Time to the Doctorate and Labor Demand for New PhD Recipients[*]

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Abstract

This paper considers the influence of labor demand for new PhD recipients on time to the doctorate. I use student-level data on all doctorates awarded by U.S. universities in seven humanities and social science fields together with the annual number of job listings by field from 1975 to 2005. An increase in the number of job listings in a field does not affect the completion probability contemporaneously but does increase it three to six years later. Time-series variation in job listings by field can account for about 20 percent of the variation in average time to degree by entry year.

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1. Introduction

Unlike training for professional degrees such as an MBA or a JD, doctoral education is characterized by its "open-endedness" (Shulman 2010). Training for a PhD takes an amount of time that varies widely across students within a given field. In the humanities, for instance, some students complete the PhD in as little as 5 or 6 years while others take 11 or 12 years (Ehrenberg, Zuckerman, Groen, and Brucker 2009).

This paper considers the influence of labor demand for new PhD recipients on time to the doctorate. Within a field the demand for new PhDs varies from year to year as the number of employers hiring and the number of positions available depend on macroeconomic conditions, state budgets, and university priorities. As a result, two students from the same department seeking jobs in consecutive years may face quite different sets of opportunities.

The open-endedness of doctoral education allows doctoral students the opportunity to adjust their completion decisions to match the labor market, thereby reducing the influence of market risk on their job outcomes. Students can choose when to go on the job market, and even if they are unsuccessful in finding a job they can choose to remain enrolled while continuing to search for jobs. As a student in English noted, "I could certainly have finished my dissertation up to a year sooner, if I had had a job in prospect. I chose to delay my defense and graduation by one year in order to continue qualifying for a teaching assistantship, which in turn enabled me to retain my health insurance and to defer my undergrad loan repayment."[1]

Beyond students, many participants in U.S. doctoral education believe that a poor job market in a field lengthens time to degree (TTD). The Princeton University history professor Anthony Grafton, in an article on the state of

[1] This quotation is taken from a response to the survey described in Ehrenberg et al. (2009).

graduate education in the humanities, remarked, “In most years, new Ph.D.s—to say nothing of all qualified job seekers—outnumbered new jobs. No wonder, then, that the time to degree grew longer and longer, as students clung to subsistence income in the pleasant cities and college towns they already knew” (Grafton 2010, p. 34).

When the Andrew W. Mellon Foundation started its Graduate Education Initiative, which provided $58 million over 10 years (1991–2000) to 54 humanities departments at 10 major research universities, the Foundation initially planned to evaluate the program’s effects on student outcomes using changes over time within participating departments. However, the poor academic job market in the 1990s led to concerns that the job market was lengthening TTD and raising attrition. As a result, the Foundation decided to add a set of control departments to its evaluation strategy in order to isolate the effects of the program from the influence of the job market (Ehrenberg et al. 2009).

Although beliefs such as these are common, there is no credible evidence that TTD is related to labor demand for new PhDs. Determining the effect of labor demand on TTD is important so that researchers and practitioners can understand the relative effects on TTD of labor demand and other factors such as financial support, program characteristics (e.g., advising), and student characteristics (e.g., gender).[2] Institutions are increasingly concerned about long TTD and high attrition rates in PhD programs (Ehrenberg et al. 2009). The extent to which TTD is influenced by labor demand can inform decisions on institutional policies such as whether to set limits on TTD or the number of years PhD students may receive institutional funding. It can also determine the extent to which time-

[2] Prior research on the influences on TTD includes Abedi and Benkin (1987), Ehrenberg et al. (2007), Ehrenberg and Mavros (1995), Groen, Jakubson, Ehrenberg, Condie, and Liu (2008), Siegfried and Stock (2001), Stock and Siegfried (2006), and Tuckman, Coyle, and Bae (1990).

series fluctuations in TTD for particular fields of study are due to changes in labor demand for new doctorates.

The primary reason for the lack of empirical evidence on this relationship is the difficulty of measuring labor demand for new doctorates. Stephan and Ma (2005, p. 72) remarked: "Measures of the strength of the job market are notoriously difficult to construct. For example, information on academic job vacancies is not readily available."[3] Although such information is not widely available, this paper demonstrates that vacancy-based statistics can be constructed for seven academic fields in the humanities and social sciences over a 31-year period. Furthermore, the paper provides several pieces of evidence that the annual number of job listings in a field is a credible measure of the labor demand for new PhDs.

The remainder of the paper proceeds as follows. The next section presents a conceptual framework of student progress towards the PhD and discusses the potential role of variation over time in labor demand. Section 3 describes the data used in the empirical analysis, which is based on comprehensive student-level data and annual counts of job listings by field from 1975 to 2005. Section 4 presents the empirical approach that is used to capture the influence of labor demand on expected TTD. The empirical estimates are presented in Section 5, and Section 6 concludes.

2. Conceptual Framework

To motivate the empirical analysis, this section outlines a conceptual framework for understanding how labor demand for new PhDs may affect student progress towards the PhD. Prior to discussing the problem at the micro level, it is useful to situate the problem at the macro level. Consider the academic labor

[3] Given this difficulty, some papers (e.g., Abedi and Benkin 1987) did not even attempt to control for changing market opportunities for doctorates in different fields over time. Other papers (e.g., Ehrenberg and Mavros 1995; Stephan and Ma 2005) used proxies, but these proxies do not adequately isolate the demand for new doctorate recipients.

market in the United States in a particular field (such as history or economics) in terms of a standard model of supply and demand. The demand for labor in the field changes over time due to changes in state appropriations, the size of college-going cohorts, the demand for undergraduate courses in the field, the performance of university endowments, and other factors.

When the demand curve shifts out, the market equilibrium moves along the (short-run) supply curve, and both wages and the quantity of labor increase. The amount that quantity increases depends on the elasticity of supply. One component of the supply elasticity is the responsiveness of the production of new PhDs to a change in demand. Given the typical length of time from entering a doctoral program to earning a PhD, it is not feasible for new entrants to PhD programs to generate an increase in the number of doctorate recipients in the short run in response to an increase in demand.

However, students who are already enrolled in PhD programs and working on their dissertations could speed up their progress in order to move more quickly into the job market. At the market level, then, this paper addresses whether the number of PhDs produced in a field responds to short-run changes in demand in the academic labor market via completion behavior of existing students. The overall elasticity of supply is also affected by the responses of other potential suppliers, including doctorate holders who are not currently working, those working in the non-academic sector, and those working in other countries.[4]

At the micro level, the speed at which a student progresses towards the PhD is determined by a variety of factors. Some of the factors relate to the student's institution or department, such as funding, advising, and course requirements. Other factors are largely in students' control, including the effort

[4] Figure 1 in Ehrenberg (1992) illustrates the complexity of the supply side of the academic labor market.

and amount of time they devote to their studies and research as compared to leisure activity and outside employment.

Students can be expected to influence their degree progress by balancing the costs and benefits of additional time spent working on their research and writing. Chief among the benefits is the quality of the dissertation; in turn, a better dissertation may lead to a better job. Other benefits that are productive for students include access to library resources at their universities and access to advisors, classmates, and others on campus. Remaining a student rather than finishing the PhD also confers several consumption benefits, including on-campus student housing, subsidized health insurance, and the student lifestyle.

