

Budgeting for Oregon Opportunity Grant Allocation:

The determinants of award acceptance and the relationship between the labor market and financial aid applications

By

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Budgeting for Oregon Opportunity Grant Allocation:

Abstract: Working with the Oregon Student Assistance Commission (OSAC), we examine 1) The determinants of an individual's decision to accept an Oregon Opportunity Grant. 2) The relationship between labor market conditions, as represented by the unemployment, and the number of applications OSAC receives from community college students. With respect to unemployment we find that a one percentage point increase in the unemployment rate leads to a 4% increase in the number of college applications OSAC receives, nine months after the unemployment increase. We also find that in general, need based financial aid calculated via federal expected contribution increases a student's chances of attending by up to 11% per \$1000 in some cases, and also has a strong effect on retention.

Approved: _____
Prof. Bill Harbaugh Date

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I. Introduction

Since 1971, the Oregon Student Assistance Commission (OSAC) has awarded need-based grants to low-income college students who wish to attend Oregon community colleges and 4-year institutions, both public and private.¹ In the past thirty-seven years, the name of the grant changed from the Oregon Need Grant to the Oregon Opportunity Grant (OOG) and the average nominal award has grown from \$500 to a range of \$1400-\$4500 (depending on the institution), but the eligibility requirements for the grant have changed very little. If eligible, students are awarded a fixed amount based on household income and family size. For the 2007-2008 school year, dependent students in a typical household of four needed a maximum household income of \$33,600 to qualify to the OOG. Single independent students with an income below \$9,600 qualified for the OOG-- anybody above this income level did not qualify for the grant. In general, dependent students qualified for the OOG if their income was 55% of Oregon's median family income, independent students with dependents qualified if their income was 50% of Oregon's median, and single independent students qualified if their income was 30% of the median. Beginning in the 2008-2009 school year, this will all change.²

In 2007 the Oregon State legislature approved an increase in funding of roughly \$32 million for the OOG. This means for the 2008-2009 school year, OSAC has roughly \$72 million to give to Oregon students in grant money. Given this infusion of new money, OSAC has changed eligibility requirements for the grant and changed the model

¹ Note: In some cases, OSAC awards the OOG for Oregon residents who choose to attend out-of-state schools. For the history of the OOG see "Opportunity Grant History: 1958-2003" http://www.osac.state.or.us/ong_timeline.html. Accessed 11 March 2008.

² "Opportunity Grant Eligibility Tables for 2007-2008" published by the Oregon Student Assistance Commission. 17 November 2006. <http://www.osac.state.or.us/doc/OppGrant%20Eligibility%202007-08%20FINAL.pdf>. Accessed 11 March 2008.

used to determine the award amount. Where awards were previously fixed, OSAC now plans to coordinate the award with federal financial aid. A new variable model has been developed where the award amount varies depending on need, using on the student's federal Expected Family Contribution (EFC) and Pell Grant award. Under this new model, students with family incomes of up to 70,000 will now be eligible for the OOG, and average award amounts may increase or decrease depending on need.

OSAC sets this variable guideline for the OOG award by employing something called the Shared Responsibility Model (SRM) to determine the size of a student's grant. Under the SRM, a student's award depends on 1) the estimated cost of attending the school: for example, for 4-year schools in the Oregon University system, this value is roughly \$16,000; 2) the FAFSA Expected Family Contribution: the EFC depends on a number of factors including student's independent/dependent status and their family's income, 3) the student's contribution: for example the student will be expected to finance about \$8500 of the 4-year cost of attendance through loans, scholarships, and part-time work, and finally 4) the federal government contribution: this is the amount the student and his/her family receives from the Pell Grant and federal tax breaks. So according to the shared responsibility model,

$$\text{OOG award} = (\text{Cost of Attendance}) - (\text{EFC}) - (\text{Student Contribution}) - (\text{Federal Aid}).$$

The goal of this model is to cover the total cost of attending college in Oregon. Simply put, by loosening eligibility requirements and adopting the SRM, OSAC hopes to give

more money to more students in a fair manner and do a better job of tailoring it to meet financial needs.

Currently, OSAC does not have a model to predict the number of students who will qualify for funding in a given year and the average award amount. Under the current system, OSAC simply allocates money until the funds run out. So students who might accrue the greatest marginal benefit from the grants may not receive grant money if they apply too late. Does a grant aid increase the probability that an applicant will attend college? Historically, OSAC has been able to estimate the increase based on similar-over-year estimates and pure intuition. However, given the increase in funding and the fundamental change in the way the grant is awarded, we might expect a dramatic change in the award amount and distribution due to the change in coverage. For instance, where the maximum award used to cover 50% of community college tuition, it now covers almost 90%. We would expect students to have some elasticity of demand for financial aid and therefore expect significant changes, especially considering that the increases have been publicized.

Also, to predict the number of students who qualify for an award in a given year OSAC needs to know how many applications they will receive. Currently, OSAC can predict the number of applications for Oregon University System and private institutions fairly accurately, but they cannot explain the variation in the number of community college applications they receive in a given month. OSAC wants to know the relationship between labor market conditions and the number of community college applications.

So the question becomes, how many students can we expect to use the OOG in future years? Specifically: 1) What are the determinants of a student's decision to accept

or reject an award? 2) What is the relationship between changes in the labor market and the number of community college applications OSAC receives? If we can develop a budget method that not only the number of students who will require funding in a given year, but also the different award amounts needed for these students under the SRM, OSAC could use such a method to efficiently allocate the \$72 million over an entire year.

II. Literature Review

Effect of college financial aid on enrollment/retention decisions literature

A wide amount of research has been done on the effects of student financial aid. There is even a professional journal published quarterly by the National Association of Student Financial Aid Administrators (NASFAA). One current example of such research is an NBER paper by Curs, Singell and Wadell (2005) that studied national institution-level data from the Pell program between 1989 and 2002. Following with the majority of current research, the authors continue to assert that need-based grants such as the federal Pell award have a significant effect on the decision to attend college.

There is also a good deal of research specific to state aid. Harvard researcher Susan Dynarski has established some very solid theories on both state aid and federal aid. Utilizing national data from the Social Security Administration, she examined (1999) the effects of ending the federal social security grant benefit program in 1982, finding that \$1000 of grant aid increased the probability of attending by about 4%, as well as overall educational attainment by .16 years. Her study on the Georgia Hope Scholarship, (2000) a combined merit/need-based grant, indicated a similar result. Based on state-level Census samples, BLS unemployment statistics, and institution-level DoE surveys, she

yielded around a 4% increase in enrollment with \$1000 in state aid, as well as estimating an overall elasticity of demand to grant aid of 0.7 to 0.8.

Not all of the studies are in consensus. A professional state-level study in the NASFAA journal by Baird (2006) found that federal need-based aid did *not* affect student enrollment, but state aid and investment in capacity did. And a study by Lisenmeir, Rosen, and Rouse (2006) found that when examining individual data from an anonymous high-tuition private university, switching from loan-based aid to need-based aid did not yield an increase in the enrollment of low-income students, an important policy consideration since need-based programs like the OOG are targeted at lower incomes.

