothing overly objectionable about using this estimation technique,
it has two clear downsides. First, it does not capture the full picture of unemployment or income for either group due to excluded observations. Again, survey participants providing non-specialized labor or labor which cannot be classified as STEM or Non-STEM are excluded. Additionally, it cannot be certain that each survey participant is accurately classified. Workers holding STEM Bachelors degrees can still obtain jobs classified as Non-STEM and vice versa. For example, a Biology student can obtain a job as a Social Worker. Similarly, a Psychology student with computer skills can obtain a job as a Computer Programmer. Although, due to these limitations, the true calculations of unemployment and income cannot be determined for 4-year STEM and Non-STEM degree holders, this estimation technique reveals important differences between a fairly large targeted sample of STEM and Non-STEM job holders.

3.3 Time Series & Granger Causality Testing

Granger causality is a simple econometric concept designed to explain the presence of a predictive relationship between one time series variable and another. It is tested whether or not future values of one time series can be more accurately predicted by looking solely at the lagged values of itself or by looking at the lagged values of itself in combination with the lagged values of another variable. This is not to say that one variable causes the other but rather that one contains information which is helpful in making more accurate predictions for another. Therefore, while the presence of Granger causality would provide evidence in favor of a predictive relationship between enrollment and labor market forces, it would not indicate that labor market forces are the clear cause for any change in enrollment or vice versa. The following analysis is merely a first step approach to the topic at hand and is in no way meant to provide all-encompassing solution to the question
being posed.

Three sets of Granger causality tests are used to determine whether or not trends in earnings or unemployment offer any predictive information for STEM or Non-STEM student enrollment. Two methods for testing Granger causality are attempted. First, Haugh’s Residual Cross-correlation test is attempted but ultimately could not be used to provide a means for testing Granger causality (Haugh, 1976). Next, a standard Granger causality test is performed using a Vector Autoregressive (VAR) model of first-differenced data (Granger, 1969).

The preferred method of using Haugh’s Residual Cross-correlation test was unsuccessful. This method requires a two-stage process. First, the researcher produces Autoregressive Integrated Moving Average (ARIMA) models for each variable. ARIMA models are univariate time series models which use information from lagged values to help predict future values. This step provides the added advantage of being able to make predictions and perform additional analysis, which is why this method is preferred. Unfortunately, this step could not be completed because none of the variables for this particular time period are good candidates for ARIMA modeling. Data is checked for stationarity and corrected, if necessary, by differencing. The number of differencing provides what is referred to as the integrated (I, d) term. The number of autoregressive (AR, p) and moving average (MA, q) terms are identified by checking significant lags of Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF). Models are then estimated and calibrated. Below are examples of the basic format:

\[
Enl_t = \beta_0 + \beta_1 Enl_{t-1} + \beta_2 Enl_{t-2} + \epsilon_t \tag{3.1}
\]

\[
Inc_t = \alpha_0 + \alpha_1 Inc_{t-1} + \alpha_2 \epsilon_{t-1} + \epsilon_t \tag{3.2}
\]

\[
Unem_t = \gamma_0 + \gamma_1 Unem_{t-1} + \epsilon_t \tag{3.3}
\]
Equation 3.1 indicates an ARIMA model with two autoregressive terms. Equation 3.2 indicates an ARIMA model with one autoregressive term and one moving average term. Equation 3.3 indicates an ARIMA model with one autoregressive term. The data indicates no significant lags and therefore, no AR(p) or MA(q) terms could be applied. This is perhaps due to the yearly frequency of the data. Had ARIMA models been produced, the second step of Haugh’s Residual Cross-correlation test is to test for cross correlation among the residuals of each ARIMA model (Haugh, 1976).

