Attachment 27

"Discovering One's Talent: Learning from Academic Specialization"

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The author examines an exogenous difference in the timing of academic specialization within the British system of higher education to test whether education yields information about one's match quality in different fields of study. In distinguishing between systems requiring early and late specialization, he predicts the likelihood of an individual switching to an occupation unrelated to one's field of study. If higher education serves mainly to provide specific skills, the model predicts more switching in a system requiring late specialization since the cost of switching is lower in terms of foregone skills. Using the Universities Statistical Record from 1972 to 1993 and the 1980 National Survey of Graduates and Diplomates, he finds that individuals who specialize early, as in the case of England, are more likely to switch to an unrelated occupation, implying that the benefits to increased match quality are sufficiently large to outweigh the greater loss in skills from specializing early.

higher education, specialization, choice of major

DISCOVERING ONE'S TALENT: LEARNING FROM ACADEMIC SPECIALIZATION

OFER MALAMUD*

The author examines an exogenous difference in the timing of academic specialization within the British system of higher education to test whether education yields information about one's match quality in different fields of study. In distinguishing between systems requiring early and late specialization, he predicts the likelihood of an individual switching to an occupation unrelated to one's field of study. If higher education serves mainly to provide specific skills, the model predicts more switching in a system requiring late specialization since the cost of switching is lower in terms of foregone skills. Using the Universities Statistical Record from 1972 to 1993 and the 1980 National Survey of Graduates and Diplomates, he finds that individuals who specialize *early*, as in the case of England, are more likely to switch to an unrelated occupation, implying that the benefits to increased match quality are sufficiently large to outweigh the greater loss in skills from specializing early.

With regard to instruction, economists have made substantial progress in specifying and identifying the economic value of higher education, as it increases the value productivity of human agents as workers . . . the much neglected activity is that of discovering talent. It, too, can be approached by treating it as a process which provides students with opportunities to discover whether they have the particular capabilities that are required for the type and level of education at which they are working.

— Theodore W. Shultz (1968: 331)

More than 40 years have passed since Theodore Shultz argued that higher education provides students with the opportunity to discover their talents, but relatively little research has actually explored this important aspect of higher education. In this paper, I use an exogenous difference in the timing of specialization across British systems of higher education to test whether education *can* provide valuable information about one's talents. In one system, students are required to choose a field of study before

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A data appendix with additional results, and copies of the computer programs used to generate the results presented in the paper, are available from the author at malamud@uchicago.edu.The raw data files are available from the UK Data Archive at http://www.data-archive.ac.uk.

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they apply to college. In the other, students must postpone the decision until later in their college careers. Such differences in the timing of academic specialization highlight the trade-off between accumulating skills in a particular field versus gathering additional information about alternative fields before selecting one in which to specialize. In this paper, I exploit these differences to examine the importance of higher education in helping students to discover their talents and tastes for different fields of study.[1]

I introduce a simple model of academic specialization in which individuals, by taking courses in different fields of study, accumulate field-specific skills and receive noisy signals of match quality to these fields. Though later specialization provides students with more time to learn about match quality to different fields, it affords less time to acquire field-specific skills once they have chosen a field of specialization. If higher education serves mainly to provide specific skills, the model predicts that students in a system with late specialization will be more likely to switch to an occupation that is unrelated to their field of study. This is because the cost of switching in a late system is lower in terms of foregone skills. Conversely, if higher education serves mainly to provide information about match quality, the incidence of switching to an unrelated occupation will be higher in a system requiring early specialization. This is because the benefit associated with the increase in expected match quality when switching in an early system will outweigh the greater loss of field-specific skills. Since its focus is on individuals' decision to switch to an unrelated occupation, the model generates comparative static predictions that account for individuals' pecuniary and non-pecuniary considerations.