The costs of longer TTD include direct financial costs (i.e., tuition and related expenses) as well as the opportunity cost of remaining a student compared with finishing up and getting a job. This cost reflects the greater payoff in the labor market to having a PhD due to being qualified for academic jobs and other jobs requiring a PhD.[5] The financial payoff to obtaining a PhD in a field is a function of starting salaries for academic positions, the number of academic positions available, and the availability of nonacademic alternatives for those with doctorates. Beyond opportunity costs, longer TTD can be costly by providing a negative signal of individual ability or effort; if student takes 5 years to finish a dissertation, how much research can he or she be expected to produce as an assistant professor? Even in the humanities (a set of fields with long average TTD), degree times longer than 8 years are associated with worse job outcomes (Ehrenberg et al. 2009).

Labor demand for new PhDs in a given field would influence the speed of student progress (and hence TTD) primarily through opportunity costs. An

[5] The relationship between opportunity costs and PhD TTD has been emphasized in general terms by Breneman (1976) and Tuckman et al. (1990). The role of opportunity costs in influencing undergraduate TTD has been considered by Messer and Wolter (2010).

increase in labor demand would raise the financial payoff to obtaining a PhD, thereby increasing the opportunity cost of remaining a student. This cost can be considered an increasing function of the probability of getting an academic job, the starting salary of that job, and the status of that job (e.g., tenure status and type of institution).

Conceptually, the decision problem faced by doctoral students is similar to unemployed workers searching for a job in the presence of time-varying labor-market conditions (e.g., Ham and Rea 1987). Just as a long duration of unemployment can be associated with a high reservation wage, a long TTD can be associated with high standards for an academic placement. A difference between these two problems is that it can be productive for doctoral students to refrain from searching for jobs at particular times (for example, during the coursework stage); this is analogous to an unemployed worker interrupting search to seek additional training.

3. Data

3.1. Student Data

The empirical analysis in the paper is based on micro data on students who received doctorates from 1975 to 2008. These data come from the Survey of Earned Doctorates (SED), which is a census of research doctorates from U.S. universities. The survey, which is sponsored by the National Science Foundation and five other U.S. government agencies, is administered to doctorate recipients once they finish their degree requirements. The response rate is very high (usually over 90 percent annually), and basic information for nonrespondents (field of study, degree date, doctorate institution, and gender) is obtained from their degree-granting institutions and from public records (Hoffer et al. 2006).

The measure of TTD used in this analysis is the number of years from graduate entry to the PhD, where "graduate entry" is defined as the entrance into the first institution after the first baccalaureate was earned. For students who completed a stand-alone master's degree before entering a PhD program, graduate entry would reflect the start of the master's program. As a result, for some students this measure of TTD overstates the amount of time spent in a PhD program.

In addition to TTD, several other variables are created from the student responses to the SED. Financial aid received by students is summarized by the primary source of support during graduate school. Information on each student's institution, field, and year of graduate entry are used to assign a rank of the doctoral program, based on the 1981 and 1993 National Research Council ratings (see the Appendix for details).[6] Programs are ranked within each field by the average rating of the scholarly quality of program faculty. Also available from the SED are standard demographic variables (age, gender, and race/ethnicity) along with citizenship. Unfortunately, the SED data do not include a measure of student ability such as test scores.

The SED sample used in this paper covers seven fields in the humanities and social sciences: anthropology, classics, economics, English, history, philosophy, and political science. The sample is restricted to these fields because the time-series data on job listings was available for these fields (see Section 3.2). These fields represent 51.8 percent of all doctorates awarded in the humanities and social sciences from 1975 to 2008. Table 1 summarizes the personal characteristics of doctorate recipients in these fields. Table 2 summarizes the distribution of TTD by field. Median TTD is largest in anthropology (9.8 years) and smallest in economics (7.3 years). In each field the mean TTD exceeds the median, reflecting the long right tail of the distribution. Within fields there is substantial variation in TTD across students, with a difference of 5 years between

[6] The National Research Council also conducted an assessment in 2005, but I do not use ratings from that assessment because the methodology was substantially different from the one used in the 1983 and 1995 studies (Ostriker, Holland, Kuh, and Voytuk 2010).

the 25th and 75th percentiles being typical. In anthropology, for example, one-fourth of doctorate recipients took 7.7 years or less while one-fourth took 12.9 years or more.

3.2. Job Listings

I measure labor demand for new PhDs using the annual number of job listings in each field. I collected these data from a professional association for each of the seven fields (see the Appendix for details). Each association serves a vital organizing role in the labor market for doctorate recipients in a discipline by publishing listings (advertisements) of job vacancies. The counts of job listings used in this paper are a more direct measure of labor demand than the proxy variables used in the literature on the academic labor market. For example, Ehrenberg and Mavros (1995) used the mean starting salary for new assistant professors in a field, and Stephan and Ma (2005) used the percentage change in total current-fund revenue of public institutions.

Despite their appeal at a conceptual level, counts of listings in disciplinary employment services are an imperfect measure of the labor demand for new doctorate recipients for several reasons. First, these counts typically include listings for positions of all ranks, including positions for full professors as well as those for assistant professors. Second, a given listing is often published multiple times (for instance, in October and November), and in some cases the annual total number of listings that is available includes only new listings whereas in other cases the total includes both new and repeat listings. Third, a given listing can advertise multiple vacancies; in some cases the figure I collected is the total number of listings whereas in others the figure is the total number of vacancies. I deal with the second and third issues by allowing differences across fields but ensuring consistency over time within a field.

Another measurement issue is that at a given point in time, a given job service contains most but not all of the listings that are of interest to new doctorates in a given field. A potential concern with the time series is that the composition of jobs that are included in the listings could change over time.[7] This could happen if either (1) the types of jobs that are included changes over time, or (2) there is differential growth in the jobs that are included in and excluded from the listings. An example of (1) is if non-academic jobs are increasingly included in the listings. An example of (2) is if non-tenure-track jobs are excluded from the listings but grow faster over time than tenure-track jobs (Cross and Goldenberg 2009; Ehrenberg and Zhang 2005).

Given these measurement issues, I provide several pieces of evidence that counts of job listings are a credible measure of the labor demand for new doctorate recipients. First, time-series trends are similar across fields, as shown by Figure 1. This pattern is clearest in the bottom panel of the figure, which normalizes the number of job listings by the field-specific average over 1984–2002 (the period over which listings are available for all fields); the scale is set so that the field-specific average is 10.[8] (The normalized measure of job listings is the one that is used in the remainder of the empirical analysis.) That time trends are similar suggests that listings are a good measure of labor demand because field-specific demands should be positively correlated due to the influence of common factors, such as state appropriations.

Second, job listings are correlated with fiscal variables that are plausibly related to labor demand. As shown in Table 3, variation over time in job listings (controlling for field differences) is correlated with the national unemployment

[7] I expect that nearly all academic vacancies are included in these listings in order to comply with university anti-discrimination provisions and to satisfy the professional obligation to advertise open positions. For example, the Ethics Guide of the American Political Science Association (APSA) reads: “It is a professional obligation of all political science departments to list in the APSA Personnel Service Newsletter all positions for which they are recruiting at the Instructor, Assistant, and Associate Professor levels. In addition, the listing of openings at the Full Professor level is strongly encouraged. It is also a professional obligation for departments to list temporary and visiting positions” (quoted in Brintnall 2005).
[8] The raw correlation between any two fields in the normalized listings ranges from 0.34 to 0.92.

rate (negatively), state appropriations per student at public universities (positively), expenditures per student at public universities (positively), and faculty salaries (positively).

The time-series relationship of job listings and the national unemployment rate is shown in the top panel of Figure 2. The measure of job listings shown is the average across fields in the normalized counts. A negative correlation between the series is obvious: The time pattern of job listings is nearly a mirror image of the pattern of the unemployment rate. The bottom panel of Figure 2 compares job listings to a standard proxy for vacancies across the economy—the Conference Board's help-wanted index, which is based on help-wanted advertisements in 51 major newspapers and on the internet.[9] Although the series are not highly correlated, they follow a similar time pattern, with each peak and trough in job listings coming one or two years after the corresponding one for the help-wanted index.

