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Survive Then Thrive: Talent, Research Motivation, and Completing the Economics Ph.D.

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Abstract

This study investigates the completion of the Ph.D. in Economics. We use *ex ante* information, based solely upon reviewing a set of individual applications from former doctoral students. Estimation for determining success is done by logit, multinomial logit, and generalized ordered logit. We find that students need different skills and attributes to succeed at each distinct and sequential stage of the doctoral program. Significant determinants for passing the comprehensive exams include high GRE verbal and quantitative scores, a Masters degree, and a prior focus on economics. Research motivation and math preparation play significant roles in completing the dissertation, but having a Masters degree and economics preparation becomes insignificant. GRE scores disappear as a significant determinant for completion in the generalized ordered logit estimates, which emphasize the sequential nature of the Economics Ph.D. program.

Economics of Education; Economics—Graduate work; Economics students; Prognosis of success—Graduate schools; Higher education.

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Survive Then Thrive: Talent, Research Motivation, and Completing the Economics Ph.D.

1. Introduction

Every spring a global talent search occurs when doctoral admission committees pore over applications to select candidates for their Ph.D. programs.[1] Beyond normal attrition, Economics departments clearly have a stake in seeing a significant proportion of students finish the program. Aside from wherever additional university resources may accrue to departments with high completion rates, professors and departments receive prestige and gratification from the placement and success of their completed Ph.D. students in good academic institutions or private sector jobs. Since pursuing a doctorate in economics constitutes a much riskier venture than attending medical school, an MBA program, or law school (Ehrenberg, 1992), information that helps identify success in completing the Ph.D. has significant value to doctoral admission committees, departments, and administrators.[2] The nature of the Economics Ph.D. program implies greater risk relative to these alternatives. For rather than satisfying a singular threshold or set of criteria, obtaining a Ph.D., like many training programs, requires clearing a series of distinct hurdles.

This paper empirically investigates what determines successful completion of the Economics Ph.D. The data we use is retrieved from individual files of former Ph.D. students at Syracuse University (Carnegie Classification: Doctoral Research Universities II-Extensive). Our study breaks new ground in several areas. First, it consists of an *ex ante* study of variables that determine doctoral degree completion. It exclusively uses information known by the admission committee at the time of the selection process. Second, in addition to demographic information and GRE scores, we extract from this data a number of variables that have never been used in doctoral success studies. Third, we examine success for each of the three distinct and sequential stages of the Ph.D. program. This approach can be applied to other sequentially structured training programs. Fourth, this study provides results for a mid-level program rather than an elite one. In so doing, it focuses on the class of programs that produce the vast majority of Ph.D.s in Economics.

Although the Economics Ph.D. has been awarded for over a century in the United States, surprisingly little scientific evidence has been obtained on the set of skills and attributes that best predict who will earn a doctorate in economics.[3] Empirical work on this topic is meager primarily because existing studies include little data of students' aptitude and attributes. In addition, the few compiled data sets of doctoral completion (e.g. Ehrenberg, 1992) use either data from select elite institutions or highly aggregated data sets that do not identify individual institutions.

Bowen and Rudenstine (1992) amassed data on all entrants to graduate programs in six fields, including economics, at ten research universities over a 25-year period.[4] Using two-way comparisons of means they show that completion rates depended on the primary type of financial support the students received, department size (smaller was better), and varied markedly by discipline.[5] Using a duration model, Ehrenberg and Mavros (1995) confirm the importance of financial support for completion rates of Cornell University Ph.D. students in four disciplines, including economics, over a 24 year period. Among economics students, completion rates were highest for those with research assistantships, then for fellowships, and the least likely for teaching assistants.[6] In addition, they find that completion rates are higher for entering students with master degrees, lower for Americans, but unrelated to student ability as measured by GRE scores. Booth and Satchell (1995), in a retrospective national data set (individual institutions were not identified) of over 480 students who began British Ph.D. programs in 1980, also reached the conclusion that measured student quality does not affect completion rates.[7] In contrast to Ehrenberg and Mavros (1995), though, they also find that financial support (i.e., research council funding) failed to influence the likelihood of finishing the degree.

Our study takes a different approach. The authors in the foregoing papers all estimate how changes in doctoral students' lives during the course of their study (e.g., sources of funding, grades in the Ph.D. program, marriage, children, job prospects of those with the doctorate, etc) influence the probability of completing the degree.[8] Instead, we investigate the determinants of student outcomes *ex ante* to their entry in the program. The variables that we use come directly from the application files, the information known to the selection committee at the time of selecting candidates in the spring. The only other *ex ante* study in this area that we are aware of is Krueger and Wu (2000), who estimate what characteristics of the more than 300 applicants to Princeton's Economics Ph.D. program determine admission and subsequent job placement.

To better measure the set of skills and attributes necessary to complete a Ph.D. in Economics, our study analyzes a rich set of individual-level data extracted directly from the application files. Studies in this area typically rely on institutional records (e.g. Bowen and Rudenstine 1992, Ehrenberg and Mavros 1995). While this work has the virtue of analyzing multiple departments and (with the former) multiple universities, it contains limited information about individual ability, as both these sets of authors lament. Following the advice of Ehrenberg and Mavros (1995), we use "additional information about a student's true ability." Besides demographic variables and GRE scores, our data set -- taken from individual student application forms, transcripts, and personal statements -- enables us to test for a remarkably wide array of determinants for success in an Economics Ph.D. program.

As another distinction, we focus on the various stages in the Economics Ph.D. program. Our data set contains information on individual outcomes for each of the three major steps: Theory Comprehensive Exam, Field Comprehensive Exam, and Completion of the Dissertation. Rather than treat success either as earn or fail to earn the doctorate or analyze how the probabilities change each year, we separately estimate what characteristics predict success at each stage of the Ph.D. program. The emphasis on each stage is fundamentally important given the structure of most Ph.D. programs in economics, but has not been examined in any existing empirical literature we are aware of. Thus, while we define ultimate success as completing the doctoral program, we empirically investigate whether students need different skill sets to pass the comprehensive exams, as opposed to what is needed to pursue an original research project and finish the dissertation.

As a final difference between this study and others, we examine students at a mid-level program rather than at elite Economics Ph.D. departments as is the case with Ehrenberg and Mavros (1995), Krueger and Wu (1989), Bowen and Rudenstine (1992), and Espenshade and Rodriguez (1997). With this feature, our data may provide more variation that lend themselves to study of the production of Economics Ph.D.s. For example, top censoring may limit the usefulness of many important determinants at places like Princeton where the mean score of admitted students for the GRE Quantitative Exam was 774 out of a maximum of 800 (Krueger and Wu, 1989, Table 1, 84). Our results are of particular importance to the large number of Economics Ph.D.s produced outside the very elite.[9] In 2003, programs outside the top ten produced 78 percent of that year's doctorates in Economics (National Science Foundation 2005, Roessler 2005). In this regard, our study provides a blueprint for individual departments to make their own analyses as to what determines success in completing the Ph.D.