In place of Haugh’s Residual Cross-correlation test, Vector Autoregressive (VAR) functions are produced and tested for Granger causality. VAR functions treat all variables as endogenous, producing functions for each variable that include lagged values of themselves and all other endogenous variables in a system:

\[
Enlt = a_{10} + a_{11} Enl_{t-1} + a_{12} Unemp_{t-1} + e_{1t}
\] (3.4)

\[
Unemp_t = a_{20} + a_{21} Unemp_{t-1} + a_{22} Enl_{t-1} + e_t
\] (3.5)

VAR models are produced to test Enrollment by discipline against Unemployment and Income individually, as well as all three variables together. STEM and Non-STEM Enrollment was tested with each possible combination of labor market data for Granger causality. Each variation is attempted with up to four lags. The VAR model variation with the lowest Schwarz’ Bayesian Information Criterion (SBIC) is used. Finally, a series of Granger causality tests are performed.

### 3.4 Results

None of the results from the above tests return significant. Not one t-score for any of the coefficients of any of the VAR models is significant at the 0.05 or even the 0.10 level.
The most efficient VAR model includes the variables: Non-STEM Enrollment, STEM Unemployment and STEM Income. This model is more effective than the VAR model including Non-STEM Enrollment, Non-STEM Unemployment and Non-STEM Income. In all cases, we fail to reject the null hypothesis that no single variable Granger-causes any other variable. Sample outputs of this analysis are provided below.

Table 3.1, a VAR model composed of $DNonSTEMEnl$, $DSTEMUnemp$ and $DSTEMInc$, has the lowest SBIC (-16.2426) and the highest r-squared (0.1861) of any other model tested. As previously mentioned, no coefficients are statistically significant.
Table 3.1: Vector Autoregression: $DNonSTEMEnl$, $DSTEMUnemp$ & $DSTEMInc$

<table>
<thead>
<tr>
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<tr>
<td>$DNonSTEMEnl$</td>
<td></td>
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<tr>
<td>$L.DNonSTEMEnl$</td>
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<tr>
<td>$L.DNonSTEMEnl$</td>
<td>0.0392</td>
<td>(0.37)</td>
</tr>
<tr>
<td>$L.DSTEMUnemp$</td>
<td>0.230</td>
<td>(0.88)</td>
</tr>
<tr>
<td>$L.DSTEMInc$</td>
<td>0.00925</td>
<td>(0.14)</td>
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<td>Constant</td>
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<table>
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<td>$L.DNonSTEMEnl$</td>
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<tr>
<td>Constant</td>
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N 19

$t$ statistics in parentheses
Table 3.2: Granger Causality Wald Tests

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<th>Equation</th>
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<th>F</th>
<th>Prob &gt;F</th>
</tr>
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<tr>
<td>DNonSTEMEnl</td>
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<td>.3932</td>
<td>.5400</td>
</tr>
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<td>.35785</td>
<td>.5586</td>
</tr>
<tr>
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<td>ALL</td>
<td>.53022</td>
<td>.5991</td>
</tr>
<tr>
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<td>DNonSTEMEnl</td>
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<td>.7143</td>
</tr>
<tr>
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<td>DSTEMInc</td>
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<td>.8897</td>
</tr>
<tr>
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<td>.9323</td>
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<td>DNonSTEMEnl</td>
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<td>.1971</td>
</tr>
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<td>DSTEMUnemp</td>
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<td>.7181</td>
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<tr>
<td>DSTEMInc</td>
<td>ALL</td>
<td>.96357</td>
<td>.4039</td>
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</table>

Table 3.2 demonstrates that \(DSTEMUnemp\) and \(DSTEMInc\) do not Granger-cause \(DSTEMEnl\). None of the probabilities are within the statistically significant range. Additionally, we fail to reject the null hypothesis in each case for all other variables, meaning there is no Granger causality present in the data.