In order to test whether education provides valuable information about one's talent, I exploit an exogenous difference in the timing of specialization within the British system of undergraduate education. In England, students apply to a specific field of study at a particular university while still attending secondary school. Once admitted to study a certain field, they usually follow a narrow curriculum that focuses on the chosen subject and allows for few courses in other fields.[2] In contrast, Scottish students are typically admitted to a broad faculty or school rather than to a specific field. Moreover, they are generally required to study several different fields during their first two years before specializing. Using university administrative data and survey data on college graduates, I compare the likelihood that Scottish versus English students will switch to an unrelated occupation later on in their careers. I account for non-random selection by instrumenting for English and Scottish degrees with region of prior residence, and I contrast the findings at the undergraduate level with those at the *graduate level* at which the timing of specialization between England and Scotland is similar. I focus on the comparison between England and Scotland because, although their educational systems are separate and arguably exogenously different, their labor markets are relatively well integrated and their macroeconomic policies are determined by a common government. Furthermore, students in neighboring Wales serve as a useful "placebo test" because specialization there occurs at roughly the same time as it does in England.

The notion that individuals may discover their talents and learn about their match quality to different fields is a prominent feature in many models of job turnover.[3] Relatively few papers, however, have explicitly considered the role of education. Johnson (1978) postulated that education provides workers with information about their general ability and concluded that education

[1] In a related paper, Malamud (2010), I use a similar framework to explore the consequences of early and late specialization on wages and other labor market outcomes.

[2] More recently, and outside the time period of the present analysis, some English universities have introduced course structures that offer more breadth and greater flexibility. This might suggest a growing perception that specializing too early may have some drawbacks.

[3] McCall (1990), Miller (1984), Neal (1999), Shaw (1987) and Jovanovic and Nyarko (1996) have extended the notion of job match quality presented by Jovanovic (1979) to the occupational level and presented some evidence for learning about occupational match quality.

may lower job mobility by reducing its role in acquiring information. Altonji (1993) introduced a formal model in which individuals learn their preference between two fields of study by attending college. More recently, Stange (2009) built on Arcidiacono's (2004) structural model of student learning to estimate the option value of college enrollment in the presence of uncertainty and learning about academic ability. Stinebrickner and Stinebrickner (2009) documented the role of learning about ability on the college dropout decision. In still another paper, Wiswell (2008) introduced a model in which teacher licensing requires students to specialize in teaching earlier, reducing the accumulation of general skills that are useful for those who decide not to teach. Finally, Hvide (2003) extended Spence's (1973) signaling model to allow for learning about overall ability and suggested that certain types of education, such as U.S. college degrees, may primarily provide information about ability, whereas others, such as U.K. college degrees, serve to augment productivity. I aim to contribute to this literature by embedding both skill acquisition and learning within a model of academic specialization. Applying this model to the British system of higher education, I am able to derive and test a simple comparative static prediction for the importance of learning about one's talents through higher education.

A Simple Model of Academic Specialization

Suppose individuals take n courses in each of k fields of study prior to specialization. Each course in a given field provides field-specific skills and a noisy signal of match quality in that field. In specializing, individuals choose a field and take $(N - nk)$ additional courses in this chosen field of study.[4] After completing a total of N courses, individuals choose whether to work in an occupational field that is related to their chosen field of study or to switch to an unrelated occupation. Upon entering the labor market, match quality is revealed and individuals receive returns that are increasing in both match quality and field-specific skills. I describe this basic setup in greater detail below. Then, I proceed to compare the probability of switching between an early system in which individuals are required to specialize after n^E courses in each field and a late system in which individuals are required to specialize after n^L courses in each field, where $n^E < n^L$. Analytical proofs are relegated to the Mathematical Appendix, which offers a more formal treatment of the model.

Setup

Assume that individuals are risk-neutral and have identical prior distributions on match quality for each field. Prior to undertaking schooling, however, match quality is unknown. Specifically, assume that match quality, θ_i, in each field i is a random draw from a normal distribution with the same mean and variance, so that $\theta_i \sim N(\ , \sigma^2_0)$. Match quality is therefore uncorrelated across fields and can include any field-specific components of education that affect returns, such as innate ability or interest, that contribute to productivity or enjoyment of working in a specific field.[5] In the empirical analysis, I attempt to control for indicators of predictable match quality so that the remaining components of match quality are random. In fact, prior distributions may differ across fields. Allowing for different prior means is straightforward and would not alter any of the results from the model. Differences in prior variances would introduce option value considerations similar to ones considered by Johnson (1978) and Miller (1984), so I abstract from them to keep the model parsimonious. In the "extensions"

[4] I assume that students are not constrained in choosing their field of study. In practice, there may be restrictions due to limited slots. Therefore, in the empirical analysis, I consider a specification that restricts attention to students with top high school grades who are clearly free to choose their fields, unconstrained by admissions requirements and the availability of slots.