Section 2 introduces our models and discusses the variables we extract from the graduate student files. In section 3, we empirically investigate the determinants of doctoral student success at each stage of evaluation. We use three estimation techniques: logit, multinomial logit, and generalized ordered logit. While each of the three methods provides its own interpretation, generalized ordered logit in particular emphasizes the sequential nature of the Ph.D. economics program. In general we find that students who pass the comprehensive exams exhibit intellectual firepower (high verbal and quantitative GRE scores), have a Masters degree, and focused on economics as reflected in the number of economics courses taken beforehand. But having passed the comprehensive exams, what it took to complete the degree was strong research motivation and more math preparation. We find that research motivation, measured by whether the student mentioned in their personal statement a paper that they had done, is a significant indicator for successful completion of the dissertation. The significant determinants of passing the comps generally become insignificant for the dissertation step.

In section 4 we use factor analysis to extract seven "factors," or underlying latent behavioral variables, from our data set. We conduct the same analysis as in section 3 using the factors. Our logit and multinomial logit results tell the same straightforward story: overall intelligence plays a significant role in success for each step, but completing the dissertation also requires motivation and research desire. The findings from generalized ordered logit estimation affirm those results and provide evidence that passing the comprehensive exams additionally requires math talent.

All told, then, we find that students need different skills for success at the various stages of the doctoral program. Surviving the comprehensive exams requires talent and acquired tools.

To thrive in the dissertation stage, though, additionally requires motivation for doing economics research. Section 5 concludes the paper.

2. Models and Data

The models we investigate can all be expressed in the following form. For the *i*th student, as $i = 1, 2, \ldots, T$, the probability of success is in the *j*th step is given by:

$$P(Success_i \mid x_i) = F(x_i^{'}\beta_j), \tag{1}$$

where the qualitative variable *Success* is a measure of success which may be binary (e.g. Pass versus Fail) or ordinal (e.g. Failed Theory Comprehensive Exam, Passed Theory Comp But Did Not Complete, Completed Dissertation), F is a cumulative distribution function, x is a vector of exogenous variables for the individual which affect the outcome, and β is the parameter vector. A more explicit description of the model specifications for each of the estimation procedures appears in the Appendix.

The equation falls into the class of limited dependent variable models. The underlying latent dependent variable can be regarded as the cumulative number of unobservable "performance units" that determine success. If the student's performance units meet or exceed the department standard, the student succeeds or passes; otherwise he/she fails. Given the student's *ex ante* characteristics, he/she acquires these performance units in the graduate program based upon academic ability, work ethic, and behavioral or emotional characteristics.

We obtain the data by reviewing all the available individual files of recent Ph.D. students in the Syracuse University economics department. The sample consists entirely of students that completed all the requirements, left the program voluntarily, or failed the theory or field comprehensive exam in two attempts. It includes no current students in the program, even if they have finished one or more steps. As a result, the sample size is the same for all our estimations. Extracting this detailed individual information from well-over 100 files yields 78 observations with data for all the outcome variables and determinants.

Summary statistics appear in Table 1. Overall, we find the sample means and variation in the data reasonably representative of the Ph.D. program at Syracuse. The first three rows of data consist of the *Success* or outcome variables, which encompass the major steps in the Ph.D. program. The variable *Theory Comp* equals one if the student passed the Theory Comprehensive Exam, zero otherwise. *Field Comp* and *Completed* are defined correspondingly, based upon the Field Comprehensive Exam and the Dissertation. We do not distinguish between whether the student passed the Theory or Field Comp on the first or second attempt.

To avoid giving up too many observations and degrees of freedom, we made several choices regarding the outcome variables. Students who left the program before attempting a given step receive a value of 0 for this outcome. Some students in this group decided that they do not have the performance units to reach the expected standard and decided not to try. Others who transferred from the program before attempting the outcome (they receive a 1 on any previous outcomes in which they succeeded) may have the necessary academic abilities to succeed, but did not seek to obtain the necessary performance units through study. We make no effort to distinguish between voluntary and involuntary leavers, since our goal is to evaluate what determines which students completed the degree in this program.

The sequential structure of the Economics Ph.D. program implies that for all students, the steps appear in the same distinct order—Theory Comprehensive exam, Field Exam, and

Completion (of dissertation). The program does not allow a student to even attempt a step until they have succeeded in all the previous ones. This property implies dependence within the outcome variables. Observations where *Completed* equals 1 necessarily have values of 1 for the other two outcome variables. For the same reason, observations with values of 0 for any outcome have zeros as well for subsequent outcomes.

The remaining variables in Table 1 make up the determinants of success. The next block consists of determinants other than dummy variables for citizenship. The first three variables in this group are the student's GRE scores—Verbal, Quantitative, and Analytic.[10] These variables represent performance on standardized tests and are required for all applicants to the Syracuse Ph.D. program. They might be regarded as measures of innate aptitude.

Ehrenberg and Mavros (1995) argue that GRE scores poorly measure student quality, which accounts for the lack of association with degree completion in their study. The absence of a statistically significant relationship between GRE score and degree completion is also reported by Zwick (1991), Zwick and Braun (1988), and Dawes (1975). On the other hand, Attiyeh and Attiyeh (1997) and Krueger and Wu (2000) show that GRE scores, especially from the quantitative section, strongly predict admission to economics doctoral programs. But if these standardized test scores do not predict degree completion, then the use of GRE scores by institutions of higher education may be, as McCloskey (1994) comments, merely placing "crowns on the heads of the 'brightest," so measured at age 21. Hansen (1971) finds a larger role of the quality of the undergraduate institution and GPA than for GRE scores, but GRE quantitative scores help to predict second year grades and who continues to the second year.[11] Krueger and Wu (2000) show that GRE scores, especially from the quantitative section, are a statistically significant predictor of applicants' subsequent job placement—perhaps the ultimate measure of success.[12]

The next two variables come from our examination of the students' transcripts and are not used in other studies to our knowledge. The variable *Math Courses* refers to the number of courses in the mathematics department Calculus I or above that appear in the student's transcript. Similarly, *Econ Courses* denote the number of economics courses the student has taken. With either variable, we do not distinguish whether the student had taken them as a matriculated undergraduate, after graduation, or in a graduate program. Consequently, one student who majored in economics as an undergraduate and completed two Masters programs amassed 40 courses in the subject![13]

The dummy variable *Masters* equals 1 if the student had a Masters degree coming into the Ph.D. program. Ehrenberg and Mavros (1995) find that possession of a Masters degree increases completion rates for Economics Ph.D.s at Cornell. Note that test scores and transcript information all come from institutional records, rather than from student surveys. The results of Maxwell and Lopus (1994) indicate that students' systematically overestimate self-reported aptitude information.