Further studies on policy yield some interesting results. A study by St John, Et al on the impact of state strategies, (2004) used biannual state-level data from the National Association of State Student Grant and Aid and the NCES to reproduce Dynarski's results, and reached several interesting policy conclusions on optimal aid strategies, including: states should coordinate their aid with federal aid (this is what OSAC is doing); states should provide need-based grants amounting to at least 25% of average tuition costs; ideally maximum state-federal combined financial aid award should equal 100% of tuition, 2/3 of which should be state funds; states should be required to provide information on financial aid to all low-income 8th-graders, namely those who qualify for free/reduced lunch.

The Unemployment Rate and Community College Enrollment Literature

Much of the literature on the relationship between cyclical changes in the economy and college enrollment postulates that an increase in the unemployment rate

leads to an increase in college enrollment. Economists have studied this relationship by looking at both four-year and two-year institutions and have found varying results. Also, the results of this research not only depend on the type of school studied, but also the geographic area and the time range from which the researchers have data.

Betts and McFarland (1995) look at the relationship between the unemployment rate and enrollment at community colleges from 1969 to 1985 and conclude a 1 percent increase in the unemployment rate leads to rise in full time enrollment of high school graduates by 0.5 percent. Also, a 1 percent increase in the unemployment rate is connected to 4% increase in the enrollment of adults (ages 18-65 who did not *recently* graduate from high school). The authors posit that college enrollment is a function the unemployment rate for people with varying levels of education, the estimated present discounted value of people with varying levels of education, college costs/fees, expected college costs/fees, per capita income, year, population divided by the number of four year colleges, the population divided by the number of two year colleges, and financial aid (both allocated and expected). As mentioned above, the authors focus on the relationship between the unemployment rate and enrollments and find a significant correlation. This, they argue, has significant policy implications because “the high elasticity of enrollment with respect to unemployment implies that the government does not need to create programs to encourage people to attend community college in recessions for retraining”³ (Betts McFarland 1995, 763). Overall, Betts and McFarland’s analysis shows a significant relationship between labor market conditions and enrollments for *two year*

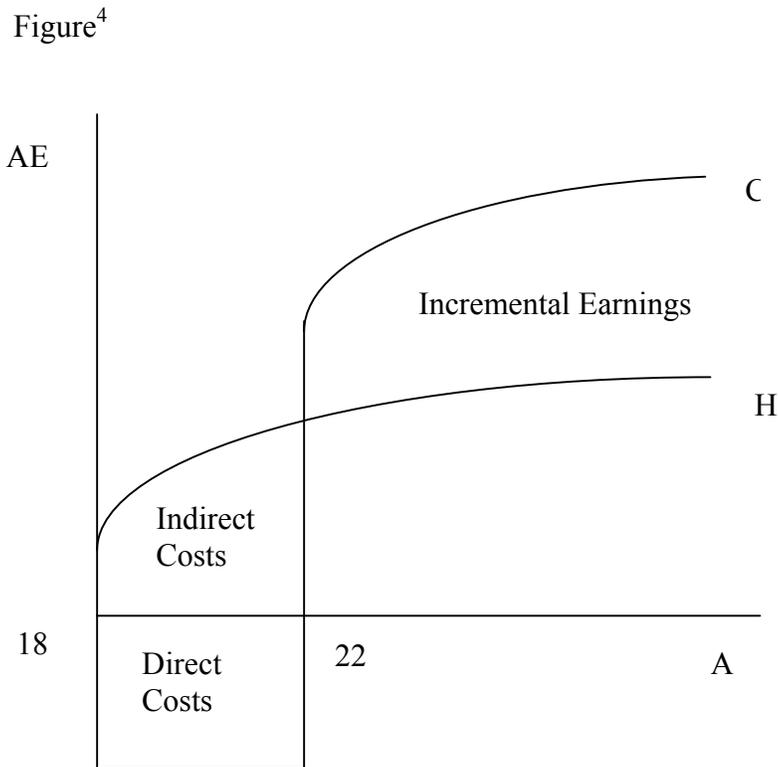
³ This conclusion is relevant to our analysis of the number of financial aid applications and the unemployment rate. If we find similar results, we can address the question of should the state government provide FAFSA assistance during economic hard times or will the labor market push more people towards higher education regardless?

colleges only. What does more current data on both community colleges *and* four-year institutions tell us?

Dellas and Sakellaris use data on both four-year and two-year higher education institutions and find results similar to those of Betts and McFarland. First, the authors use a probit model and conclude that a an increase of 1% in a state's unemployment rate leads to a increase 0.28 percent increase in the probability that a student will enroll. Second, the authors found that individuals were more or less responsive to the unemployment rate depending on when they enrolled in college. While from 1968 to 1978 the marginal effect of the unemployment rate on enrollment rates was 1.44 (with a standard error of .21), from 1978 to 1988 that value dropped to 0.59 (0.20). In short, after 1978 people were less responsive to the unemployment when making enrollment decisions. Why? Dellas and Sakellaris attribute this change to demographic changes and changes in perceived returns of higher education. Third, the authors find that full-time enrollment levels are much more responsive to changes in the unemployment rate than part-time enrollment. With full time enrollment, they find that a 1 percentage point increase in the unemployment rate is correlated with an increase in the probability of enrollment of .6 points (with part-time enrollments, the probability increases by .17 points). Finally, like Betts and MacFarland, Dellas and Sakellaris find that changes in the unemployment rate have a higher marginal effect on community college enrollments than on enrollments at four year institutions.

III. Economic Theory and Hypothesis

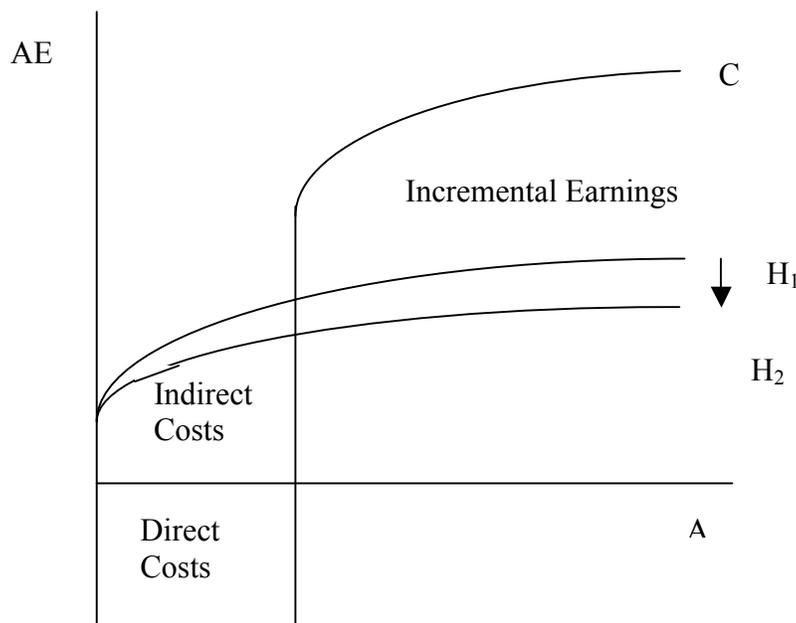
The established economic theory on college attendance approaches it as a decision to invest in human capital. The theory predicts that if the opportunity cost of pursuing a higher education decreases and/or an individual's expected earnings in the long or short run with a given level of education, at some margin, the individual will decide to acquire more education. In general, an individual will compare the difference between expected earnings with more schooling and without more schooling (in the long-run) to the sum of the indirect (opportunity) costs and the direct costs, such as tuition and books. If the difference in earnings over an individual's working life is greater than the indirect and direct costs combined, the individual should choose to invest in a postsecondary education



⁴ The x-axis, A, represents Age and the Y axis, AE, represents annual earnings.