[5] More generally, match quality can include imperfect information about the rewards to certain fields in the labor market or uncertainty regarding the likelihood of completing a field of study in university.

section, I discuss extending the model to allow for different prior variances and risk aversion.

By taking courses in a given field, individuals will accumulate field-specific skills and receive noisy signals of their match quality to that field. For simplicity, assume that the quantity of skills accumulated in a field, s_i, is equivalent to the number of courses spent studying in that field. Each course of study j in field i also provides a signal of match quality in that field: $x_{ij} = \theta_i + \varepsilon_{ij}$ where $\varepsilon_{ij} \sim N(0, \sigma^2)$ and $j = 1, \ldots, n$. Noise in the signal may be due to any number of idiosyncratic factors, such as the quality of instruction or the particular circumstances of the student at the time. I assume that skills are perfectly specific to a particular field, but I will discuss the possibility of spillovers across fields below.

The overall returns to field i upon entering the labor market is an increasing function of both match quality and skills: $u_i = u(\theta_i, s_i)$ with $(\partial \upsilon/\partial\theta) > 0$ and $(\partial u/\partial s) > 0$. Consequently, match quality is revealed upon entering the labor market. For simplicity, I assume that returns are a linear function of match quality and skills: $u(\theta_i, s_i) = \alpha\theta_i, \beta s_i$. I take (α/β) as an indication of the return to match quality relative to the return to specific skills. There may be additional random shocks that cannot be learned about in advance. Furthermore, returns may differ across different fields. In the empirical analysis, I compare outcomes for individuals controlling for field of study so that mean differences across fields can be ignored.

Choice of Field at Specialization

The posterior distribution of match quality after studying n courses in field i is a normal distribution with mean ${}'_i$ and variance σ'.[6] Further, the quantity of skills in each field at the point of specialization is $s' = n$. In specializing, therefore, risk neutral individuals with identical prior distributions across fields will choose the field of study with the highest expected returns:

$$\begin{aligned} \textit{choose } i^* &= \underset{i=1,\ldots k}{\arg\max}\left\{E\left[u(\theta_i, s_i) \mid \{x_{ij}\}^{j=1\ldots n}\right]\right\} \\ &= \underset{i=1,\ldots k}{\arg\max}\left\{\alpha\ {}'_i + \beta s'\right\} \end{aligned}$$

Since the quantity of specific skills in each field is identical, individuals simply choose the field with the highest posterior mean of match quality, $i^* = \arg\max_{i=1,\ldots k}\{\ {}'_i\}$.[7] Thus, the posterior mean of match quality in the chosen field at the time of specialization will be ${}'_{i^*}$[8]

Decision on Whether to Switch

Following specialization, individuals take $(N - nk)$ additional courses in the chosen field. Hence, the quantity of skills in the chosen field prior to entering the labor market is $s'' = n + (N - nk)$. Individuals will also receive additional signals in the chosen field, i^*. Define these signals as $y_{i^*l} = \theta_{i^*} + \varepsilon_{i^*l}$, where $l = nk, \ldots, N$. Consequently, the posterior distribution of match quality in the chosen field after $(N - nk)$ additional signals will be a normal distribution with mean ${}''_{i^*}$ and variance σ''.[9] Now, given the opportunity to switch to another field prior to entering the labor market, individuals will compare expected returns in the chosen field with expected returns in the next best field:

$$\begin{aligned} \textit{field switch} &\Leftrightarrow E\left[u(\theta_i, s_i) \mid \{x_{ij}\}^{j=1\ldots N}\right] \\ &< \max_{i \neq i^*}\left\{E\left[u(\theta_i, s_i) \mid \{x_{ij}\}^{j=1\ldots N}\right]\right\} \\ &\Leftrightarrow \alpha\ {}''_{i^*} + \beta s'' < \max_{i \neq i^*}\left\{\alpha\ {}''_{i^*} + \beta s'\right\}. \end{aligned}$$

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[6] The posterior mean is a weighted average of the prior mean and the mean of the signals: ${}'_i = (\ \sigma_0^{-2} + \sigma^{-2}\, n\bar{x}_i) / (\sigma_0^{-2} + n^{-2})$ where $\bar{x}_i = n^{-1}\sum^j x_{ij}$. The posterior variance is $\sigma' = \left(\sigma_0^{-2} + n\sigma^{-2}\right)^{-2}$. See DeGroot (1970) for a detailed explanation.