For a third piece of evidence, I consider whether job listings, the unemployment rate, or the help-wanted index best predicts job outcomes for new PhDs.[10] The unemployment rate has been used as a measure of labor demand in studies of cohort effects for college graduates (Kahn 2010; Oreopolous, von Wachter, and Heisz 2012). The help-wanted index has been used as a proxy for job vacancies (e.g., Abraham and Katz 1986; Shimer 2005). Although the unemployment rate and help-wanted index are widely used in analysis of the economy as a whole, these measures may not adequately represent the demand for new PhDs because the labor market in a particular discipline is very specialized.

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[9] As explained in the Appendix, the help-wanted index used here is the newspaper index through December 1994 and then a composite index based on the newspaper index and the number of online advertisements (Barnichon 2010).

[10] Oyer (2006) showed that the number of academic job listings in economics at the time of completion is correlated with the quality of initial placement.

To measure the job outcomes of new PhD recipients, I use their responses to questions in the SED regarding postgraduation plans. The survey asks whether a graduate has made a definite commitment for work or further training (such as a postdoc). For those who have a definite work commitment, the survey also asks about the type of employer. I construct five indicator variables for job plans and regress each on a measure of labor demand in the year of completion. These regressions are linear probability models that include controls for field, rank of the doctoral program, TTD, and demographic characteristics. Because the regressions include controls for field, the estimated effect of job listings on job outcomes is identified from variation in job listings over time within fields.

Among the three measures, job listings is the best predictor of the job outcomes of new PhD recipients. Table 4 reports the estimated coefficient on the demand measure in each regression. For job listings, the coefficient is positive and statistically significant for all five job outcomes. By contrast, the estimated coefficient is of the expected sign and statistically significant for none of the outcomes when either the unemployment rate or the help-wanted index is used.

4. Empirical Approach

4.1. Econometric Model

I use a duration model to capture the influence of the labor market on doctoral completions. Because the counts of job listings are constructed on an annual (academic-year) basis, I use a discrete-time model. For each graduate, I determine the academic year of entry to graduate school (t_e) and the academic year of the PhD (t_p). (For the latter, I assign PhDs awarded in the fall to the prior academic year.) Then I compute TTD as the number of academic years between entry and completion ($t_p - t_e + 1$). Following Ham and Rea (1987) and Jenkins (1995), I arrange the student data with one observation per year for each student. These data are then matched by year and field to the counts of job listings.

For a student who enters graduate school in academic year t_{0i}, I assume that the probability of completing the PhD in Year t of the program (starting in Year 4), given that the student has not yet graduated, takes the form

$$\lambda(t_{0i}, t) = \frac{\exp[y_i(t_{0i}, t)]}{1+\exp[y_i(t_{0i}, t)]}, \text{ where } y_i(t_{0i}, t) = \theta + \psi_t + \gamma' X_i + \beta Z_i(t_{0i} + t - 1).$$

In this equation, θ is a constant; ψ_t is a fixed effect for year t of the program; X_i is a vector of time-invariant student and program characteristics; and Z_i is the count of job listings for the student's field in academic year $t_{0i} + t - 1$, when the student was in Year t of the program.

The estimation sample contains students who graduated between 1975 and 2008 and who had TTD between 4 and 15 years. Each student contributes one observation for each academic year spent in the program, starting with Year 4. I match the student data to the counts of job listings by field and academic year, which are available for 1975–2005 or a portion of this period for some fields. To be included in the sample, students must have jobs data for their fourth year; beyond that, when jobs data are not available I drop the student-year observations from the sample. As a result, some students in the estimation sample have incomplete spells, though most have completed spells.

For the completed spells, we observe graduation in academic year $t_{0i} + t_i^* - 1$; thus, TTD is t_i^* years. The probability of the completed spell is

$$g_i(t_{0i}, t_i^*) = \left\{\prod_{t=4}^{t_i^*-1} [1 - \lambda_i(t_{0i}, t)]\right\} \lambda_i(t_{0i}, t_i^*).$$

For the incomplete spells, TTD is right censored at $\overline{t_\iota}$ (i.e., we know only that TTD exceeds $\overline{t_\iota}$). The contribution to the likelihood function for these cases is

$$[1 - G(t_{0i}, \overline{t_\iota})] = \prod_{t=4}^{\overline{t_\iota}} [1 - \lambda_i(t_{0i}, t)].$$

The likelihood function is then

$$L = \prod_{i \in C} g_i(t_{0i}, t_i^*) \prod_{i \in IN} [1 - G(t_{0i}, \overline{t_\iota})],$$

where C denotes completed spells, and IN denotes incomplete spells. Parameter estimates are obtained by maximizing L with respect to the parameters. This can be done using a standard logit program with a dependent variable equal to 1 for the year the student graduates and equal to 0 for other years. Because the measure of job listings does not vary across student-year observations in the same year and field, I compute standard errors that allow for correlation in the error term within cells defined by year and field.

To aid the interpretation of the estimates, I compute the implied marginal effect of job listings on expected TTD. Given the parameter estimates, expected TTD is

$$E(TTD) = \sum_{t=4}^{T} t \cdot g(t_0, t),$$

where T is the maximum TTD in the sample. For this calculation, I set the X variables at their mean values. The effect of changing demand conditions on expected TTD can be obtained by numerically differentiating this equation. The interpretation of this effect is how expected TTD would respond to a permanent increase in the number of job listings.

4.2. Implementation

In the way that I have specified the model, the probability of completion in a year can be affected by job listings in that year but cannot be affected by job listings in prior years. However, the precise timing of any effect of labor demand on completion probabilities is an empirical question. To allow for delayed effects, I estimate models separately for different formulations of job listings, including listings in the current year and listings in prior years, with lags from one to eight years. If labor demand affects the behavior of students and their advisors with a lag of one or more years, then the estimated effect of a particular lag of job listings should be greater than the estimated effect of contemporaneous job listings.

Due to the requirement that sample members completed a PhD by 2008, the completion hazard is artificially high for the years leading up to 2008. As a result, the time trend in the completion hazard involves a form of selection bias. This is illustrated in Figure 3, which plots the completion hazard over time separately for students in the 5th, 7th, and 9th years of their doctoral programs. For Year 5, for example, the completion hazard increases sharply after 2001. The reason is that the composition of the sample changes over time, with the sample in later years having a shorter average TTD. In 2005, for instance, the sample of students in Year 5 is those with TTD of 8 years or less. By contrast, the sample of students in Year 5 for 2002 is those with TTD of 11 years or less.

For Year 5, the first year that is subject to selection bias is 1999 because the sample for that year is students with TTD of 14 years or less. The first year that is subject to selection bias varies by year in program—a pattern that is evident in Figure 3. Generically, for Year X, the last year that is *not* subject to selection bias is $2008 - (15 - X)$; this is 1998 for Year 5, 2000 for Year 7, and 2002 for Year 9.

I use two approaches to eliminate selection bias from the estimates. The first approach is to remove from the estimation sample the student-year observations in cells that are subject to selection bias. The second approach is to group the data into cells defined by field (f), academic year (y), and year in program (X) and adjust the cells that are subject to selection bias. Specifically, for each cell I compute the probability of completion and multiply it by $\Pr(TTD \leq Z|f;X)$, where $Z = X + (2008 - y)$. For Year 5, for example, the factors are $\Pr(TTD \leq 8)$ for 2005 and $\Pr(TTD \leq 11)$ for 2002. The adjustment factors are estimated using the student data in cells that are not subject to selection bias. This multiplicative adjustment removes the selection bias by converting the probability of completion for the cell from one for the observed sample (those who finish by 2008) to one for all students with TTD of 15 years or less (including those who finish after 2008). As illustrated in Figure 3, this adjustment removes the steep upward trend in the completion hazards at the end of the sample period.