Figure shows how an eighteen year old might compare direct and indirect costs to the difference in earnings for a college graduate and a high school graduate (not taking time preference into account). If the area under curve C and above curve H is greater than the combined area shown by direct and indirect costs, and we assume the individual values a dollar today the same as a dollar in the future, then he or she will choose to invest in human capital.⁵ Given this model, how would a change in labor market conditions affect an individual's decision to invest in a post-secondary education?

If there is a downturn in the labor market, as represented by an increase in the unemployment rate, across the entire economy more individuals face lower indirect costs of attending college, and possibly, a higher difference in earnings with a college education.



⁵ We can apply the “no time preference” assumption to the figure if we assume that annual earnings aren’t nominal annual earnings, but instead, earnings adjusted for the individual’s discount rate.

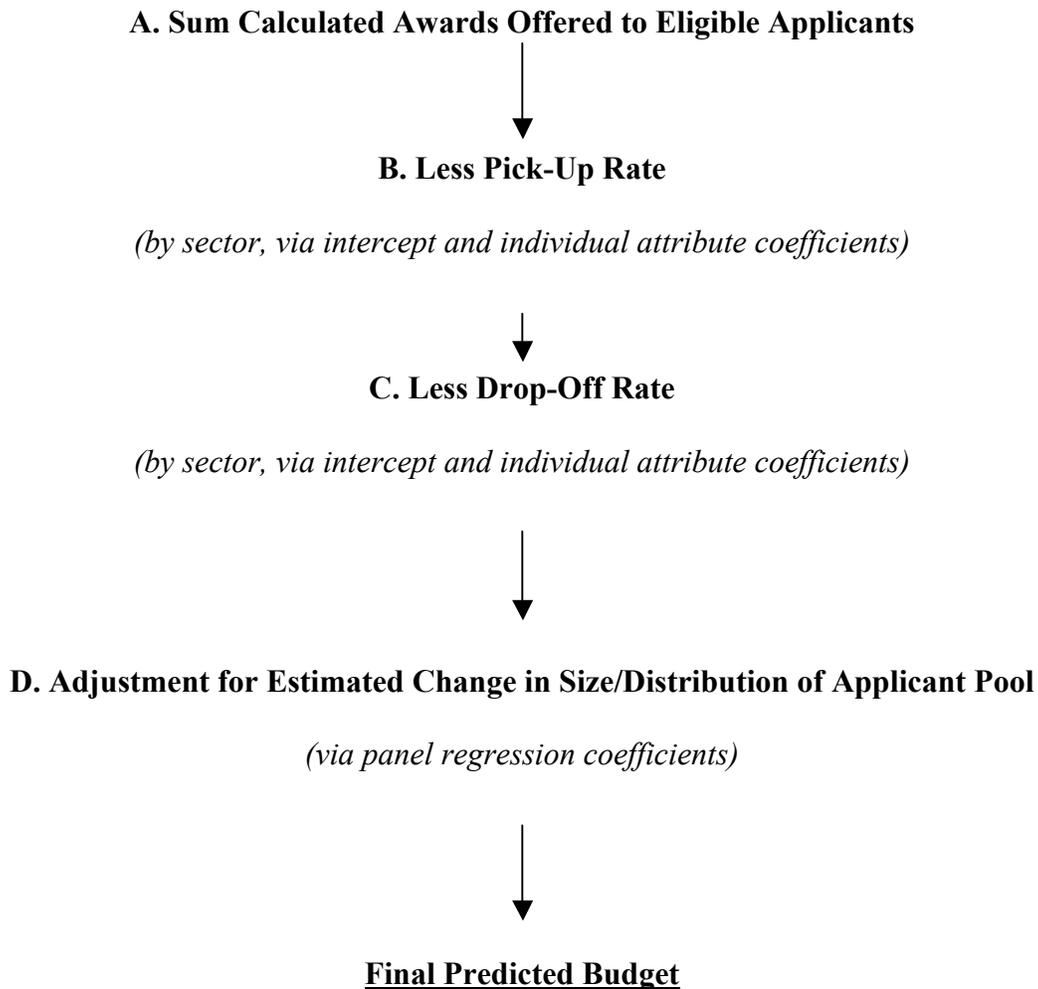
For the individuals who lose their jobs during a downturn in the labor market, until they find a new job, their expected earnings go to zero. When the individual's expected earnings fall, the indirect costs for the person to attend college falls as well. Also if the individual is in an industry particularly sensitive to economic downturns, their expected earnings in the long-run may fall as well.⁶ As H_1 shifts to H_2 , at some margin, incremental earnings will exceed the sum of indirect costs and direct costs. When this happens, an individual, who prior to high unemployment did not plan to pursue a post-secondary education, will go to college. For this reason, we hypothesize that a downturn in the labor market, as shown by an increase in the unemployment rate, will lead to an increase in the number of community college applications

IV. Methodology

With a new, sliding-scale method of distribution in effect, OSAC needed a way to predict who would take the award and how much of it they would spend. With the eligibility pool changing so drastically, they could no longer use a simple year-over-year method to predict their budget. What we planned to do was develop a budgeting model that used econometric coefficients to determine what the individual effects would be for this new pool of applicants. OSAC likes to view college students in “sectors,” divided by dependency status and three different college types: 2-year public, 4-year public, and

⁶ Note: Although the figure shows that an increase in the unemployment rate will permanently decrease the annual earnings of an individual with a high school education, this is not necessarily the case—annual earnings could easily return to “pre-economic downturn” levels. Also, while the graph may show that a poor labor market will, overall, decrease the earnings of low-skilled workers, this is not necessarily the case. High skilled workers could be hit just as hard by high unemployment. Still, regardless of the level of education, given a rough labor market, the opportunity cost of higher education is lower, which makes human capital investment relatively less costly.

private. To calculate the overall award, we suggested the following 4-step prediction method:



Award acceptance/retention model

The first step is to calculate the award offers to the current group. This can be done by applying the new calculation (A) method to last year's (fully completed) pool, and later adjusting for expected changes in the distribution (D). Since OSAC receives a

good deal of applications by the time that awards start being authorized, they might also use one of their current seasonal prediction methods to estimate the applicant field.