[7] Strictly speaking, expected future utility should include expected skills rather than the quantity of skills at the point of specialization. But since expected match quality and skills are separable and individuals are risk-neutral, this will lead to the same choice at the point of specialization.

[8] Specifically, ${}'_{i^*} = (\ \sigma^{-2} + \sigma^{-2} n \max_i \bar{x}_i) / (\sigma_0^{-2} + n\sigma^{-2})$.

[9] So that ${}''_{i^*} = (\ \sigma_0^{-2} + \sigma^{-2} n \max_i \bar{x}_i + \sigma^{-2}(N - nk)\bar{y}_{i^*}) / (\sigma_0^{-2} + n\sigma^{-2} + \sigma^{-2}(N - nk)\sigma^{-2})$ where $\bar{x}_i = n^{-1}\sum^j x_{ij}$, $\bar{y}_i = (n - NK)^{-1}\sum^j y_{i^*l}$ and $\sigma'' = \left(\sigma_0^{-2} + n\sigma^{-2} + (N - nk)\sigma^{-2}\right)^{-1}$.

Individuals will switch if the posterior mean of match quality in the chosen field falls sufficiently far below the posterior mean of another field to outweigh the loss in specific skills from switching. Note that, if individuals do decide to switch, they will always choose the field with the second-highest posterior mean since all fields other than the one chosen are associated with the same quantity of specific skills and posterior variance. The decision about whether to switch can therefore be framed as a comparison between the first best field, i^*, and the field that was second best at the time of specialization, i^a. The field selected after the second stage will be denoted i^{**} where $i^{**} \in \{i^*, i^a\}$.

Probability of Field Switching

Now consider the likelihood of an individual switching to an alternative field prior to entering the labor market. Recall that individuals in an early system are required to specialize after n^E courses in each field whereas individuals in a late system are required to specialize after n^L courses in each field, where $n^E < n^L$. Posterior distributions at the time of specialization will be more diffuse for individuals in the early system. Moreover, these individuals will receive more signals in the chosen field after specializing than their counterparts in the late system. Thus, in the early system, assessments of perceived match quality in the chosen field will experience relatively greater updating and make individuals more likely to conclude that they made a mistake when they initially inferred which field had the highest match quality.[10] However, in switching, individuals will lose the additional skills acquired in the chosen field of study through specialization. Individuals will therefore switch only if the posterior mean of the first-best field falls sufficiently below that of the second best field to outweigh the loss in specific skills. Since the loss in specific skills is always greater in the early system, whether switching is higher in the early or late system will depend on the relative return of match quality. This intuition is expressed more formally in the following proposition:

Proposition 1: A system with early specialization, n^E, will have a higher rate of field switching than a system with late specialization, n^L, if and only if the return to match quality is sufficiently higher than the return to specific skills:

$$P(switch)^E > P(switch)^L \Leftrightarrow \frac{\alpha}{\beta} > C > 0.$$

Figure 1 plots the probability of switching for an early and a late system over the full range of relative returns to match quality, which are normalized by taking $\beta = (1 - \alpha)$ so that (α/β) goes from 0 to ∞ as α goes from 0 to 1.[11] Since the model abstracts from other reasons for switching fields, no switching occurs in either system if the return to match quality is sufficiently low. However, by introducing an additional stochastic element to the model, such as $u(\theta_i, s_i) = \alpha\theta_i = \beta s_i + \varepsilon_i$ where $\varepsilon_i \sim N(0, \tau^2)$, switching can take place even if the return to match quality is zero. Allowing for these additional random shocks, I derive the following corollary:

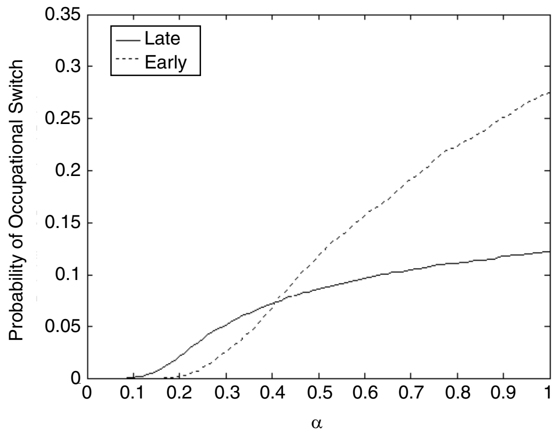
Corollary 1: If there is no return to match quality ($\alpha = 0$) or courses do not provide information about match quality ($\sigma^2 = \infty$), then a system with early specialization, n^E, will have a lower rate of switching than a system with late specialization, n^L.