The next three variables come from careful reading of the individual student's personal statement, and have not been included in any other doctoral completion papers. The variable *Mention Paper* equals 1 if the student referred to a paper they had done in their personal statement, 0 otherwise. The paper they mention could be from an undergraduate course they had taken, a senior thesis, a Masters project or thesis, or a project in which they had participated in as a research assistant. This variable is an indicator of the student's demonstrated interest in doing economics research, which possibly motivated them to pursue the Ph.D. It turns out to be a significant determinant of success, especially in completing the dissertation.

We extracted data from the personal statements on two other determinants. *Specific Topic* equals 1 if the statement mentions one or more specific topics that the student possibly wishes to study, 0 otherwise. Although this does not have to be the topic they ultimately will pursue for their dissertation, the variable provides a measure of research focus. *Specific Member* equals 1 if the personal statement lists one or more department members whose work interests the student, 0 otherwise. This variable measures departmental familiarity and the potential for effective matching with a dissertation advisor.[14] The next two variables are standard demographic measures—*Age* denotes the student's age in calendar years when he/she began the Ph.D. program, and *Female* equals 1 if female, 0 if male.[15]

The last six variables consist of dummy variables for citizenship. Our classifications are American, Chinese, Other Pacific Rim (e.g. South Korea), Other Asian (e.g. India, Pakistan), European (including Turkey), and Middle Eastern/African. The sample consists of nearly 60% American students. This percentage may be higher than found in many Ph.D. programs, but is historically representative of the Syracuse program, especially with its emphasis within the Maxwell School of Citizenship and Public Affairs on policy-oriented research.

3. Empirical Results: Determinants of Success

This section presents findings from estimating limited dependent variable models involving the distinct steps in the Ph.D. program. The determinants come from the variables listed in Table 1. For purposes of examining as many determinants as possible, we include all the characteristics for each outcome.

We also include several interaction terms, interacting *GRE Quantitative* with *GRE Analytic*, *Math Courses*, and *Econ Courses*. These terms test for a possible "compensation effect," involving students who seek Ph.D. study in economics but have a low GRE Quantitative score. If the GRE Quantitative exam measures quantitative aptitude, demonstrating analytic ability or bulking up on math or economics courses may increase the probability of success more strongly for students deficient in this attribute.

To illustrate how this behavior works within the model, consider for example the effect of *Math Courses*. Let α_1 and α_2 be the parameters corresponding to *Math Courses* on its own and the interaction of *Math Courses* and *GRE Quantitative*. Then the marginal effect of *Math Courses* on the probability of success includes the term

$$\alpha_1 + \alpha_2(\textit{GRE Quantitative}), \qquad (2)$$

and carries the same sign as well.

The compensation effect implies that $\alpha_1 > 0$ and $\alpha_2 < 0$. The marginal effect has positive sign only if *GRE Quantitative* is less than the threshold value of $-\alpha_1/\alpha_2$. Thus, math courses only help students with relatively low GRE Quantitative scores. In addition, a lower GRE Quantitative score generates a marginal effect with larger magnitude. Math courses taken beforehand have a stronger effect on the probability of success for students who are more deficient in quantitative aptitude.

Before proceeding to the estimations, we must address several econometric issues inherent to studies of this type. Two potential selection problems arise, because we do not observe the outcomes of all students who apply for the program in Syracuse. The first selection problem occurs in the decision to offer admission, since only a limited set of individuals are picked. The second selection problem results from decisions made by students once the offer was made, as most get offers from other schools and many choose not to enter the Syracuse program.

To receive an offer, a student must meet certain threshold criteria. Therefore, because the program makes offers to a select group of candidates, they may be systematically different than the group that was not selected. However, since students who did not get accepted are screened on the basis of their applications materials alone, the selection is based purely on observable factors. Therefore controlling for observed characteristics in the estimations lets us control for selection on observables (Angrist and Krueger 1999). Controlling for selection applies to students who were not given the offer either because they were regarded as too weak or because they were regarded as a bad fit with the program (e.g. differences in field interests versus offerings).

However, another selection problem may arise when students have offers from Syracuse University but choose not to enroll in the program. If students who enter the program are systematically different from students who do not come, then selection would be done on unobservable characteristics, and the estimated coefficients for success could be biased. For example, a student's success may be based not only on the characteristics observed by the admission committee, but other characteristics such as motivation or persistence. Only the individual student has complete information on his/her entire set of qualities. And if they have an offer from a higher ranked program, the more ambitious students may systematically choose that program over Syracuse. Therefore, students who choose Syracuse may have the same values for observable characteristics like GRE scores or number of math courses as students who do not come to Syracuse, but may have lower probability of success.

Like most studies in this and related areas, we do not attempt to correct for potential selection problems. In this way, we estimate the effects observed for individuals who have chosen to join the Syracuse University program. We assume that the unobservable characteristics for selection are not correlated with the independent variables in the model, so our coefficients have the interpretation of partial correlation coefficients.

The models are estimated using Version 7 of Stata. All models employ the Huber-White sandwich variance-covariance estimator to produce standard errors that correct for heteroskedasticity (White 1980). Estimated models in this section include a constant term and citizenship dummy variables for all groups except Other Asian, although their parameter estimates are not reported in the Tables.[16]

We begin by estimating the probability of success at each of the three separate stages in the Ph.D. program. This set of estimations focuses on the following probabilities independently:

$$\begin{aligned} &P(\mathit{Success} = \text{Passed Theory Comprehensive Exam}),\\ &P(\mathit{Success} = \text{Passed Field Exam}),\\ &P(\mathit{Success} = \text{Completed Dissertation}). \end{aligned}$$

Logit estimations for determinants of success appear in Table 2 (probit estimations generate very similar results). The Table reports estimates of equation (1) with the binary variable *Pass* versus *Fail*, for each stage of the Ph.D. program.

For the Theory Comprehensive Exam, the findings show significantly positive effects for GRE Verbal and Quantitative exams and for having a Masters degree. The effect of *GRE Verbal* is much smaller in magnitude relative to *GRE Quantitative*. The results suggest a possible compensation effect for *GRE Analytic*, but not for either math courses or economics courses. None of the personal statement variables show significant effects.

Moving to the Field Comprehensive exam, we find similar results. The variables *GRE Verbal* and *GRE Quantitative* again have significantly positive effects, with magnitudes similar to the estimates for the Theory Comp. None of the personal statement variables turn up significant as well. But several results differ from those of the Theory Comprehensive Exam. Possession of a Masters degree does not significantly help to pass the Field Exam. And the results indicate a compensation effect for economics courses.