Next is the use of logistic regression to determine the probability of a FAFSA applicant attending based on past data (the pick-up rate) (B), a similar approach to Dynarski (2003). We assumed that the relationship will resemble the form:

$$\begin{aligned} &P(\text{Eligible Applicant Attending}) \text{ and Ratio of Award Accepted}^7 = \\ &+ \text{Grant Awards [Calculated Federal Grant, State Grant, and/or Combined} \\ &\quad \text{Grant in absolute terms and/or as percentage of average tuition cost]} \\ &+ \text{Financial Background [EFC, Adjusted Gross Incomes, Assets]} \\ &+ \text{Other Background [ZIP Code]} \\ &+ \text{Personal Attributes [Gender, Age, Marital Status, Citizenship Status,]} \\ &+ \text{Opportunity Cost Factors [Year of application]} \\ &+ \text{College Specifics [Specific Institution, College Class Standing,]} \end{aligned}$$

From here, the same method can be repeated, but this time using the “acceptance ratio” (D) as our left-hand variable to determine the drop-off rate. This will tell us how much of their award people actually end up using, thus estimating the average effects on dropping out, losing eligibility, transferring, etc.

Ideally, we hoped that we could do the entire budget calculation with econometrics, but the new award calculation method was deemed too sensitive to share⁸. Even without doing the new award calculation within the regression, we can still perform the last come up with relevant coefficients and intercepts. In practice, this is more realistic and useful for our client as we do not expect them to take the regression model into their own hands and try to improve estimations. Knowing the general trends in intercepts will allow them to look at percentage changes for specific variables in the

⁷ These are attributes that we were able to actually use from our dataset. There are many other data that would have improved our model had they been available. See conclusion for a partial list.

⁸ The problem with sharing a complete award model is that universities can use the information to price discriminate, offsetting the effects of awards.

applicant pool and make a correction. Using this, they can do a better job of predicting pick-up and drop-off rates for their budget estimation.

Unemployment Model

The purpose of the employment model is to show the relationship between unemployment and the number of community college financial aid applications (D). To analyze how labor market conditions impact the number of community college applications OSAC receives in a given month we use a panel of application number, per capita income, and unemployment rates broken down by each county in Oregon and month (from January 2001 to May 2008). Panel data methods are useful because they allow us to see how the numbers of applications vary with respect to the unemployment rate in different counties in different months. In addition, because the distribution of applications in a given year is skewed heavily towards January and February, we include dummy variables for each month to control for seasonality. We also include dummy variables for each county to control for variation in the number applications due to county differences. Our employment model is:

$$\frac{\text{Number of CC Applications}}{\text{Population of the given county}} \times 1000 = f(\text{unemployment}_{n-p}, \text{percapitainc}, \text{month}, \text{county})$$

First, the number of community college applications, listed as “appnumber”, is the total number of applications received by OSAC in a given month from a given county. Because the number of applications from a certain county will depend on the size of the county, we divide by the total population and multiply the value by 1000. Our dependent variable, later referred to “appthou,” is the number of community college applications per

1000 residents in a given county. Second, “Unemployment” is the unemployment rate in a given county in a given month. We hypothesized that prospective students won’t immediately respond to an increase in the unemployment rate, but instead, wait several months before they decide to seek financial assistance for college. This is why we will test not only the present unemployment rate, termed “unemployment,” but also lags of the unemployment rate. We list unemployment lags as “Unemp’ P ” where p =the number of months lagged. Third, “percapitainc” measures annual per capita income by county. Finally the variables “month” and “county” are sets of dummy variables for each month and each county within our sample—we include these to control for variation by season and county.

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Finally the variables “month” and “county” are sets of dummy variables for each month and each county within our sample—we include these to control for variation by season and county. We perform a random effects regression because it allows us to include variables that are constant for each county, such as the county dummies. Also, we drop all counties with populations below 50,000 residents from our regression, so small counties and large counties aren’t weighted equally.

V. Data

Award Acceptance Model Data

Our data consisted of demographic and financial information from the FAFSA (Free Application for Federal Student Aid), which is a blanket application for the majority of federal financial aid. Our sample was drawn OSAC’s records, which included a complete set of all FAFSA’s filed in the state of Oregon for the past seven years. The data sample that we finally obtained from OSAC was a sample of selected FAFSA statistics from the 7 most recent years (01-02 through 07-08) of what OSAC considered “viable” applicants: undergraduate Oregon residents with remaining time in a 4-year eligibility window. In all, we had about 750,000 entries, including about 353,000 unique individuals, many of whom filed for multiple years.

The FAFSA contains a wide range of data, especially focusing on the financial situation of the student and parents with a breakdown of income and different types of assets: savings, businesses, and investments. Based on this information, the FAFSA formulation outputs a variable called “expected family contribution,” which is the key determinant of federal Pell grants and loans. Along with the calculated “adjusted gross income”, EFC is one of the primary determinants of many types of need-based financial

aid including the new OOG formula. Using data about income, assets, and the EFC combined with college cost information gave us a comprehensive picture of the student's financial situation.

The data also included detailed information on the historical disbursement of OOG's, including the amount awarded versus the amount actually claimed. In addition, there is plenty of college-specific data: part-time/full-time, class standing, 2year/4year and public/private statuses of the institution, and even the student's specific college.

Descriptive Statistics for Numerical Variables

<u>Variable</u>	<u>Obs</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min</u>	<u>Max</u>
Age	753206	24.7222	6.3579	17	68
Par. Household Size	753376	1.848815	2.183984	0	15
Stu. Household Size	753376	1.826683	1.348884	1	15
Stu. AGI	629942	13613.86	19025.52	-50000	999999
Par. AGI	350969	57406.41	50166.2	-50000	999999
Stu. Savings	753376	718.1835	4310.715	0	977000
Stu. Investments	753376	1367.99	15061.74	0	999999
Stu. Businesses	753376	77.81215	5482.437	0	999999
Par. Savings	356437	6030.903	24692.55	0	999999
Par. Businesses	753376	1964.049	29897.5	0	999999
Par. Investments	357713	30910.05	105077.2	0	999999
Fed. EFC	753376	5829.912	10955.72	0	99999

There was also reasonable amount of personal information, with the notable exception of race. Gender, age, marital, and citizenship status are all included. Regional information was available through zip codes. Finally, an individual identifier allowed us to track people over multiple years.

A good deal of data handling and transformation was needed before we could begin our regression analysis. The data was in a relatively raw, comma-delimited format that required a good deal of parsing and encoding to get our software to work correctly. Many of the financial data had numerical codes for special cases that had to be manually

restored to proper null values. Date strings required modification at the character level to read in as proper dates. String variables like those for college names had to be converted to dummy variables. Dummies were also created for controls such as class standing and zip codes.

Our theory called for the creation of a left-hand dependent dummy variable that would indicate whether a student accepted the award or not. Both award “authorizations” (offers) and disbursements were separated by individual term, so they were summed into annual amounts. The dummy was then generated. Anyone who was disbursed at least 1 dollar of the award was considered to be an accepter. The regression result would therefore determine the basic pick-up rate.

The discrepancy between the amount offered and the amount actually disbursed was also recorded in a percentage variable called the “accept ratio” which could be used as a left-hand variable in a second set of regressions. One problem that arose was that some students transferred schools during the year, resulting in a multiple entry of both the unique identifier and application year. We summed the total award amount for these students and compared it to the initial award offer, a method that we felt was the best way for a budgeting approach. With the true disbursement ratio calculated for all recipients, we now had a method to calculate the determinants of drop-off as well as pick-up, making for an complete approach to budgeting.