The first approach, because it retains the student-level detail in the estimation sample, has the advantage of being able to control for individual characteristics such as demographics and financial support. A disadvantage of this approach is that, by discarding the observations in cells subject to selection bias, it reduces coverage of the years at the end of the sample period. The second approach, by contrast, covers the entire sample period. But because it requires collapsing the data into cells, estimation under this approach does not allow for individual-level controls.

In the student-level and group-level models, the key explanatory variable is the number of job listings in a year relative to the field-specific mean (scaled so that the field-specific average is 10). The other time-varying explanatory variables are year-in-program indicators (single years 4–13 and years 14 and 15 combined). Both models include controls for field. The student-level model includes additional time-invariant explanatory variables: gender, citizenship/race, age at graduate entry, primary source of support, and rank of the doctoral program. Program rank is parameterized using 11 categories, with 10 of these for deciles of the distribution within field and one category for unranked programs.

The dependent variable in the student-level model, as discussed above, is a binary variable indicating whether the student completed the PhD in the year of the observation. For the group-level model, by contrast, the dependent variable is the probability of completion in the year for the cell. As a result, for the group-level model a linear specification is used instead of the logit specification that is used for the student-level model. Given the differences in functional form, the coefficient estimates for the student-level and group-level models are not directly comparable. However, the marginal effects of job listings on expected TTD are constructed to be comparable—in both models, the marginal effects are for an increase in job listings of 10 percent. In order to produce results that are comparable to those from the student-level model, the group-level regressions are weighted by the number of students in each cell.

5. Results

Table 5 presents the estimated effects of job listings in a series of regressions that differ across two dimensions: (1) whether the model adjusts for selection bias, and (2) whether job listings are measured in the current year or in a prior year. When job listings are measured in the current year and the student-level model is estimated without adjusting for selection bias (specification 1), the estimated coefficient on job listings is 0.031 and statistically significant. Since it is positive, the estimated coefficient suggests that stronger labor demand increases the probability of completion in a given year—which translates into a shorter TTD. The estimated marginal effect of an increase in job listings of 10 percent is a reduction in expected TTD of 0.064 year (or about 0.8 month).

When we adjust for selection bias in the student-level model (specification 2), the estimated coefficient on job listings is reduced substantially and becomes statistically insignificant. The marginal effect of job listings on expected TTD for this specification is essentially zero, at -0.003 year. Comparing these two specifications suggests that selection bias creates the apparent association between current job listings and expected TTD in specification 1. The role of selection bias in this association is driven by artificially large completion hazards over the final 8 years of the sample period (see Figure 3), when job listings were above their historical average in most fields (see Figure 1). A similar pattern emerges from the group-level specifications: Not adjusting for selection (specification 3) produces a marginal effect of current job listings on expected TTD of -0.061 year, whereas adjusting for selection (specification 4) produces a marginal effect of essentially zero.

In the models that adjust for selection, the estimated effects of job listings in prior years are greater than the effects of current job listings. In the group-level model, the estimated coefficient on job listings is positive and significant when job listings is specified with a lag of three to six years. The coefficient is largest when job listings is specified with a lag of five years; for this specification, the estimated marginal effect of job listings on expected TTD is -0.052 year. In the student-level model, the estimated effect is also largest for a five-year lag, with a marginal effect of -0.033.

These results indicate that although current job listings are not associated with the probability of completion, job listings in prior years are associated with the probability of completion. The lack of an association with current job listings suggests that an effect of labor demand on TTD does not operate when students are actively searching for a job. Instead, the presence of an association with listings in prior years suggests that an effect operates through choices made by students earlier in their graduate programs, such as the dissertation topic and the research plan for the dissertation. These choices are heavily shaped by advisors, and the fact that many advisors do not have a student on the market every year may contribute to the lag between job listings and completion probabilities.

To gauge the magnitude and importance of the estimated effects of job listings in prior years, I use the estimated model to simulate expected TTD by entry year and compare this to the time-series pattern of average TTD by entry year in the raw data.[11] The simulated values are based on the parameter estimates from the group-level model with a five-year lag and the data on job listings by field and year. The actual values are averages by entry year for students with TTD of 4–15 years. The comparison covers entry years 1977–1991 or a shorter period in fields for which the jobs data starts after 1975. Based on the R^2 from a

[11] See Bowen, Lord, and Sosa (1991) on the importance of organizing the data by entry year, rather than PhD year, when analyzing time-series trends in TTD.

regression of simulated values on actual values, the variation in the simulated values represents an average across fields of 20.6 percent of the variation in the actual values.[12] This indicates that time-series variation in labor demand is an important factor in time-series trends in TTD within fields.

Next, I allow for heterogeneity in the effects of job listings (five years ago) by field and graduate-program rank by replacing the job-listings variable with a full set of interactions between job listings and indicators for the relevant set of field or rank categories. The estimated coefficients and marginal effects reported in Table 6 reflect the effect of job listings for particular subgroups.

In terms of effects by field, the strongest results are for anthropology, history, and political science: The estimated effects are in the expected direction (an increase in job listings is associated with a decrease in expected TTD), the estimated coefficients are statistically significant, and the estimates are consistent across the student-level and group-level models. For classics and English, the estimated effects are not statistically significant for both types of models. For economics, the estimated effects are in the expected direction for both types of models but they are significant only for the group-level model. For philosophy, the estimated effect is opposite of the expected direction and significant for the student-level model but essentially zero for the group-level model.

The estimated effects of job listings by graduate-program rank are in the expected direction for each of the five ranking groups, but the effect is statistically significant for only the middle ranking group, for the top 30–60 percent of graduate programs by field. Moreover, the estimated effect is highest for this group. The group with the next highest effect is the top 10 percent of programs; the estimated effect for this group is similar to the overall effect. This may be

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[12] The sample for the regression is pooled across fields; to account for differences in TTD across fields, prior to estimating the regression the actual and simulated values are adjusted by subtracting the field-specific means. The estimated coefficient on the (adjusted) simulated values is 2.17 (s.e.=0.49).

surprising at first glance because students from these programs are among the most-qualified job candidates in any job market, good or bad. However, the reputation of top programs depends critically on the quality of student placements (see Breneman 1976).

Table 7 reports the effects of demographics, financial support, and student quality on the probability of completion based on student-level models that adjust for selection and include job listings from five years earlier. The first specification reports estimates from the base model, which includes controls for demographics but does not include controls for financial support or student quality. The estimates imply that, all else equal, women have longer TTD than men. This finding is consistent with several analyses of gender differences in TTD, including Tuckman et al. (1990) and Bowen and Rudenstine (1992). The estimates also imply that non–U.S. citizens have longer TTD than white U.S. citizens, and that among U.S. citizens, non-whites have longer TTD than whites. The implied pattern of TTD by citizenship differs from Ehrenberg and Mavros (1995) and Siegfried and Stock (2001), both of which found lower TTD (higher completion hazards) for non–U.S. citizens than U.S. citizens.[13]

Adding primary source of support to the model (specification 2) results in little change in the estimated coefficient on job listings. Compared with using personal funds, each of the major sources of support (teaching assistantship, research assistantship, and fellowship) is associated with a larger probability of completion (shorter TTD). This relationship may reflect that higher-ability students are more likely to be awarded support, because student ability is not controlled for in this specification.