Estimates for success in the last step, Completion, generate several notable distinctions as well. *GRE Quantitative* remains a significant determinant, but *GRE Verbal* no longer plays a significant role. The coefficients of *GRE Analytic* and *Math Courses* are significant with evidence of compensation effects, but the results provide little evidence regarding economics courses. In addition, the variable *Mention Paper* has a significantly positive effect on the probability of completion. The overall results indicate that quantitative talent and preparation along with interest in writing research papers are the most important determinants of success in completing the Ph.D. program.

The estimations for passing the Field Exam generate a compensation effect for taking economics courses with a plausible threshold GRE Quantitative score of approximately 692, just about equal to the sample average. The threshold GRE Quantitative score for the GRE Analytic approximately equals 702 for Completion. At the same stage, the findings indicate an estimated threshold for math courses of GRE Quantitative = 743.

The logit estimations investigate the significant determinants for completion of each stage, but have little to say about where the student ultimately ends up in the program. Some students who pass the theory comprehensive exam will go on and pass the field comprehensive exam, some won't. Some students who pass the field comp will ultimately complete the dissertation, some won't.

To address this issue, we perform multinomial logit estimation. This procedure moves toward examining the terminal outcomes of students in the Ph.D. program, and the variables that determine where students place into the separate categories. In the context of the Ph.D. program, one generally classifies terminal outcomes into four categories – exam failures, or students who failed the theory comp; passers on the theory comp but not the field comp; passers on both comprehensive exams who did not complete the dissertation; and those who completed.

We make a couple of compromises due to data limitations. First, we don't have enough observations for students who passed the theory comp but not the field comp. Thus we work with three categories—Exam Failures; Passed Comp(s) Did Not Complete; and Completed. The middle classification consists of students with a 1 on the variable *Theory Comp* and a 0 on *Completed*. We find very similar results for estimations when we replace the middle category with Passed Field Comp Did Not Complete. Second, since all variables in the estimation must be represented in all categories, we need to drop the variables *European* and *Specific Member*. We make the same adjustments for the estimations in Table 4.

The multinomial logit in our context, then, takes the form of simultaneous estimation of the probabilities:

$$\begin{cases} P(\textit{Success} = \text{Passed Comp(s) Did Not Complete versus } \textit{Failure} = \text{Exam Failure}), \\ P(\textit{Success} = \text{Completed versus } \textit{Failure} = \text{Exam Failure}). \end{cases}$$

As Maddala (1998) explains, the multinomial logit technique for three categories can be regarded as extending a two-step procedure involving logit estimation of limited dependent variable models. In the context of our model, we use Exam Failures as the basis category. Step one would consist of logit estimation of Passed Comp(s) Did Not Complete versus Exam Failures. Step two would then perform logit estimation of Completed versus Exam Failures. Hence, the estimates investigate the significant determinants of what propels students beyond the point of failing the theory comprehensive exam. The multinomial logit extends the two-step procedure by performing joint estimation, preserving estimator consistency while improving efficiency.

Findings for the multinomial logit in Table 3 largely reinforce the results in Table 2. Scores on all three GRE exams are significant determinants of whether students pass one or more of the comprehensive exams but did not complete the program, with significantly positive effects for *GRE Verbal* and *GRE Quantitative*. Having a Masters degree is a significantly positive determinant for the middle category as well. The parameter for *Age* also comes in significant for the first time, being younger increasing the probability of landing in the middle category relative to failing the Theory Comp. The estimated coefficients for both variables involving math courses are significant at the 10% level but opposite in sign from what the compensation effect predicts.

For placing in the Completed category relative to failing the Theory Comp, all GRE Variables have significant effects with the Verbal and Quantitative significantly positive. Here we find evidence of significant compensation effects with *Math Courses*, *Econ Courses*, and *GRE Analyt*ic. The effects of *Masters* becomes insignificant for landing in the Completed category. And as in the logit estimations, the results indicate that *Mention Paper* has a significantly positive effect upon completion.

Where significant compensation effects occur, the estimated thresholds for the GRE Quantitative score are generally lower relative to the logit estimations. The threshold for GRE Analytic in the middle category is for a GRE Quantitative score equal to 567, and 489 for GRE Analytic in the Completed category. The estimated threshold with math courses in the Completed category is GRE Quantitative = 480. Econ courses in the Completed category generate a more plausible threshold of 639.

The estimated low GRE Quantitative thresholds for the math courses and GRE Analytic may suggest behavior in addition to the compensation effect. The estimates in fact suggest negative effects on the probability of success for students with GRE Quantitative scores above the threshold who have taken more math courses or have a higher GRE Analytic exam. While the compensation effect holds for students with GRE Quant scores below these thresholds, why might students with better GRE Analytic scores and more math courses have a decreased probability of success? Apart from shortcomings in the data and the multinomial logit technique for this application, two behaviors might account for these findings.

The first involves transferring from the program. More talented students who get into the Syracuse Ph.D. program and take some courses may decide to seek entry in a higher ranked program. At Syracuse we encounter some of this behavior, but not to a frequent extent. The second consists of adverse selection by very talented applicants who choose Syracuse over higher ranked programs. These students may have superb paper credentials but may lack motivation or work ethic, so they opt for a “less challenging” program. They quickly (and frequently to their dismay) learn that all respectable Ph.D. Economics programs demand from their students substantial amounts of aptitude, time, and work effort.

Our next estimation again examines terminal outcomes, but emphasizes the sequential nature of the Ph.D. program. We employ the generalized ordered logit. The procedure is an extension of the ordered logit technique, by allowing for the possibility of differential effects of independent variables on success probabilities at each stage. We use the same three categories as in the multinomial logit—Exam Failures, Passed Comp(s) Did Not Complete, and Completed.

Like the multinomial logit, the generalized ordered logit extends a two-step procedure by joint estimation as explained in Maddala (1998). In the context of our problem, step one consists of logit estimation of Passed Comp(s) Did Not Complete versus Exam Failures. But with the generalized ordered logit, step two consists of logit estimation of Completed versus Passed Comp(s) Did Not Complete, respectively assigned values of 1 and 0. Therefore we simultaneously estimate the following probabilities:

$$\begin{cases} P(\mathit{Success} = \text{Passed Comp(s) Did Not Complete versus } \mathit{Failure} = \text{Exam Failure}), \\ P(\mathit{Success} = \text{Completed versus } \mathit{Failure} = \text{Passed Comp(s) Did Not Complete}). \end{cases}$$

Hence, the generalized ordered logit offers a particularly interesting interpretation for the probability depicted on the bottom row. Given that the student passes the Theory Comprehensive Exam, what are the significant determinants to help him/her complete the dissertation from there?