The other major data work on the pick-up model was determining eligibility. Our data did not have a variable that simply determined eligibility; it was only a pool of “viable” applicants. Luckily, the requirements were not too complex. We generated a simple dummy for eligibility using an OSAC table of historical income limits. Our entire

pool was undergraduate students with eligibility so we did not need modifications in those areas, but OSAC only offered the award to part-time students in the 2007 school year, so all non-fulltime students before that period were considered ineligible.

Unemployment Model Data

We merged data on the seasonally adjusted unemployment rate for each Oregon county in each month from January 2001 to December 2007 with OSAC's FAFSA data set (described in the previous section). The unemployment data comes from the Oregon Employment Departments monthly reports on unemployment by county.⁹ To create our dependent variable, the number of community college applications, we simply dropped all non-community college applicants counted the number of unique observations in the FAFSA data set by county and date, and generated a new variable. This new variable, *appnumber*, tells us how many individuals for a certain county applied in a certain month. The Portland State Population center provided annual population estimates for each Oregon county from 2002 to 2007.¹⁰ We then used Census Bureau data to find county population estimates for 2001. After merging our population data with the master FAFSA data set we created our dependent variable, *Appthou*, by dividing *appnumber* by each county's respective total population (for each year). Finally, the Bureau of Economic Analysis provided annual per capita income by county.¹¹

⁹ For unemployment data see <http://www.qualityinfo.org/olmisj/OlmisZine?zineid=00000011>

¹⁰ See <http://www.pdx.edu/prc/>. For Portland State's Population Research Center's annual estimates of population by county.

¹¹ Data taken from regional data section at www.bea.gov

Unemployment Model Descriptive Statistics¹²

	Obs	Mean	Standard Deviation	Min	Max
Appthou	966	1.2039	0.9122595	0.138418	5.850983
Appnumber	966	168.43	266.0938	5	1920
Unemployment	966	6.62	1.618354	2.5	11.5
Per capita income	966	28268.47	1.618354	21446	41378

V. Results

Award acceptance model

Our regressions came up with a number of significant, satisfying results that support the use of our model as a tool for budgeting and policy. We will discuss both general results and individual coefficients across different college sectors as they apply to the pick-up and drop-off rates.

In general, dependent students had behavior that was much easier to predict than independent students. With some independent groups, only a few statistics were statistically significant. This was expected; we assume that compared to the typical high-school graduate dependent, independent students generally have much more on their plate as they are by definition financially self-reliant. They likely have higher opportunity costs in the form of giving up jobs to go to school, dependent children of their own, and not so much of the “safety net” from parents. Add in our overall sample bias (only the bottom quartile of income was eligible to receive the OOG) and the result is a group that is highly unpredictable. Dependent students were much easier to track; we came up with more statistically significant coefficients in the areas we were looking. Despite this discrepancy, we were able to find many results that applied to both sectors. In general,

¹² Descriptive statistics taken from the sample with which we used for a random effects regression. Stata dropped some values from our original sample due to missing data.

the most important factors had the similar effects on both pick-up and drop-off and had some consistency through the sectors.

Pick-Up: Dependents at 2-Year College¹³				
<u>Variable</u>	<u>Coefficient</u>	<u>Standard Error</u>	<u>Z</u>	<u>P-Value</u>
	-			
Parents Divorced ¹	0.0354188	0.01567	-2.26	0.0240
Parents Widowed	-0.021691	0.03194	-0.68	0.4970
	-			
Parents Single	0.0294816	0.01972	-1.49	0.1350
Age (In years)	0.0192128	0.0051	3.77	0.0000
Parent Household Size	0.0004661	0.00495	0.09	0.9250
Student Household Size	0.0173841	0.00798	2.18	0.0290
Student AGI (per \$1,000)	0.0033978	0.00126	2.7	0.0070
	-			
Parent AGI (per \$1,000)	0.0025304	0.00067	-3.8	0.0000
Student Savings (per \$1,000)	0.0044359	0.00417	1.06	0.2880
	-			
Student Investments (per \$1,000)	0.0016055	0.00523	-0.31	0.7590
Student Businesses (per \$1,000)	0.0015686	0.03821	0.04	0.9670
Parent Savings (per \$1,000)	0.0008791	0.00087	1.01	0.3130
	-			
Parent Businesses (per \$1,000)	0.0010784	0.00065	-1.66	0.0980
	-			
Parent Investments (per \$1,000)	0.0005858	0.00026	-2.29	0.0220
	-			
EFC	-0.104344	0.0063	16.57	0.0000
Sophomore ²	0.0625859	0.01779	3.52	0.0000
Junior	0.2211908	0.01712	12.92	0.0000
Senior	0.2506537	0.02629	9.54	0.0000
Senior+	0.1841102	0.057	3.23	0.0010
	-			
Senior++	0.3076833	0.09031	-3.41	0.0010
<i>College Name Dummies (supressed)</i>				
<i>Application Year Dummies (supressed)</i>				
N	7024			
Adj. R2	0.084			

¹³ This is an example of pick-up model. For complete pick up and drop off results, see Appendix A-B

Parent Marital Status – These were dummies for divorced, widowed, and single parents, with the excluded value being married parents. The expected signs for all three of these were negative, and the coefficients confirmed that having parents separated in some way had a negative effect on attendance across the board, likely due to social issues and potentially a less favorable financial background. Divorced had the strongest negative effect, single parents had a relatively strong effect, and widowed parents was statistically insignificant, probably due to low overall occurrence.

Age – This had a strong positive effect throughout the dependent sector, perhaps more than we expected considering that we also controlled for class standing. We think a good deal of this coefficient is explained by the idea that younger students who wait to attend college are more likely to follow through with it. By contrast, their counterparts who attend right after high school are more likely to be “testing the waters”: maybe they are unsure about what they want to do or are just following the path of least resistance.

For independent students the result was statistically insignificant. We suspect that age matters less because independent students are by definition attending to their own finances, indicating that they have a higher opportunity cost of attending. In light of this, for independent students the decision to attend is less likely to be about maturity and capacity for self-reliance, since those two attributes are prerequisites for being financially independent in the first place.

Parent/Student Household Size - We thought that this would be an important part of the general socioeconomic status picture. Knowing a household’s income and assets is only relevant if we know the household’s needs – basically, how many mouths does the net household income need to feed? The coefficient we expected was generally negative and

this turned out to be the case. But statistical significance varied. When it came to dependent students, we didn't expect their own household size to make much of a difference in their financial situation since for the most part we assumed they relied on their parents. We were correct here – the results were generally statistically insignificant. But even the parents' household size didn't matter for independents, although the level of significance generally increased with the cost of college – 2-year colleges having the least significance and private colleges having more. For independent drop-off rates, parent household size became completely irrelevant and was automatically dropped by the regression.

AGI – Student AGI was an important figure in our assessment of the financial situation. We expected the coefficient to be generally positive; both take-up and drop-off would improve with more student income available to spend on college. Our results confirmed this with some interesting conclusions. For independents, the result was statistically insignificant. We believe that this arbitrariness is due to income being a two-directional effect: on one hand, having more income simply helps pay for college. On the other hand, higher income is a substitute for investment in human capital. Students who are financially independent have higher opportunity costs of going to college than dependents.