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[13] The difference in results could reflect differences in the scope of the samples (those analyzed by Ehrenberg and Mavros [1995] and Siegfried and Stock [2001] covered doctorate recipients in only one institution or field) or differences in the timing of data collection (the SED records citizenship at the time of completion, whereas other sources record citizenship at the time of admission). Another related study, Stock and Siegfried (2006), found no differences in TTD by citizenship.

As a proxy for student ability, I use a measure of the admissions selectivity of each student's bachelor's (BA) institution. This measure comes from *Barron's Profiles of American Colleges* (1992) and is available for students who received their BA degrees from a U.S. institution (78 percent of the students in my sample). The Barron's guide groups institutions into categories based on the degree of competitiveness in their admissions, ranging from "most competitive" to "noncompetitive." This proxy for student ability captures peer quality at the undergraduate level in addition to admissions selectivity per se.

The final three columns of Table 7 show the results of including this proxy for student ability in the student-level model estimated on the sample of students who received their BA from a U.S. institution. Adding BA selectivity results in little change in the estimated effect of job listings. The effects of BA selectivity are in the expected direction: The probability of completion is higher (TTD is lower) for students who attended more-selective BA institutions, and the relationship is monotonic. In a specification with financial support, adding BA selectivity results in little change in the estimated effect of financial support. This suggests that the estimated effect of financial support on the probability of completion (and TTD) reflects more than simply differences in student ability.

6. Conclusion

The state of the job market in a field is a constant concern for PhD students and their faculty advisors. Students want to know whether they will be able to find a job, and faculty members want to know whether the number and type of jobs available in the market in a given year will be sufficient to place their graduating students and maintain their department's reputation. The influence of labor demand for new PhD recipients on time to the doctorate is an important issue in graduate education, but there is no systematic empirical evidence on this relationship. This paper makes progress on the issue by constructing credible measures of labor demand over a 31-year period and using student-level data on all doctorates awarded by U.S. universities in seven fields in the humanities and social sciences.

The demand for new PhDs is measured by the annual number of job listings advertised by professional associations in these fields. I present several pieces of evidence that counts of job listings are a good measure of the labor demand for new doctorate recipients. First, time trends are similar across fields, reflecting the influence of common factors such as state appropriations. Second, job listings are correlated with fiscal variables that are plausibly related to labor demand. Third, job listings are correlated with job outcomes of new PhD recipients, and listings are a better predictor of outcomes than is the national unemployment rate or the help-wanted index.

According to a discrete-time duration model, an increase in the number of job listings in a field is not associated with an immediate increase in the probability of completion. However, an increase in job listings does lead to an increase in the completion probability three to six years later. The size of the lag in the effect of job listings on expected TTD suggests that the effect operates through choices made by students and their advisors well before students are close to finishing their dissertations, such as the dissertation topic and the research plan for the dissertation. In terms of the direction of the estimated effects, the overall results of this analysis confirm the view articulated by many observers of U.S. doctoral education—that the timing of completions in the humanities and social sciences responds to changes in labor demand for new PhDs.

Estimates from the preferred specification imply that an increase in job listings of 10 percent reduces expected TTD by 0.05 year. Although the magnitude of this effect appears to be modest, a simulation using the model parameters reveals that time-series variation in job listings by field can account for about 20 percent of the variation in average TTD by entry year. Therefore, institutions concerned about long TTD in PhD programs should consider labor demand for new PhDs among a range of factors including program characteristics, financial support, and student composition.

The findings from this analysis carry an important implication regarding the responsiveness of academic labor markets to short-run changes in demand. The finding that an increase in the number of job listings in a field is not associated with an immediate increase in the probability of completion implies that the completion behavior of existing students does not contribute to the overall short-run elasticity of supply in the labor market in humanities and social-science fields. Instead, the supply elasticity must reflect only the responses of doctorate holders who are not currently working, those working in the non-academic sector, and those working in other countries.

Beyond time to degree, several other outcomes of doctoral students could be influenced by labor demand for new PhDs. For instance, when labor demand falls, do programs increase attrition or reduce the size of their entering cohorts? Among students who complete the PhD, how does variation in labor demand affect the types of positions they obtain? In particular, are new PhDs more likely to take non-academic or temporary academic positions when labor demand is relatively weak? These are promising avenues for future research.

Appendix: Data Sources and Variable Definitions

Definition of academic year

Unless otherwise noted, a "year" is an academic year. Academic year t is defined as going from August of calendar year t through July of calendar year $t + 1$.

Rankings of doctoral programs

Program rankings are based on the average rating of the scholarly quality of program faculty in National Research Council assessments of doctoral programs in 1981 and 1993 (Jones, Lindzey, and Coggeshall 1982a, 1982b; Goldberger, Maher, and Flattau 1995). These assessments covered most of the PhD-granting programs in a given discipline, and taken together the ranked programs represent about 90 percent of PhDs granted in a field. For each year, rankings are the percentile ranks of the average ratings within fields.

Rankings are assigned to students based on their institution, field, and year of graduate entry. In departments ranked in both 1981 and 1993, the 1981 ranking is used for students who entered in 1981 or earlier, the 1993 ranking is used for students who entered in 1993 or later, and a weighted average of the two rankings is used for students who entered between 1982 and 1992. In departments ranked in 1981 only, the 1981 ranking is used for students who entered in 1987 or earlier; students in later entry cohorts are considered to be in unranked programs. In departments ranked in 1993 only, the 1993 ranking is used for students who entered in 1987 or later; students in earlier entry cohorts are considered to be in unranked programs.

Job listings by field

- Anthropology (1975–2005): American Anthropological Association (AAA). Counts of job listings published monthly in *Anthropology News* (1975–2004) and online in the AAA Jobs Database (2001–2005).
- Classics (1984–2004): American Philological Association (APA). Annual counts of vacancies from APA placement reports for 2001 and 2004.
- Economics (1979–2005): American Economic Association. "New jobs" series (academic plus non-academic) published annually in the May issue of *American Economic Review* (e.g., Siegfried [2001]), based on listings in *Job Openings for Economists.* Data are for calendar years; I match calendar year t to the academic year starting in t (e.g., 1979 to 1979–80).
- English (1975–2005): Modern Language Association (MLA). Number of positions listed in the English Edition of the MLA *Job Information List*; counts (total including supplement) from Table 1 of Fall 2004 *MLA*

Newsletter. Data for 2004 through 2006 are taken from Table 1 of the report "Trends in the MLA *Job Information List*, September 2007."

- History (1975–2005): American Historical Association (AHA). Job openings advertised in *Perspectives*; counts based on AHA reports (2004 and 2005) and electronic data provided by AHA (1975–2003).
- Philosophy (1982–2002): American Philosophical Association. Total number of jobs advertised in *Jobs for Philosophers*; data from pp. 130–131 of American Philosophical Association (2004).
- Political Science (1983–2005): American Political Science Association (APSA). Data for 1983 through 2003 are based on Brintnall (2005); data for 2004 and 2005 were provided by APSA. Data for 1993 are missing and are imputed as the average of 1992 and 1994.

<u>Unemployment rate</u>
National unemployment rate for civilian labor force age 16 and older. Rate for an academic year is computed as the average of monthly seasonally adjusted unemployment rates for August through July. Source: Bureau of Labor Statistics (series LNS14000000).