Note the distinction between the return to match quality, α/β, and the quality of information on match quality provided by undergraduate courses, σ^2. Observing a higher

[10] Specifically, the posterior distribution is more likely to shift in response to the additional information received in the early regime. Hence, the mean of the posterior distribution of the chosen field is also more likely to move below the posterior mean of the second best field at specialization and indicate a perceived mistake. This is particularly intuitive in the case in which individuals specialize immediately prior to entering the labor market. In this case, the probability of perceiving a mistake will be zero since no additional information is received following specialization.

[11] All simulations are based on 5,000 repetitions for $k = 2$, $N = 21$, $_1 = \; _2 = 0$ $\sigma^2 = 100$ and $\sigma_0^2 = 25$. Early regimes are characterized by $n^E = 2$; late regimes are characterized by $n^l = 6$. Expected returns are determined according to $E(u_i) = E(\alpha\theta_i + \beta\hat{s}_i)$ where $\hat{s} = (s_i / (N / k)) +$ are normalized skills.

Figure 1. Probability of Occupation-Field Switching by Relative Return to Match Quality



rate of field switching in an early system rather than in a late system would imply that education provides valuable information on match quality *and* that match quality has a large impact on the returns to education.

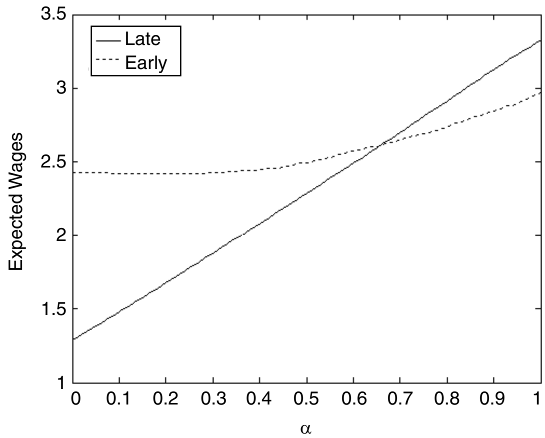
Focusing on the probability of switching to an unrelated occupation may appear to be an indirect way of testing whether education provides information about match quality. Indeed, according to this model, the trade-off between learning about match quality and accumulating specific skills is central to optimal timing of specialization in higher education. With later specialization, students have more time to learn about match quality in each field but less time to acquire specific skills once a field is chosen. Figure 2 simulates expected returns for an early and a late system over the full range of relative returns to match quality. Clearly, observing higher overall returns in the late system would also serve to indicate that the relative return to match quality is high. However, it is very difficult to obtain empirical measures that capture all of the returns to occupational choice. Since the decision to switch to an unrelated occupational field encompasses non-pecuniary considerations as well as pecuniary ones, there is a significant advantage in focusing on the likelihood of switching.[12]

Extensions

Throughout I have assumed that individuals are risk-neutral. Introducing risk aversion does not alter the decision at the point of specialization because the variances of the posterior distributions across fields are identical; individuals would continue to choose the field with the highest posterior mean. In considering a switch, however, the presence of risk aversion would make the relative variances of the posterior distributions relevant. Specifically, switches would be less common because, even in instances where the chosen field has a lower posterior mean than another field, its lower variance could be sufficiently valuable to risk-averse individuals so as to prevent switching. Moreover, this effect is stronger in the early system since the trade-off between the posterior variances at the time of specialization and the posterior variance of the chosen field after the receipt of additional signals is more extreme. Field switching would therefore decline more in the early system than in the late system due to the presence of risk aversion. This would lead to a bias towards the conclusion that the accumulation of specific skills is more important than learning about match quality.

[12] This is especially important in light of Arcidiacono's (2004) finding that most sorting across majors is due to different preferences rather than differential monetary returns to ability.