This idea was supported by the contrast with dependent students, whose results were positive, but statistically insignificant for 4-year state and private institutions. Here the students' own income is less relevant because it is smaller and the cost of college is higher. But for community college, there is statistical significance, indicating that students and parents work together to finance college. We think the determining factor is

the income relative to the cost of college. This is an important policy implication for the general notion of “shared responsibility” costs: (dependent) students are willing to help pay for college so long as the amount they contribute is significant to college costs. But faced with higher costs, they will leave it up to their parents or take out loans.

Parent AGI – We expected this coefficient to be strongly positive, for dependent students as an indicator for ability to pay and for independents as an indicator of general SES. This was not the general result we obtained.. For pick-up rates, the coefficients were slightly negative, and all statistically insignificant except for dependent students at community college. For drop-off rates, statistical significance remained in most dependent sectors and coefficients were negative, but were relatively small. For instance, in the dependent private college sector it would take a \$25,000 increase in parent income to yield a mere 1% increase in the chances of dropping out. Independent students saw no significance of parent income.

We see these tiny negative coefficients as the effect of slightly higher opportunity costs for students whose parents have more money. Wealthier parents will be more able to afford to keep children in their own household. This is a sort of “failure to launch” scenario that might also see dependents facing high opportunity costs of quitting a job to leave home (where they are getting free rent). But ultimately, parent income doesn’t seem to have that much of an effect on the decision to attend. Especially for our lowest-income-quartile sample, parents don’t have that much income available to contribute to their students in the first place.

Assets: Student/Parent Savings - We expected generally positive coefficients for savings, albeit with low magnitude as we expect personal savings to be the last part of

income or assets that a student would allocate toward the cost of college. We were met with some mixed results. Across the board, parent savings were insignificant or had coefficients too small to have much effect on pick-up or drop-off rates. This was more or less expected. The personal savings of the parents are not expected to be used to fund the student's education, especially if their child is independent.

With student savings, we expected significant, positive coefficients, at least for independent students. We encountered this for dependent students at 4-year schools and independent students at community colleges. Why significance shows up in these areas is uncertain; this unusual result may have more to do with why it doesn't show up in other regressions. If it had to do with the ratio of the savings to the cost of college, we would also expect significance in the dependent community college sector, perhaps this is confounded by people in that sector not needing their savings since their parents still provide a safety net when they live at home.

Assets: Parent/Student Businesses and Farms

We expected coefficients for student-owned businesses to be negative because the opportunity cost of going to college likely involves giving up such a business. The only place that student businesses showed statistical significance was independent students at community college, where the coefficient was positive instead of negative. There are several reasons why our prediction might have been wrong, including the possibility that 2-year students are somehow able to manage a business and go to school full time. But on the net, this coefficient is suspect due to the very low occurrence of student business ownership FACT? For this reason, student owned businesses should be considered anomalies.

Parent-owned businesses did not fare much better. While there was some significance in the coefficients, they were generally negative. One reason this might be is that students are more likely to work for their parents than choose to attend college. But the magnitude of the coefficients was also relatively small, with a change of over \$50,000 needed to effect a 1% change in attendance likelihood in some cases. On the net, parent businesses were also relatively rare, perhaps too rare to be considered accurate predictors. From the aggregate budgeting perspective, the effects on such a small group is unlikely to make a major difference.

Assets: Parent/Student Investments – Out of all of the asset types, investments yielded the most significant results. Like other sources of potential college tuition payments, we expected positive coefficients with the most significance showing up when for the student's own account according to dependency status. For student investments, independent community college students had greatly increased pick-up rates from investments: a 4% increase in attendance per \$1000. This was one of the only variables where we noticed a serious divergence between the effect on pick-up and drop-off rates: with high statistical significance of preventing drop-off in most sectors.

Compared to student investments, parent investments performed more like parent savings, with less overall effect and significance. Like savings, parent-owned investments are more likely to be used for the parents, especially for retirement. The only sector that showed any significance was for dependent students, which reflects our earlier intuition about parents of dependents taking a more collaborative approach to funding community college.

EFC – The federal Expected Family Contribution turned out to be one of our most important variables. It was also one of the most important from the theory perspective, because it serves as a good indicator of overall financial need. The coefficient we expected was negative: the more the federal government expects the family to contribute, the greater the financial need for a substitute. This was confirmed overwhelmingly; EFC was statistically significant in every regression on the pick-up side, decreasing chances of attendance by 10 to 15% per thousand dollars of additional family expectation (depending on sector). This is perhaps the strongest result of our regressions, confirming that need-based financial aid is a very effective method to improve attendance, especially in the low-income group.

EFC also had a strong effect on drop-off rates for most sectors, decreasing disbursement up to 12% for each thousand dollars of additional family contribution for independence, and retaining significant results in all sectors except for private school. This indicates that need-based financial aid not only puts students in school, but that it also keeps them there.

Class Standing – Class standing was a very effective way to control for the change in students' behavior as they advanced their way through college. OSAC provided standings of up to 6 years in college. We expected coefficients to remain positive for the first 4 or 5 years at 4-year colleges and for the first 2 or 3 years at community colleges, as greater achievement and sunk costs into the program would give stronger incentives for attendance. Afterwards they would become insignificant or negative; students who had taken that long to graduate would behave unpredictably, with a much lower rate of

success. Financial aid might even unnecessarily prolong their stay before an inevitable drop-out.

This intuition was essentially confirmed. Coefficients were largely statistically significant and positive through the first 5 years of college. They generally became stronger as standing increased, confirming our intuition about greater commitment with greater achievement. In the 6th year of college, they turned negative and lost significance, as expected. One unexpected result was that students at 2-year colleges still had predictable behavior for 5 years like their counterparts at 4-year colleges, something we failed to fully explain since we assume that full-time community college students would run out of classes to take after 3 years.

Application Year – This variable was added as a control for variation in a variety of specific school-year events, including opportunity costs. Many years were dropped due to collinearity, but those that remained served to improve our function as a whole. Since we were unable to merge much data on direct opportunity costs like the unemployment rate, we hoped to capture some significance here that would improve the accuracy of other coefficients.

Specific College Name – This was another control added to our regressions to account for both the difference in costs and any number of unique features a college might have that would affect the decision to attend. This could be any number of factors, from a successful football program that would encourage attendance to an exceptional tutoring program that would discourage drop-off. Or it might be proximity to the nearest population center; the further from a population center, the less students it might attract and retain (unfortunately, we were not able to run a more sophisticated analysis on

geographical factors). By controlling for this as well as splitting our regressions up by college sector, our results should show the least bias from cost and from unique, college-specific attributes that could not otherwise be quantified.

Unemployment Model

Magnitude of the coefficients

For each model, we found a positive relationship between the unemployment rate in a given county in a given month and the number of community college financial aid applications n months later (where n corresponds to the number of months following the increase in the unemployment rate).¹⁴ More interestingly, the magnitudes of the coefficients show that an increase in the unemployment rate by one percentage point can explain a 4 percent increase in the number of financial aid applications for community colleges, nine months later. Specifically, the coefficient on the unemplag9 regression (the unemployment rate lagged nine months) of .0483, tells us that if the unemployment rate increases by one percentage point our dependent variable, APPTHOU¹⁵, will increase by .0483 applications per thousand people. For a county such as Lane with a population of 337,870 people, on average, OSAC should expect to see an increase of about 16 applications nine months after the one percentage point increase in the unemployment rate.