<u>Help-wanted index</u>
Index for an academic year is computed as the average of the monthly seasonally adjusted index for August through July. The monthly values from August 1975 through December 1994 are from the Conference Board's index of help-wanted advertising in 51 major newspapers. The monthly values from January 1995 through July 2006 are from the composite help-wanted index created by Barnichon (2010). The composite index combines information from the newspaper index (available through May 2008) with the Conference Board's count of total online help-wanted ads (which started in May 2005).

<u>State appropriations</u>
State appropriations per full-time-equivalent student are for all U.S. public universities and are expressed in constant (calendar year 2000) dollars. Source: Grapevine database assembled by the Center for the Study of Education Policy at Illinois State University; see Rizzo (2006) for details. Data used in Table 3 are for academic years 1975–1999.

<u>College expenditures</u>
College expenditures per full-time-equivalent student are for all U.S. public universities and are expressed in constant (calendar year 2000) dollars. Expenditures are current educational and general expenditures, net of sponsored

research. Source: IPEDS, U.S. Department of Education; see Rizzo (2006) for details. Data used in Table 3 are for academic years 1975–1999.

<u>Faculty salaries</u>

Faculty salaries are the average salary of full-time instructional faculty on 9-month contracts in degree-granting institutions, and are expressed in constant (academic year 2005–06) dollars. Source: National Center for Education Statistics (2007), Table 240. Data used in Table 3 are for selected academic years in 1975–2005: 1975, 1978–1982, 1984–1985, 1987, 1989–1999, and 2001–2005.

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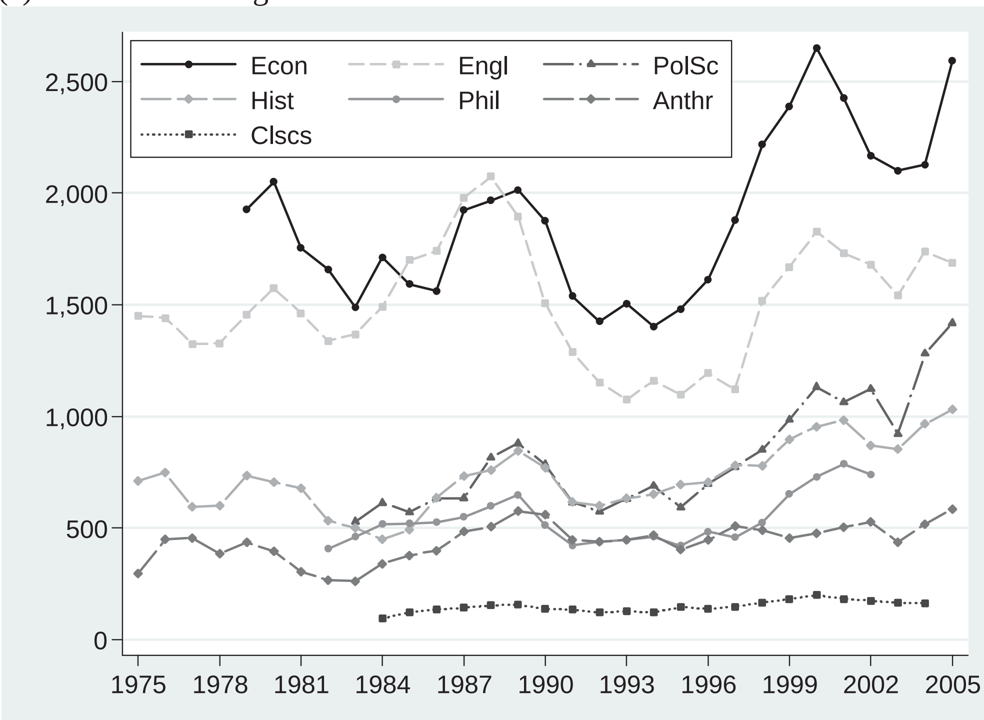
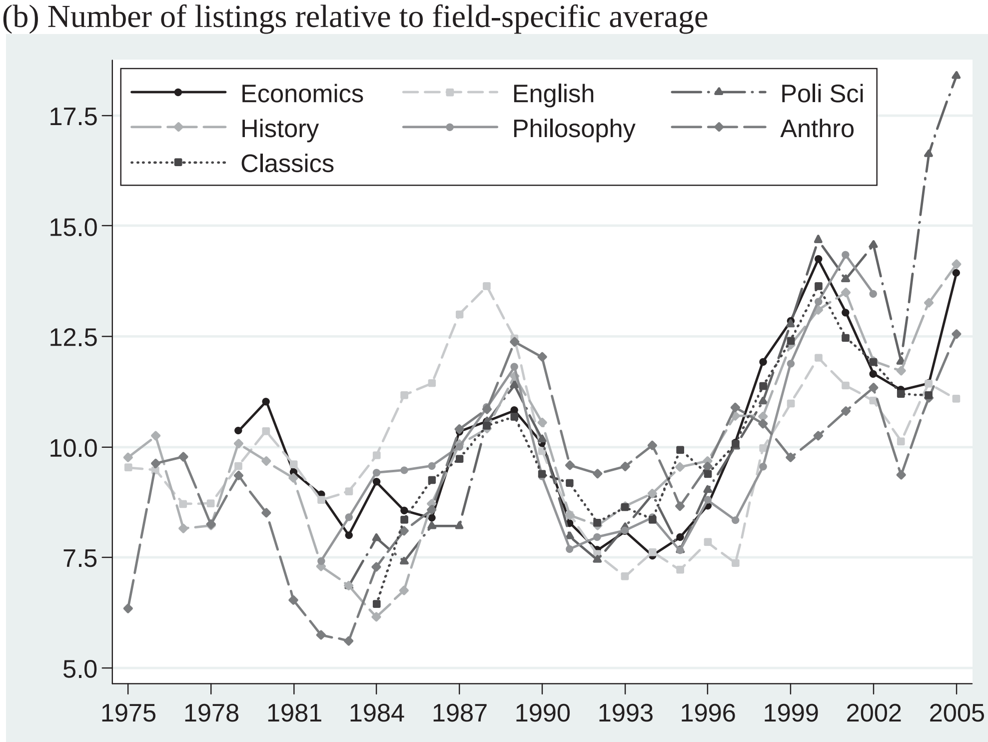
Figure 1. Job Listings by Field, 1975–2005

(a) Number of listings



(b) Number of listings relative to field-specific average

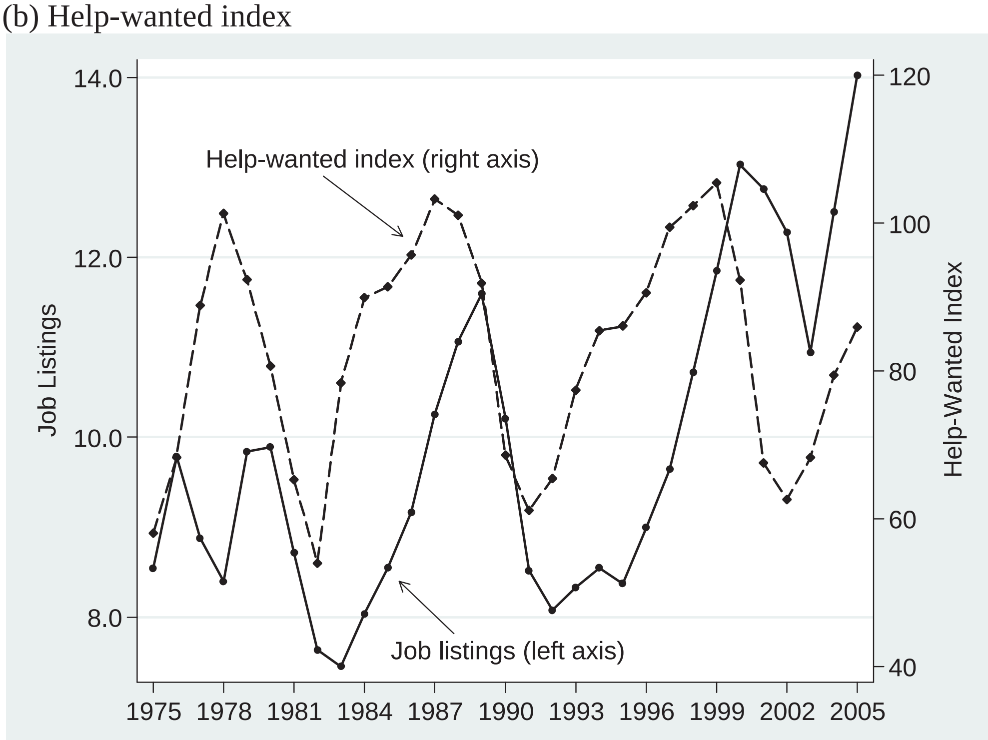


Source: See the Appendix.