Findings for the estimated generalized ordered logit model, which appear in Table 4, speak to the different skills needed in the two stages. Significant determinants of passing the Theory Comp with positive effects include *GRE Verbal* and *GRE Quantitative*, *Masters*, *Female*, and *Specific Topic*. The estimated coefficient for *Age* is negative and significantly different from zero. In this stage, *Econ Courses* show a significant compensation effect, with an estimated threshold of *GRE Quantitative* = 670.

The results put forth a considerably smaller number of significant determinants for the next step, Completion. In particular, all the variables for GRE scores, *Econ Courses*, *Masters*, and *Female* become insignificant. On the other hand, the findings suggest a significant compensation effect for completion with regard to *Math Courses*, with an estimated threshold of *GRE Quantitative* = 695. They also indicate a significantly positive effect for *Age* in the Completed category. In an interesting contrast, the results indicate that age may be a detriment to passing the Theory Comp. Once beyond that stage, though, it becomes an asset for Completion.

The effect of *Female* presents another interesting contrast. The estimate is positive and significant for the stage of Passing Comp(s) Did Not Complete, but is negative and insignificant for Completion. The findings indicate that female students have the intellectual firepower and unobserved attributes beyond the male students to pass the comprehensive exam(s), but lose this advantage in the completion stage. One possibility, based solely upon anecdotal observation, involves a greater tendency for females to leave the program due to personal reasons, such as moving to be near a significant other.

A notably more robust finding is the significantly positive effect of the *Mention Paper* variable. Even after controlling for talent and acquired skills, the interest in writing economics papers remains a significant determinant of completing the Ph.D.

Notice that the effect of GRE scores disappears in the completion stage only within the sequence-driven generalized ordered logit model. The finding suggests that both the logit and multinominal logit estimates that generated a significant effect of GRE scores were the result of not separating the Comp(s) stages from the modeling of the Completion stage. In the logit estimations, completers are compared both to failures and comp passers; the multinominal logit case compares completers to students who failed the theory comprehensive exam.

4. Empirical Results: Factor Analysis

We now examine success in the Ph.D. program using factor analysis (Johnson and Wichern 1992). This methodology assumes that the specific determinants of success reflect underlying latent behavioral factors. Factor analysis produces estimates of the factors as linear combinations of the determinants. The procedure becomes particularly advantageous when the data contain a large number of determinants relative to the sample size, since the number of factors is considerably less than the number of determinants.

Table 5 reports the estimated factors for success in the Ph.D. program. They appear as rotated factor loadings using the varimax procedure. This rotation technique generates factors that describe information in the initial factors by re-expressing them, so that loadings on a few initial variables are as large as possible. By construction latent variables follow a standard normal distribution, are orthogonal to each other, and factor loadings are constrained to one. We obtain very similar results using the promax rotation, which produces non-orthogonal factors.

The 18 determinants (including the six citizenship dummy variables) generate seven factors with a cumulative proportion of 95%. While the number of factors we selected is somewhat arbitrary, we follow several principles suggested in this literature. If there are too few factors, the variables for several distinct concepts may be merged. With too many factors, several factors may attempt to measure the same concept, causing the factors to get in each other's way. Our experience here led us to choose seven factors.

A key issue in factor analysis centers on identifying the latent behavioral characteristics. The procedure generates the linear combinations, but gives no further information. For a given factor, the researcher comes up with the behavioral characteristic(s) based upon the determinants with coefficients of economically important magnitudes in the linear combination. The signs of these coefficients provide clues as well. We choose to identify these behavioral characteristics *a priori*, before seeing how the factors perform in the estimated models.

The linear combinations generating the factors appear as columns in Table 5.[17] The general criterion we use for a determinant to be economically meaningful is for a coefficient to have an absolute magnitude of at least 0.20. This magnitude tends to result in determinants that are significantly correlated (at the 5% level) with the estimated factor. We do not confine ourselves to this criterion, though. In Table 5, we report in boldface determinants that we feel are economically important in uncovering the behavioral characteristic.

Table 5 also includes our own designations of these characteristics for each of the seven factors, listed as column headings. They come from examining all the information in the linear combination that makes up a specific factor, within the context of students who seek Ph.D. study in Economics.[18] Clearly this aspect of factor analysis revolves around judgment – different interpretations can certainly arise from the same information. Further, some factors offer much easier interpretation for designations of behavioral characteristics than others.

We designate factor (1) as *Professional Maturity*. The factor contains large positive coefficients for *Masters* and *Age*, and a large negative coefficient for *Math Courses*. The factor may reflect the behavior of professionals who return to school and seek the Ph.D. in economics. Factor (2) strongly points to *Math Talent*. This factor has *GRE Quantitative* as the only behavioral determinant with an economically meaningful coefficient. Its positive sign and large magnitude indicate that the factor measures aptitude in quantitative skills. Factor (3) highlights positive and economically important impacts of *Econ Courses*, *Masters*, and *Age*, along with negative impacts of *GRE Analytic* and *Math Courses*. We designate this factor as *Economics Background*. The factor might reflect Masters students in economics without a strong math background who wish to pursue this study at the Ph.D. level.

We refer to factor (4) as *Motivation and Research Desire*. The factor contains a number of economically important coefficients. The motivation aspect of the designation stems from the positive impact of *Math Courses* and *Economics Courses*, along with the negative impacts of *GRE Verbal* and *GRE Analytic*. This result can be interpreted as students who increase their preparation for study in Ph.D. Economics by taking more economics and particularly math courses, perhaps to overcome deficiencies in overall talent. The research desire part of the designation primarily comes from the large positive coefficient for *Specific Topic*. The factor also includes a positive coefficient for *Mention Paper*, a significant determinant of success from our previous results, which has the largest magnitude among the seven factors.

Factor (5) is designated as *Undergraduate Background*. The linear combination includes positive and economically meaningful coefficients for all three GRE scores, although the magnitudes are not as large as those in factor (7). In addition to this information, our designation comes from a positive impact of *Econ Courses* and a negative impact of *Age*. The factor seems to reflect strong overall candidates consisting of talented younger students with Bachelors degrees in economics. Factor (6) features large positive coefficients for *Specific Member* and *Age*, along with a large negative coefficient for *Mention Paper*. We refer to this factor as *Departmental Familiarity*. It appears to reflect the underlying behavior of possibly older students with knowledge of the individual department, but who have not expressed an interest in writing economics papers.

Factor (7) appears to provide a straightforward interpretation. It includes large positive coefficients for all three GRE scores. We designate this factor as *Overall Intelligence*, or sheer intellectual horsepower. Further information comes from examining the negative coefficient for *Specific Member*. This factor seems to reflect substantial overall talent, reflected in applicants who represent national candidates for Ph.D. study in economics.