More generally, given the mean number of applications per thousand people in across the counties used in the sample is 1.2, a one percentage point increase in the unemployment rate, on average, leads to an increase in the number of financial aid

¹⁴ For regression results and various unemployment coefficients see Appendix E

¹⁵ Note: Appthou is equal to the number of applications in a given month from a given county divided by the population of that county multiplied by 1000. In essence, it's the number of applications per thousand people in a given month.

applications nine months later by 4%. This marginal effect of unemployment rates on the number of applications is encouraging as it is similar to the findings of Betts and McFarland (1994). Betts and McFarland found that for adults, an increase in the unemployment rate by 1 percentage leads to an increase in community college enrollments by 4% (and .5% for graduating seniors).

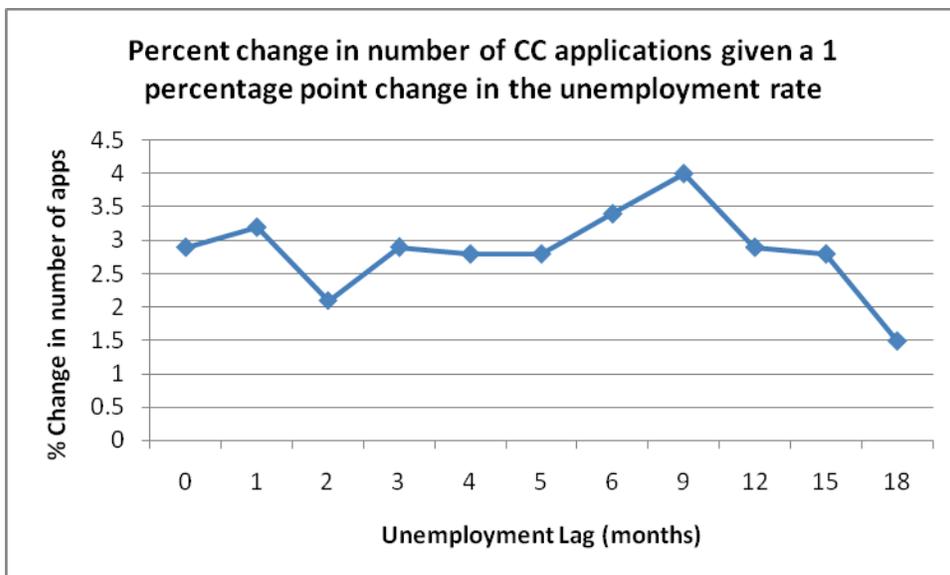
Also, the sign of the coefficients on the per capita income variable and the month dummies were as expected. While the coefficients on the per capita income variable were mostly insignificant, the negative sign tells us that higher levels of per capita income correspond to a relatively lower number of community college applications. Interestingly, in unemplag15 model, the per capita income coefficient, $-.0000312$, is significant at the 1% level. This means given a change in per capita income of 1,000 dollars in a given county in a given year, Appthou will decrease by $.0312$. That is the number of applications per thousand people will decrease by $.0312$. For a county the size of Lane, if the county's per capita income went up by \$1,000 OSAC could expect to see a decrease of ten community college applications per month. Intuitively, the negative sign on the income coefficient tells us that counties with lower levels of income will face relatively higher levels of two-year college applications

While we included the county and month dummies are included mainly to control of county specific and seasonal variation in the number of applications, the coefficients of the month dummies are as expected. Each month dummy, with the exception of February have a negative and significant coefficient. This reflects the seasonal distribution of FAFSA applications. As discussed in the data section applications most students

complete applications in January and February, and the number of applications gradually decrease over the application cycle.¹⁶

Comparison of lagged unemployment rates.

By comparing the significance and magnitude of each lagged unemployment rate, we can determine how many months it takes for a change in the number of applications to reflect a change in the unemployment rate.



Note: Not all lag coefficients are statistically significant. The nine month lag is significant at the 1% level See Figure

As shown by figure, roughly nine months after a change in the unemployment rate OSAC should expect to see the greatest change in the number of community college financial aid applications. After fifteen months, labor market conditions have little influence on the number of applications. Also while the one month lag variable is significant, the current (not lagged) unemployment rate and the two month lag do not have significant

¹⁶ For the list of included months and the coefficients on both the month and county dummies, see Appendix C and Appendix D.

coefficients. Also, the three, four, and five month lags are only significant at the 10% level. These results indicate that for those who decide to invest in human capital based on labor market conditions, it takes several months for these individuals either to decide to go to a two-year institution or to apply for financial aid.

VI. Conclusions and Policy Implications

Award Acceptance Model

In reviewing our analysis on pick-up and drop-off rates, we have several important conclusions that have strong policy implications, especially for our lowest-income quartile sample. On the wide scale, the most important conclusion is that we concur with the near consensus of opinions like those of Curs, Singell, Waddell (2005), Dynarski (1999, 2000, 2003), and St John (2004): Need-based financial aid is an extremely effective recruiting and retention tool, especially for low-income students. While we were unable to specifically estimate the effects of grants apart from other need-based aid, we believe that by demonstrating the significance of the EFC, the significance of grants like the OOG are covered at least in part since the EFC determines the similar federal Pell grant. This will be even more effective with OSAC's new "shared responsibility" method. We agree with St John (2004) that aid will be most effective when it fills in all of the gaps in ability to pay for college, and expect that the SRM will improve attendance as it seeks to do exactly that.

Our analysis also concluded that having married parents increases the chance of attending and staying in college. We attribute this to both social reasons and the greater financial support offered by multiple parents. It was also the only factor that we could

identify as a long-term SES effect since it retained some significance for independent students as well as dependents. From a financial aid perspective, the implication is to closely pay attention to the effect of having single parents on the ability to pay and ensuring that aid models fairly correct for it.

We were somewhat surprised by the limited effects of almost all types of assets on attendance and retention decisions. We assumed that assets were a more important part of the financial picture as a natural substitute for income, but in reality this wasn't the case. Of all the asset types, students only responded positively to their own investments, a figure that we believe represents college savings investments. And parents weren't willing to share any asset type with students on a consistent basis, indicating that most parent assets in this category are a "nest egg" largely kept for emergencies or to be spent on their own retirement. We surmise that there may be some sample bias here. At higher income levels, assets might still have a greater overall effect, with a diminishing marginal utility for savings beginning to occur at some level. But the general implication is to weight assets less than income in financial aid formulas like the EFC.

With income, we found evidence of financial collaboration between students and parents in the dependent community college sector where in other sectors parents' incomes didn't have much effect. We assumed that the lack of parent support was due to the fact that above the community college level, the expenses are high enough that loans are taken out rather than having parents try to foot the entire bill, especially in this low income group. We also believe that income for independent students has a two way effect: it can make college more affordable but it also serves as a substitute for investment in human capital.

There are several implications that we could take from our results on income, but it seems that when financial collaboration occurs, greater attendance and retention is achieved. By taking some degree of financial responsibility in their education, students have an incentive to remain in school. We think that shared responsibility models may be a good way to extend the positive effects into the 4-year college sectors where the “sticker prices” might otherwise deter student contribution.