Using fewer variables yields even less effective results. Table 3.3 is an example of a single-lagged VAR model between \(DSTEMEnl\) and \(DSTEMUnemp\). This model provides no predictive power and is a typical example of what is seen from other bivariate VAR models. In Table 3.5, we fail to reject the null hypothesis, meaning that again, there is no evidence of Granger Causality.
Table 3.3: Vector Autoregression: $DSTEMEnl, DSTEMUnemp$

<table>
<thead>
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<th>Prob &gt;F</th>
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<td>$DSTEMEnl$</td>
<td>.2862</td>
<td>0.6000</td>
</tr>
<tr>
<td>$DSTEMUnemp$</td>
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<td>.2862</td>
<td>0.6000</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
Chapter 4

Data Selection

The data collected for analysis in this paper comes from the California State University Division of Analytic Studies Statistical Reports (CSU, 2016) and from Current Population Survey (CPS) microdata samples (IPUMS-CPS, 2016). The CSU Statistical Reports provide student enrollment by major, each fall term. The Current Population Survey is a yearly survey conducted nation-wide by the United States Census Bureau for the Bureau of Labor Statistics and provides information on each participant’s employment status, income and occupation type. The data spans from 1995 to 2015.

Student enrollment is divided into two broad disciplines, STEM and Non-STEM. STEM is composed of Agricultural Sciences, Biological Sciences, Engineering, Health Professions, Information Sciences, Mathematics and Physical Sciences. Non-STEM is composed of everything else. Undeclared students are not reflected in the data because they do not belong to either group.

Information on STEM and Non-STEM unemployment and income is collected from the Current Population Survey. Each participant of the survey provides their employment status, income and occupational code. This information is used to categorize workers into
STEM or Non-STEM occupational groups and determine the rate of unemployment and average income for each. Only those workers with 4-year degrees are reflected in the data for this paper. Any income not earned from salary or wages is not included.
Chapter 5

Conclusion

There are two main points to take away from this research. First, as indicated by the results, no combination of STEM or Non-STEM Unemployment or Income Granger-causes Enrollment. Second, while this is the case, this is not to say that Unemployment and Income don’t have an impact on college major Enrollment. Lack of evidence is not the same as proof that a relationship doesn’t exist. More data or an alternative approach to testing is required for any determination.

In the current approach taken, the frequency of the data significantly limits the strength of the final results. As with any statistical method, more observations provide more powerful and accurate findings. Using annual results provides only 20 observations and inevitably misses movements in economic activity along the way. If data were able to be calculated quarterly or bi-annually, the results could potentially change. Unfortunately, this type of data is not available. University of California data could be used to better reflect quarterly enrollment (most CSU’s are on the semester system). However, a different quarterly or bi-annual survey would have to already exist which provides an unbiased method for calculating unemployment and income for STEM and Non-STEM workers.
over a fairly significant amount of time. Such a survey does not exist.

An alternative approach to the method presented would be to use individual-level data reflecting a variety of factors, including but not limited to labor market forces. Bamberger (1987) used data from the National Longitudinal Survey (NLS) of Young Men to analyze college major choice with respect to expected earnings in five fields of study including: Business, Liberal Arts, Engineering, Science and Education. Using longitudinal data allows Bamberger (1987) to sort out selection bias and directly link individual choice of college major to labor market forces by keeping all else constant. The results of his research indicate a statistically significant, positive relationship between choice of college major and predicted future earnings stream. Unfortunately, the most recent NLS survey took place in 1997. More recent data would be necessary to assess the impact of labor market forces on the current population. The Higher Education Research Institute (HERI) has administered the Cooperative Institutional Research Program (CIRP) Freshman Survey for the past 50 years, which would certainly provide such information. However, this data is not openly accessible and is expensive to obtain.

In the case that the null results properly indicate no predictive presence between enrollment, unemployment and income, these findings downplay the importance of SB 1195, “The Student Right to Know Before You Go Act of 2015” and provide evidence that college major choice is generally not linked with either unemployment or expected earnings. This could certainly be the case. As previously discussed, there are many individual level characteristics which influence college major choice before economic value is even considered. In previous literature, all results indicating significance between the variables of interest first control for selection bias. Therefore, it is most likely that the decision to select a major based on labor market forces is made on the margin by those who are otherwise indifferent.
Bibliography


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