From here, we examine the effects of these factors on success in the Economics Ph.D. program. We perform the same econometric investigations as before, except that we use the factors instead of the specific determinants. Table 6 reports logit estimates for all three stages of the Ph.D. program. *Overall Intelligence* is the only factor with a significantly positive effect for passing the Theory Comp and the Field Comp. The estimations generate positive parameter estimates for *Economics Background* and *Motivation and Research Desire*, but the coefficients are not estimated precisely. For the completion stage, both *Overall Intelligence* and *Motivation and Research Desire* have positive and significant effects.

Multinomial logit estimates appear in Table 7. No effects are significant in the terminal category of Passed Comp(s) Did Not Complete. *Math Talent*, *Economics Background*, *Departmental Familiarity*, and *Overall Intelligence* all have positive effects, but are not estimated with precision. Moving to the category of Completion, the results reveal significantly positive effects for *Motivation and Research Desire* as well as for *Overall Intelligence*. *Math Talent* and *Economics Background* have positive but insignificant estimates.

Table 8 reports generalized ordered logit estimates. For the terminal stage of passing the Theory Comprehensive Exam, the findings reveal significantly positive effects for *Math Talent* and *Overall Intelligence*. Given that the student passes the Theory Comp, though, the significantly positive factors for Completion consist of *Overall Intelligence* along with *Motivation and Research Desire*.

5. Conclusion

Our overall findings tell a coherent story about what determines success in the Economics Ph.D. program. They strongly indicate that students need different skills at various stages. And more directly, they point to the importance of the desire to undertake economics research as a key to completing the doctorate. Along with the necessary talent and acquired tools that enable them to survive the comprehensive exams, interest in doing economics research plays a significant role for them to thrive in pursuing the dissertation.

With the intensity of this data and the deliberate study of each step in the Economics Ph.D. program, these results provide scientific evidence that support anecdotal suspicions regarding what it takes for students to succeed. Moreover, our study provides a blueprint for departments that wish to undertake such an examination of their own Ph.D. programs in economics, and possibly other disciplines as well. This issue becomes particularly important in an era of greater program assessment.

Our results raise questions about their general applicability to Ph.D. Economics programs across the US, and even worldwide. Short of a cross-department series of investigations along these lines, what results might be basically peculiar to the Syracuse program or similar programs? We offer several thoughts in this direction.

First, as a mid-level program Syracuse may be more susceptible to students transferring and to adverse selection than higher ranked programs. This aspect suggests that the "compensation effects," involving the significant interaction terms, may not appear for other programs. Second, the Syracuse program features only four Ph.D. fields—Public Economics, Urban Economics, Labor Economics, and International Trade. It may be more important for success at Syracuse, relative to programs with more diversity of fields, to identify applicants with definitive interests in these field areas.

Third, the Syracuse program emphasizes applied research, especially since it resides within the Maxwell School of Citizenship and Public Affairs. The program produces few dissertations in pure theory. This characteristic may be important in explaining the significance of mentioning a paper for success. The research papers in which nearly all these applicants would be involved would be those that use economic data and estimate models. This aspect might be especially important given that their subsequent dissertation consists of applied research, albeit with more advanced theoretical methods, modeling, data, and econometric technique.

Caveats aside, our study provides a number of intriguing findings regarding success in the Ph.D. Economics program that lend themselves to extension and further study. Along with talent, our results provide empirical evidence that motivation and interest in doing economics research play a significant role in success, especially with completion. This brings to mind a recent conversation between one of us as a Director of Graduate Studies and an applicant with outstanding academic credentials. The student stated that admission directors at several Ph.D. programs had informed him that, "Nobody reads the personal statements." Perhaps they're missing something.

Appendix: Explicit Specifications For The Estimated Models

The structural models are based upon the latent variable $Success^{*}$, defined as the number of performance units. All models are described in terms of the *i*th student and the *j*th step, with μ denoting the residual and x and β defined previously.

Logit

The structural model for success is given by:

$$Success_i^{*} = x_i^{'}\beta_j + u_i.$$

We define $Success_i = 1$, if $Success_i^{*} \geq 0$, and 0 otherwise,

and model probability as:

$$P\left(Success_i = 1 \mid x_i\right) = 1 - F(-x_i^{'}\beta_j),$$

where $F(x_i^{'}\beta_j) = e^{x_i^{'}\beta_j} / (1 + e^{x_i^{'}\beta_j})$.

Multinominal Logit

The structural model for j = 0, 1, 2, is given by:

$$Success_i^{*} = x_i^{'}\beta_j + u_i, \text{ with } \begin{cases} Success_i = 0, \text{if} & Success_i^{*} < 1; \\ Success_i = 1, \text{if } 1 \leq & Success_i^{*} < 2; \\ Success_i = 2, \text{if} & Success_i^{*} \geq 2. \end{cases}$$

The model is estimated using the following probability specification, with $Success = 0$ as the reference category:

$$P\left(Success_i = j \mid x_i\right) = \frac{e^{x_i^{'}\beta_j}}{1 + \sum_{j=1}^{2} e^{x_i^{'}\beta_j}}.$$

Generalized Ordered Logit

The structural model for j = 0, 1, 2, is given by:

$$Success_i^* = x_i'\beta_j + u_i, \text{ with } \begin{cases} Success_i = 0, \text{ if } \quad Success_i^* < 1; \\ Success_i = 1, \text{ if } 1 \leq Success_i^* < 2; \\ Success_i = 2, \text{ if } \quad Success_i^* \geq 2. \end{cases}$$

The model is estimated using the probability specification:

$$\begin{cases} P(Success_i = 0 \mid x_i) = F(-x_i'\beta_1), \\ P(Success_i = 1 \mid x_i) = F(-x_i'\beta_2) - F(-x_i'\beta_1), \\ P(Success_i = 2 \mid x_i) = 1 - F(-x_i'\beta_2), \end{cases}$$

where $F(x_i'\beta_j) = e^{x_i'\beta_j} / (1 + e^{x_i'\beta_j})$.