Figure 2. Job Listings and Economywide Labor-Market Indicators, 1975–2005

(a) Unemployment rate

(b) Help-wanted index



Source: See the Appendix.

Figure 3. Adjustment for Selection Bias

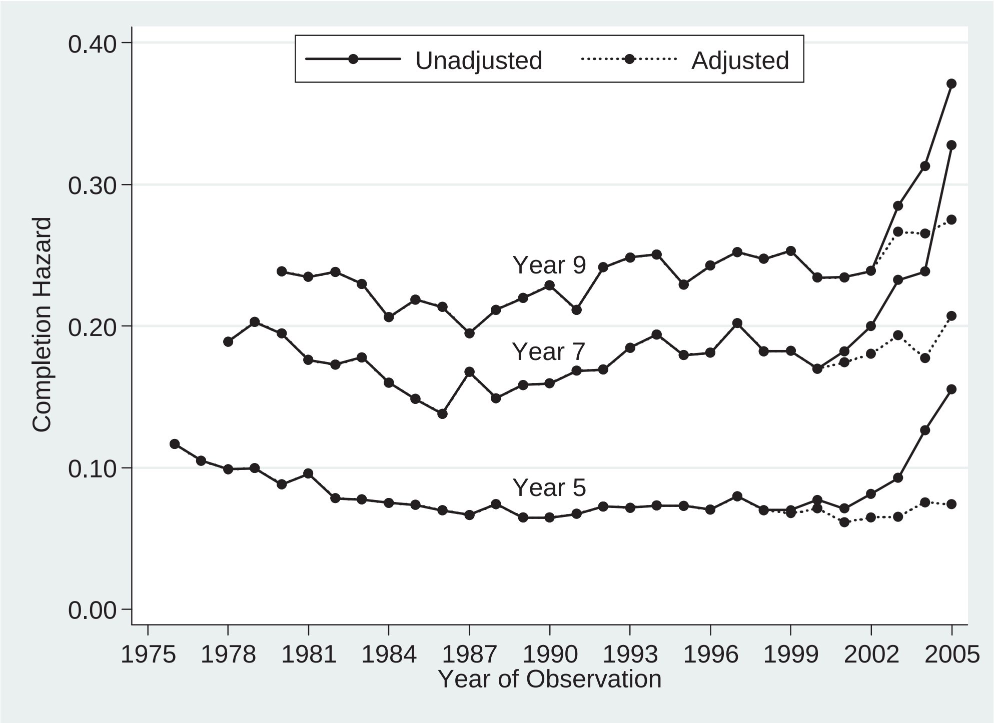


Table 1. Characteristics of Doctorate Recipients in Seven Fields, 1975–2008

Characteristic	Percent	Median TTD	Mean TTD
Gender			
Men	62.12	8.67	9.95
Women	37.88	9.26	10.88
Citizenship/Race			
Non–U.S. citizen	21.82	8.42	9.31
U.S. citizen, non-white	8.12	9.25	10.80
U.S. citizen, white	68.54	8.92	10.56
Missing	1.52	8.67	10.04
Primary Source of Support			
Teaching assistantship	29.61	8.25	9.22
Research assistantship	4.90	7.67	8.57
Fellowship	22.76	7.92	9.03
Personal funds	29.86	10.76	12.56
Other source	3.54	9.67	11.16
Missing	9.33	9.67	11.01
Age at Graduate Entry			
21 or younger	7.32	9.67	11.48
22	26.11	8.67	10.20
23	18.90	8.67	10.06
24	12.86	8.75	10.05
25	8.78	8.92	10.23
26	6.38	8.92	10.22
27	4.37	9.09	10.27
28 to 29	5.38	9.25	10.43
30 to 33	5.05	9.34	10.59
34 or older	4.84	9.50	10.36
Total	100.00	8.92	10.30

Notes: N=119,961. Tabulations of financial support are based on 1977–2008 because primary source of support was not requested by the survey prior to 1977.

Table 2. Time to Degree by Field, 1975–2008 Doctorate Recipients

Field	Median	Mean	25th Pctile	75th Pctile	75th – 25th	N	N/year
Anthropology	9.76	11.12	7.67	12.92	5.25	13,168	387.3
Classics	8.34	9.87	6.67	11.34	4.67	1,916	56.4
Economics	7.25	8.37	5.67	9.92	4.25	26,711	785.6
English	9.67	11.11	7.25	12.93	5.68	27,537	809.9
History	9.75	11.37	7.67	13.26	5.59	25,018	735.8
Philosophy	8.67	10.04	6.67	11.67	5.00	9,407	276.7
Political Science	8.75	10.01	6.67	11.76	5.09	16,204	476.6

Table 3. Correlation of Job Listings with Fiscal Variables, 1975–2005

Fiscal Variable	Mean	Coef.	S.E.	R^2	N
Unemployment rate	6.12	-0.872*	(0.161)	0.33	185
Help-wanted index	83.36	0.018	(0.020)	0.04	185
State appropriations per student[a]	6.37	2.221*	(0.360)	0.38	147
College expenditures per student[a]	10.96	0.246*	(0.071)	0.16	147
Faculty salaries[a]					
All faculty	62.45	0.272*	(0.066)	0.28	152
Full professor	82.81	0.205*	(0.039)	0.37	152
Associate professor	61.39	0.318*	(0.070)	0.32	152
Assistant professor	50.84	0.343*	(0.078)	0.32	152
Instructor	41.93	0.207*	(0.038)	0.35	152
Lecturer	44.15	0.621*	(0.152)	0.33	152
No rank	53.45	-0.345	(0.202)	0.12	152

Notes: Each row is a separate regression of job listings (mean = 10.0) on the fiscal variable and a set of indicators for field. The unit of observation is a field-year. Standard errors allow for correlation in the error term by year. See the Appendix for details on the fiscal variables.

[a]In thousands of dollars.

*p < .05

Table 4. Predicting Job Outcomes of New Doctorate Recipients, 1975–2005

		Measure of Labor Demand			
Outcome	Mean	Job Listings	Unemp. Rate	Help Wanted	N
Definite job	60.16	0.455*	0.689*	0.005	92,782
		(0.079)	(0.118)	(0.011)	
Definite job or training	66.21	0.997*	-0.079	0.007	92,782
		(0.077)	(0.114)	(0.010)	
Definite job and type reported	70.97	1.381*	-0.109	-0.040*	77,267
		(0.082)	(0.119)	(0.011)	
Definite job with U.S. employer	64.24	1.322*	0.168	-0.029*	77,267
		(0.085)	(0.123)	(0.011)	
Definite job with U.S. academic	48.55	1.084*	0.875*	-0.081*	77,267
		(0.089)	(0.130)	(0.012)	
Predictor mean		9.98	6.11	82.89	

Notes: Each cell comes from a separate regression (linear probability model). Standard errors are reported in parentheses. Dependent variables are indicators (0/1) multiplied by 100. In addition to the relevant demand measure shown, the other independent variables are field, program rank, TTD, gender, citizenship/race, and age at PhD completion. "U.S. academic" includes 4-year institutions and 2-year colleges.