Finally, we confirmed the general intuition that commitment to college increases with class standing. The closer to graduation students get, the harder they try. However if they have not graduated from a school within 5 years, they become less likely to do so. One interesting policy implication might be to adjust the allocation of aid according to standing. This could be in either direction. If more funds were awarded to more advanced students, then they would serve as a financial reward for success. Or more funds might be awarded to new students, encouraging them to progress to higher levels where consideration of opportunity and sunk costs would make them want to complete college anyway. Given the arbitrary intuition about this, more research would be needed, or it could be left alone – need-based aid could arguably be left exclusive to *financial* need.

Unemployment Model

While our award acceptance model showed determinants of a student’s decision to accept an award, our other model, the unemployment model shows how unemployment might be related to a student’s decision to apply for financial aid. Specifically, we found an increase in the unemployment rate by one percentage point leads to an increase in the number of applications from a given county and given month

by 2.9 percent to 4.0 percent depending on how many months prior we see the increase in the unemployment rate. For example, while we see an increase of 4.0 percent nine months after the one percentage point spike in unemployment, twelve months after the increase in unemployment, we see an increase in the number of applications of 2.9 percent. Simply, people don't immediately respond to a spike in the unemployment rate when deciding to invest in human capital. But what does this mean for OSAC?

Our unemployment model will allow OSAC to predict the number of future community college applications in a given month more accurately. If a large Oregon county, such as Multnomah County, experiences a significant increase in their unemployment rate, OSAC can expect to see an increase in the number of community college applications six to twelve months later. This, ultimately, will help OSAC solve the problem of allocating too much money early in the year, and not having any money left for late applicants.

Possible Improvements and Future Applications

It is without question that our analysis lacked data in several areas that would have improved our results. For the pick-up/drop-off models, we can first identify some variables that would likely become available to us had we been able to get more assistance from OSAC in translating the data. The OOG amount offered to students would have been very important, and helped us to address the debate about whether it makes a difference if aid is loan-based or grant-based (see Lisenmeir (2006)). To get a more complete picture of the financial situation, loan awards would have also been useful. Scholarship data was available, but not in numbers sufficient to yield relevant

regressions. While federal EFC substitutes as a blanket variable for financial aid, knowing the effects of specific types of aid would have been helpful. Unfortunately, these models lacked unemployment data due to translation problems, so we would like to add it and other opportunity cost factors to our functions.

For the unemployment model, the biggest improvement would be more time. 7 years was not enough to catch the full effects of a recession, and barely enough to effectively establish reoccurring cycles. We would prefer a dataset at least twice the length that would include the full effects of at least one recession. Such data would allow us to reach a much more solid conclusion about time-specific effects.

More general improvements could be made as well. The outstanding one is our sample; we would prefer to work with the initial dataset of all FAFSAs filed in the state of Oregon in its complete form. Leaving out certain vital statistics for certain groups (such as leaving out award offers for those that didn't accept) limited our ability to work and probably biased some results. Finally, we could ask for a long list of determinants and controls, including but not limited to: parental educational attainment, high school codes, gender, high school GPA, cost of living, colleges' distance to population centers

We are presenting OSAC with a solid, feasible budgeting method that greatly improves their ability to respond to changes within their application pool. They will be able to better respond to changes in the distribution of socioeconomic status, as well as be able to forecast application pool changes based on unemployment. Our analysis will also give them more information about what students do with the money once they get it. The net result will be the ability to distribute aid in a way that better meets their preferences.

We also feel that our analysis furthers the conclusions of the established academic literature on the topic. We have identified many results that shed light on specific trends in parent and student behavior when it comes to dealing with the financial burden of college. The policy implications of these results extend to the entire realm of financial aid at the very least. There is also room for plenty of future research on the path we have started. Hopefully, future research will continue to improve the effectiveness of financial aid policy.

VII. References

- Curs, Singell, Wadell (2005). Money for Nothing? The Institutional Impact of Changes in Federal Financial Aid Policy. *2005 NBER Working Group on Higher Education*. Retrieved via www.nber.org/~confer/2005/hieds05/curs.pdf.
- Dynarski, S. (1999). Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion. *NBER Working Paper w7422*. Retrieved via www.nber.org/papers/w7422.
- Dynarski, S. (2000). Hope for Whom? Financial Aid for the Middle Class and its Effect on College Attendance. *NBER Working Paper w7756*. Retrieved via www.nber.org/papers/w7756.
- Baird, K. (2006). Access to College: The Role of Tuition, Financial Aid, Scholastic Preparation and College Supply in Public College Enrollments. *NASFAA Journal of Student Financial Aid*. Vol 36, No. 3.
- Lisenmeir, Rosen, Rouse (2006). Financial Aid Packages and College Enrollment Decisions: An Econometric Case Study. *The Review of Economics and Statistics*. No. 88, pp. 126-145.
- St John, E.P. et al (2004). Expanding College Access: the Impact of State Finance Strategies. *Indiana Education Policy Center at Indiana University Lumina Research Foundation*. Retrieved via ERIC.ed.gov, link ED484236.

Betts, J. and McFarland, L. (1995). Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollments. *The Journal of Human Resources*, Vol. 30, No. 4 (Autumn, 1995), pp. 741-765.

Humphreys, B. (2000). Do Business Cycles Affect State Appropriations for Higher Education? *Southern Economic Journal*, Vol 67 (2000), pp. 398-413.

Romano, RM. Millard, T. (2006) If Community College Students Are So Poor, Why Do Only 16.9% of Them Receive Pell Grants? *Community College Journal of Research and Practice*.

Silliman, An Analysis of the Use of College Tax Credits at Four Public Community Colleges. *NASFAA Journal of Student Financial Aid*. Vol 35, No. 3.

Appendix C: County Dummies

Appthou	Unemplag9 regression
Unemplag9	0.0482943***
	(0.0190371)
percapitaincome	-0.0000165
	(0.000012)
Clackamas	0.4501232***
	(0.0969129)
Coos	0.2590095**
	(0.0892583)
Deschutes	0.0141905
	(0.0694161)
Douglas	0.3740307**
	(0.0868323)
Jackson	-0.1254449*
	(0.075341)
Josephine	0.6869915***
	(0.1031801)
Klamath	0.2429769**
	(0.0938168)
Lane	0.6671721***
	(0.0789369)
Linn	0.238448*
	(0.0916446)
Marion	0.0716708
	(0.0833537)
Multnomah	0.0794099
	(0.0901392)
Oregon(dropped)	
Polk	0.3890641***
	(0.0955788)
Umatilla	-0.246357**
	(0.1057224)
Washington	-0.4857533***
	(0.0684001)
Yamhill	0.8470889***
	(0.0805276)

Appendix D: Month Dummies

Appthou	Unemplag9 Regression
February	0.1637203
	0.0572075
March	-0.4281719
	0.0572089
April	-1.179644
	0.0572309
May	-1.35906
	0.0574685
June	-1.444831
	0.0561192
July	-1.709841
	0.0572359
August	-1.530708
	0.0572398
September	-1.783347
	0.0572398
October	-2.08698
	0.0572084
November	-2.111489
	0.0572109
December	-2.18775
	0.0572079