Table 1 – Summary Statistics (Sample Size = 78)

Variable	Mean	Standard Deviation	Minimum	Maximum
Theory Comp	0.628	0.486	0	1
Field Comp	0.551	0.501	0	1
Completed	0.410	0.495	0	1
GRE Verbal	522.821	123.034	280	780
GRE Quantitative	692.051	80.362	440	800
GRE Analytic	646.154	110.773	290	800
Math Courses	2.910	2.649	0	15
Econ Courses	9.654	6.976	0	40
Masters	0.295	0.459	0	1
Mention Paper	0.462	0.502	0	1
Specific Topic	0.667	0.474	0	1
Specific Member	0.064	0.247	0	1
Female	0.397	0.492	0	1
Age	25.730	4.856	20	50
American	0.590	0.495	0	1
Chinese	0.154	0.363	0	1
Other Pacific Rim	0.051	0.222	0	1
Other Asian	0.103	0.306	0	1
European	0.064	0.247	0	1
Middle Eastern/African	0.038	0.194	0	1

Table 2 – Logit Estimates: Determinants of Success

Determinant/Outcome	Theory Comp	Field Comp	Completed
GRE Verbal	0.0107 (0.0039)**	0.0085 (0.0039)**	0.0039 (0.0030)
GRE Quantitative	0.0849 (0.0360)**	0.0964 (0.0448)**	0.0928 (0.0337)**
GRE Analytic	0.0532 (0.0353)	0.0606 (0.0407)	0.0618 (0.0297)**
GRE Analytic*GRE Quantitative	-0.00009 (0.00005)*	-0.00009 (0.00006)	-0.000088 (0.000043)**
Math Courses	-0.3739 (1.4599)	2.0141 (1.4429)	3.7170 (1.4386)**
Math Courses*GRE Quantitative	0.0002 (0.0021)	-0.0032 (0.0021)	-0.0050 (0.0021)**
Econ Courses	0.6411 (0.6065)	1.0523 (0.6023)*	0.9254 (0.7460)
Econ Courses*GRE Quantitative	-0.0011 (0.0009)	-0.00152 (0.00085)*	-0.0013 (0.0010)
Masters	2.4420 (0.9575)**	0.4334 (0.8876)	-0.3658 (1.0003)
Mention Paper	1.2925 (0.8660)	1.1106 (0.7983)	1.9105 (0.8105)**
Specific Topic	0.6835 (0.8093)	0.5272 (0.7239)	0.0602 (0.7201)
Specific Member	0.2772 (1.0965)	-0.2595 (0.9807)	0.4582 (1.0762)
Female	-0.1993 (0.7026)	0.0027 (0.6540)	-0.4339 (0.7711)
Age	-0.0906 (0.0736)	-0.0089 (0.0808)	0.1030 (0.0723)
Pseudo R^2	0.3393	0.3100	0.2792
Log Likelihood	-34.0078	-37.0196	-38.0615

Notes: Standard errors appear in parentheses. All estimated models include an intercept and dummy variables for citizenship, except for Other Asian. The symbols * and ** denote significance at the 10% and 5% levels.

Table 3 – Multinomial Logit Estimates: Determinants of Success

Determinant/Outcome	Passed Comp(s) Did Not Complete	Completed
GRE Verbal	0.0126 (0.0061)**	0.0082 (0.0037)**
GRE Quantitative	0.0986 (0.0348)**	0.1164 (0.0354)**
GRE Analytic	0.0850 (0.0386)**	0.0685 (0.0326)**
GRE Analytic*GRE Quantitative	-0.00015 (0.00006)**	-0.00014 (0.00005)**
Math Courses	-6.0111 (3.3833)*	2.4962 (1.5763)
Math Courses*GRE Quantitative	0.0080 (0.0046)*	-0.0052 (0.0022)**
Econ Courses	-0.0219 (1.0649)	1.2782 (0.7782)*
Econ Courses*GRE Quantitative	-0.0003 (0.0014)	-0.0020 (0.0011)*
Masters	3.8951 (1.4138)**	1.8565 (1.2160)
Mention Paper	-0.2792 (1.1127)	2.0343 (0.8962)**
Specific Topic	1.2576 (1.0459)	0.7893 (0.8788)
Female	0.4667 (0.8830)	-0.7217 (0.8190)
Age	-0.5148 (0.2391)**	-0.0562 (0.0797)
Pseudo R^2	0.3680	
Log Likelihood	-52.5241	

Notes: Standard errors appear in parentheses. The estimated model includes an intercept and citizenship dummy variables (except for Other Asian and European) in each outcome equation. The symbols * and ** denote significance at the 10% and 5% levels.

Table 4 – Generalized Ordered Logit Estimates: Determinants of Success

Determinant/Outcome	Passed Comp(s) Did Not Complete	Completed
GRE Verbal	0.0180 (0.0057)**	0.0088 (0.0065)
GRE Quantitative	0.1537 (0.0923)*	0.0128 (0.0468)
GRE Analytic	0.1168 (0.0876)	-0.0417 (0.0523)
GRE Analytic*GRE Quantitative	-0.00019 (0.00013)	0.00006 (0.00008)
Math Courses	-5.8363 (4.2372)	8.1993 (4.3874)*
Math Courses*GRE Quantitative	0.0076 (0.0063)	-0.0118 (0.0062)*
Econ Courses	2.6792 (1.1400)**	1.2422 (0.9330)
Econ Courses*GRE Quantitative	-0.0040 (0.0017)**	-0.0015 (0.0013)
Masters	4.9254 (1.7898)**	-1.4344 (1.4721)
Mention Paper	1.3296 (1.1660)	2.3931 (1.2968)*
Specific Topic	2.1582 (0.8237)**	-0.2801 (1.2415)
Female	2.3709 (1.2823)**	-2.3585 (1.8263)
Age	-0.5749 (0.3400)*	0.6538 (0.2997)**
Pseudo R^2	0.4783	
Log Likelihood	-43.3575	

Notes: Standard errors appear in parentheses. The estimated model includes an intercept and citizenship dummy variables (except for Other Asian and European) in each outcome equation. The symbols * and ** denote significance at the 10% and 5% levels.

Table 5 – Rotated Factor Loadings (Varimax Rotation)

Determinant/Factor	(1) Professional Maturity	(2) Math Talent	(3) Economics Background	(4) Motivation and Research Desire	(5) Undergraduate Background	(6) Departmental Familiarity	(7) Overall Intelligence
GRE Verbal	-0.173	-0.026	-0.084	**-0.250**	**0.276**	0.096	**0.541**
GRE Quantitative	-0.008	**0.489**	-0.032	0.065	**0.280**	0.162	**0.472**
GRE Analytic	-0.266	0.054	-0.232	**-0.215**	**0.286**	-0.041	**0.633**
Math Courses	**-0.394**	-0.020	**-0.224**	**0.169**	0.148	0.149	**-0.208**
Econ Courses	-0.122	-0.108	**0.374**	**0.256**	**0.233**	-0.199	-0.055
Masters	**0.417**	0.184	**0.245**	**0.359**	-0.027	0.147	-0.145
Mention Paper	-0.109	-0.021	-0.195	**0.147**	-0.064	**-0.510**	-0.036
Specific Topic	0.039	-0.027	0.024	**0.281**	-0.050	0.062	0.082
Specific Member	-0.191	-0.102	-0.124	**0.154**	0.170	**0.356**	**-0.282**
Female	-0.131	0.028	0.168	-0.039	0.187	-0.502	-0.170
Age	**0.402**	-0.015	**0.208**	0.144	**-0.328**	**0.280**	-0.112
Cumulative Proportion	0.263	0.443	0.584	0.713	0.825	0.899	0.950

Notes: Rotated Factor Loadings include citizenship dummy variables for all six groups (see Table 1). Factor names come from the authors. Numbers in bold denote important determinants for each factor, as identified by the authors.