*$p < .05$

Table 5. Selection and Timing

	(1)	(2)	(3)	(4)
Level	Student	Student	Group	Group
Adjust for Selection	No	Yes	No	Yes
Job listings in t	0.0307*	0.0016	0.0031*	0.0002
	(0.0082)	(0.0063)	(0.0011)	(0.0005)
	[-0.0639]	[-0.0033]	[-0.0614]	[-0.0046]
Job listings in t-1	0.0261*	-0.0040	0.0026*	-0.0001
	(0.0077)	(0.0058)	(0.0010)	(0.0005)
	[-0.0541]	[0.0083]	[-0.0507]	[0.0019]
Job listings in t-2	0.0268*	-0.0050	0.0028*	0.0001
	(0.0070)	(0.0059)	(0.0009)	(0.0005)
	[-0.0555]	[0.0104]	[-0.0545]	[-0.0013]
Job listings in t-3	0.0446*	0.0035	0.0051*	0.0013*
	(0.0082)	(0.0060)	(0.0011)	(0.0005)
	[-0.0917]	[-0.0072]	[-0.0996]	[-0.0258]
Job listings in t-4	0.0555*	0.0114	0.0067*	0.0022*
	(0.0097)	(0.0068)	(0.0013)	(0.0006)
	[-0.1136]	[-0.0237]	[-0.1281]	[-0.0435]
Job listings in t-5	0.0587*	0.0160*	0.0072*	0.0026*
	(0.0111)	(0.0072)	(0.0015)	(0.0006)
	[-0.1193]	[-0.0329]	[-0.1356]	[-0.0515]
Job listings in t-6	0.0464*	0.0126	0.0055*	0.0021*
	(0.0127)	(0.0079)	(0.0016)	(0.0007)
	[-0.0940]	[-0.0259]	[-0.1039]	[-0.0416]
Job listings in t-7	0.0237*	0.0106	0.0027	0.0012
	(0.0120)	(0.0076)	(0.0014)	(0.0007)
	[-0.0480]	[-0.0217]	[-0.0515]	[-0.0243]
Job listings in t-8	0.0022	0.0112	0.0001	0.0006
	(0.0115)	(0.0069)	(0.0013)	(0.0006)
	[-0.0046]	[-0.0228]	[-0.0018]	[-0.0125]

Notes: Each cell comes from a separate regression. All specifications include controls for field and year in program. Student specifications also include controls for program rank, gender, race/citizenship, and age at graduate entry. Marginal effects on expected TTD (in brackets) are for an increase in job listings of 10 percent. Standard errors (in parentheses) allow for correlation in the error term within cells defined by year and field.

*$p < .05$

Table 6. Heterogeneity in Effects by Field and Program Rank

	(1)	(2)		(1)
Level	Student	Group	Level	Student
Adjust for selection	Yes	Yes	Adjust for selection	Yes
Field			Doctoral-Program Rank	
Anthropology	0.0482*	0.0037*	Top 10 percent (1–10)	0.0177
	(0.0176)	(0.0014)		(0.0117)
	[-0.0929]	[-0.0705]		[-0.0363]
Classics	0.0400	0.0051	Next 20 percent (10–30)	0.0105
	(0.0303)	(0.0027)		(0.0089)
	[-0.0789]	[-0.0902]		[-0.0218]
Economics	0.0173	0.0032*	Next 30 percent (30–60)	0.0295*
	(0.0228)	(0.0015)		(0.0091)
	[-0.0356]	[-0.0622]		[-0.0592]
English	-0.0078	0.0006	Bottom 40 percent (60–100)	0.0074
	(0.0101)	(0.0011)		(0.0123)
	[0.0162]	[-0.0140]		[-0.0154]
History	0.0519*	0.0048*	Unranked	0.0084
	(0.0119)	(0.0009)		(0.0125)
	[-0.0990]	[-0.0855]		[-0.0175]
Philosophy	-0.0303*	-0.0001		
	(0.0108)	(0.0018)		
	[0.0613]	[0.0023]		
Political Science	0.0176*	0.0031*		
	(0.0089)	(0.0004)		
	[-0.0362]	[-0.0600]		

Notes: Coefficients reported in the table are for interaction terms between job listings in t-5 and indicators for the relevant set of field or rank categories. Marginal effects on expected TTD (in brackets) are for an increase in job listings of 10 percent. Standard errors (in parentheses) allow for correlation in the error term within cells defined by year and field. Student specification includes controls for field, year in program, program rank, gender, race/citizenship, and age at graduate entry. Group specification includes controls for field and year in program. The group specification cannot be estimated with interactions by rank.

*$p < .05$

Table 7. Demographics, Financial Support, and Student Quality

	All Students		BA from U.S. Institution		
Variable	(1)	(2)	(3)	(4)	(5)
Job listings in t-5	0.0160*	0.0165*	0.0108	0.0119	0.0120
	(0.0072)	(0.0073)	(0.0076)	(0.0076)	(0.0074)
	[-0.0329]	[-0.0338]	[-0.0215]	[-0.0236]	[-0.0236]
Female	-0.0940*	-0.0999*	-0.1022*	-0.1083*	-0.1116*
	(0.0123)	(0.0124)	(0.0125)	(0.0125)	(0.0125)
Non-U.S. citizen	-0.2657*	-0.2983*	0.0881*	0.0775	0.0855*
	(0.0190)	(0.0185)	(0.0398)	(0.0403)	(0.0405)
U.S. citizen, white	—	—	—	—	—
U.S. citizen, non-white	-0.1759*	-0.1895*	-0.1521*	-0.1740*	-0.1685*
	(0.0243)	(0.0240)	(0.0241)	(0.0237)	(0.0237)
Teaching assistantship		0.3119*		0.3393*	0.3384*
		(0.0213)		(0.0218)	(0.0218)
Research assistantship		0.3765*		0.4078*	0.4105*
		(0.0353)		(0.0415)	(0.0412)
Fellowship		0.2960*		0.3453*	0.3292*
		(0.0253)		(0.0261)	(0.0260)
Personal funds		—		—	—
BA: Most competitive			—		—
BA: Highly competitive			-0.1105*		-0.1105*
			(0.0213)		(0.0213)
BA: Very competitive			-0.1466*		-0.1325*
			(0.0211)		(0.0207)
BA: Competitive			-0.1795*		-0.1745*
			(0.0219)		(0.0212)
BA: Less competitive or noncompetitive			-0.1814*		-0.1723*
			(0.0283)		(0.0273)
BA: Unranked			-0.3357*		-0.2856*
			(0.0605)		(0.0602)
Pseudo R^2	0.132	0.134	0.139	0.142	0.142
N	279,870	279,870	218,116	218,116	218,116
Students	46,636	46,636	36,414	36,414	36,414
Mean TTD	8.88	8.88	8.87	8.87	8.87

Notes: All specifications are from student-level models that adjust for selection and include controls for field, year in program, program rank, and age at graduate entry. Marginal effects on expected TTD (in brackets) are for an increase in job listings of 10 percent. Standard errors (in parentheses) allow for correlation in the error term within cells defined by year and field.

*$p < .05$