Table 6 – Logit Estimates: Factors

Factor/Outcome	Theory Comp	Field Comp	Completed
Professional Maturity	-0.0564	-0.3039	-0.0935
	(0.3275)	(0.3628)	(0.3058)
Math Talent	0.4018	-0.1276	0.1539
	(0.2908)	(0.2421)	(0.2446)
Economics Background	0.3072	0.1935	0.0755
	(0.2725)	(0.2616)	(0.2357)
Motivation and Research Desire	0.4298	0.5707	0.7831*
	(0.3059)	(0.3907)	(0.4459)
Undergraduate Background	-0.2322	-0.3027	-0.1201
	(0.2319)	(0.2243)	(0.2352)
Departmental Familiarity	0.1964	-0.0421	-0.1267
	(0.3032)	(0.3260)	(0.3530)
Overall Intelligence	0.8802**	1.0450**	0.8605**
	(0.3319)	(0.2642)	(0.3027)
Pseudo R^2	0.1354	0.1425	0.1201
Log Likelihood	-44.5014	-46.0061	-46.4589

Notes: Standard errors appear in parentheses. All estimated models include an intercept. The symbols * and ** denote significance at the 10% and 5% levels.

Table 7 – Multinomial Logit Estimates: Factors

Factor/Outcome	Passed Comp(s), Did Not Complete	Completed
Professional Maturity	0.0270 (0.3735)	-0.0982 (0.3474)
Math Talent	0.4783 (0.3321)	0.3644 (0.3159)
Economics Background	0.4419 (0.3132)	0.2446 (0.2964)
Motivation and Research Desire	-1.2951 (1.3617)	0.6516* (0.3997)
Undergraduate Background	-0.2859 (0.2994)	-0.2133 (0.2580)
Departmental Familiarity	0.5126 (0.4487)	0.0769 (0.3621)
Overall Intelligence	0.6564 (0.4362)	1.0488** (0.3609)
Pseudo R^2	0.1304	
Log Likelihood	-72.2634	

Notes: Standard errors appear in parentheses. Each equation in the estimated model includes an intercept. The symbols * and ** denote significance at the 10% and 5% levels.

Table 8 – Generalized Ordered Logit Estimates: Factors

Factor/Outcome	Passed Comp(s), Did Not Complete	Completed
Professional Maturity	0.0480 (0.3617)	0.0321 (0.3050)
Math Talent	0.5446* (0.3087)	0.1657 (0.2665)
Economics Background	0.3663 (0.2749)	0.0761 (0.2492)
Motivation and Research Desire	-0.6475 (0.5914)	2.0732* (1.1303)
Undergraduate Background	-0.2647 (0.2449)	-0.0743 (0.2505)
Departmental Familiarity	-0.1467 (0.3137)	-0.2197 (0.3733)
Overall Intelligence	1.0017** (0.4038)	0.8930* (0.5090)
Pseudo R^2	0.1616	
Log Likelihood	-69.6749	

Notes: Standard errors appear in parentheses. Each equation in the estimated model includes an intercept. The symbols * and ** denote significance at the 10% and 5% levels.

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Endnotes

[1] For a study of the admission selection process itself, see Marsh and Zellner (2004).

[2] National data on completion rates into doctoral programs are not systematically collected, but Ehrenberg (1992) reports completion rates ranging from 40-70 percent for economics students at selected research universities, over 90 percent at major medical schools, over 98 percent at the top 20 law schools, and 80-95 percent at top MBA programs.

[3] While the first two-year economics Ph.D.'s were awarded by Harvard, Yale, and Johns Hopkins in the 1870s, by 1900 dissertations became more sophisticated and specialized, indicating professional skills rather than the mark of a cultured gentleman (Hansen 1991).

[4] Their ten schools are the University of California (Berkeley), Chicago, Columbia, Cornell, Harvard, the University of Michigan, Princeton, Stanford, the University of North Carolina (Chapel Hill). For a damning critique of that book, see McCloskey (1994).

[5] Bowen and Rudenstine (1992) report that economics completion rates are generally below the natural sciences and above political science and the humanities (Table G.7-1, p. 400).

[6] Espenshade and Rodriguez (1997) reach similar conclusions using Bowen and Rudenstine's data set plus the University of Pennsylvania.

[7] They measured student quality with A-level scores, whether the degree was first class, and whether the student had attended a polytechnic or college. Only highly aggregated subject areas mattered, with arts and languages having lower and science and engineering having higher completion rates than the social science students.

[8] Van Ours and Ridder (2003) use a competing risks model to study completion rates of Economics Ph.D. students at three Dutch universities, emphasizing the role played by the student's thesis supervisor.

[9] The output of Economics Ph.D.s was extremely concentrated in the early 1920s, but since the late 1970s constitutes a much more diverse market. A Herfindahl-Hirschman Index of the output of economics doctorates exceeded 1000 in the early 1920s, but has hovered around 200 in the last three decades (Scott and Anstine 1997).

[10] Beginning in the 2003-04 academic year, the Analytic part of the GRE exam was replaced with a writing section with scores of 1.0-6.0, with 6.0 the best. These applicants are not included in our sample.

[11] A number of GRE validity studies, for example, estimate whether GRE scores are good predictors of first and second year graduate school grades. For a summary of over 600 such studies, see Schneider and Briel (1990).

[12] The other *ex ante* determinants of job placement are the subjective ratings of the admission committee and the prominence of the reference letter writers.

[13] We also recorded Grade Point Averages in math, economics, and overall. However, we find that we lost too many observations when we include this data, especially due to different grading structures across schools and countries.

[14] We also examine letters of recommendation, but could not come up with any usable measures based upon this information. Most letters consist of non-specific positive information about the applicants. Although Krueger and Wu (2000) find that having a letter from a prominent economist is a key determinant of later career success, we can't identify a straightforward criterion for prominence, much less prominence across different fields.

[15] Unfortunately, we cannot use a dummy variable for minority status for an American student. Our observations do not include a minority student who completed the dissertation.

[16] The dummy variables are insignificant, for the most part. The results show some evidence of significance toward success in the early steps for the Middle Eastern/African group. This result may reflect the self-paying status of many Middle Eastern Ph.D. students. We find little if any significance in the citizenship dummy variables in the estimations for completion. A complete set of results is available from the authors upon request.

[17] We do not use the interaction terms for the factor analysis. In that case, the technique tended to produce large coefficients for the determinant and the interaction term with the same determinant. The factors and the subsequent estimation results are similar to those reported here.

[18] Although we include the citizenship dummy variables in the factor analysis, we refrain from using the magnitudes of their coefficients for designating factors to avoid any stereotyping.