Figure 2. Expected Returns by Relative Return to Match Quality



Notes: All simulations are based on 5000 repetitions for k = 2, N = 21, μ = 0, $\sigma 0$ = 25, and σ = 100. Early regimes are characterized by $n^E = 2$; late regimes are characterized by $n^L = 6$. The relative returns to match quality are normalized by taking $\beta = (1-\alpha)$ so that (α/β) goes from 0 to ∞ as α goes from 0 to 1. Expected returns are determined according to $E(u_j) = E(\alpha\theta_i + \beta_{si})$ where $si = [s_i/(N/k)] + \mu$ are normalized skills.

The assumption that prior distributions on match quality are identical across fields implies that individuals do not need to consider the possibility of later switching when making their initial choice of field at the point of specialization. Allowing for prior variances on match quality to vary by field introduces option value considerations. These would push individuals to specialize in riskier fields because they could switch in the case of a bad realization. Moreover, fields with a larger prior variance would have greater option value in the early system than in the late system. With more signals following specialization, greater updating in the early system generates a higher probability that the ultimate posterior mean will surpass that of the chosen field. Hence, individuals in the early system would be more likely to choose a field with a lower posterior mean at the point of specialization because of the greater option value. Since, on average, such fields have lower expected match quality than those with the highest posterior mean, we should expect more switching in the early system due to option value considerations. This would lead to a bias towards the conclusion that learning about match quality is more important than gaining specific skills.[13]

As it stands, the model contains no truly general skills. A person has general skills only in the sense of having greater levels of specific skills in a variety of alternative fields, and this affects returns only when switching into one of these fields. Nevertheless, it would be relatively simple to incorporate general skills by including some measure of average skill in the fields not chosen for specialization: $\bar{s} = \frac{1}{J}\sum^{j \neq j^*} s_j$. Allowing for such general skills would serve to provide further benefits to later specialization. More generally, we could consider the possibility of spillovers in skills across fields. This would serve to reduce the trade-off between skills and match quality because additional learning about match quality would be less costly

[13] However, this effect is likely to be small because all fields are sampled prior to specialization and the option value needs to be greater than the difference in the posterior means of match quality between the relevant fields. Furthermore, risk aversion would counteract the benefits of having high variance in the posterior distributions.

in terms of forgone skill acquisition. Finally, if there is an additional benefit to match quality accrued while taking courses because people enjoy courses to which they are well matched, this would serve to heighten the trade-off between skills and match quality.

Background: Higher Education in Britain

The British system of higher education provides a particularly appropriate setting in which to examine the predictions of the model. Undergraduate education in England and Scotland, though similar in aim and overall structure, varies widely in the timing of academic specialization. In England, students apply to a specific field of study at a particular university.[14] Once admitted to a specific field, English students usually follow a narrow curriculum that focuses on the main field and allows for little exposure to other fields.[15] Indeed, most universities in England require students who change fields of study to start university anew (though some do allow for limited changes). In contrast, Scottish students are typically admitted to a broad faculty or school rather than a department; in some universities, admission is to the university at large.[16] Furthermore, they are required to study several different fields during their first two years. As an undergraduate prospectus for the University of Edinburgh explains:

> You would normally take courses in three or more subjects in the first year and, commonly, these are followed by second courses in at least two of the subjects in your second year. This will then give you a choice from two, or even three, subjects to pursue to degree level, and you can delay this decision until quite a late stage . . . In choosing courses to be taken in the first two years, you can select from a very wide range of courses offered across several faculties.

Similar course structures exist in most Scottish universities. They allow for substantial choice among fields of study within faculties, and, to some degree, across faculties as well.[17] Moreover, students in Scotland are *required* to take a broader range of courses and choose a field of study much later than their English counterparts.[18] The *Handbook for Students and their Advisors* for the years 1980–82 (Briggs 1980: 17–18) explains that "the standard English degree, whether in science, humanities or social sciences, is a single subject honours degree" whereas "universities in Scotland had traditionally offered a wide range of subject options with multi-subject examinations at the end of the first year." This information is also supported by empirical evidence, provided in later sections, indicating that the proportion of individuals who change their field of study between admission and graduation in Scottish universities is substantially higher than in English universities. Given these differences, it is quite natural to regard the English system of higher education as an early system and the Scottish system of higher education as a late system.

There is variation in the average length of the undergraduate degree between England and Scotland. Although there is some heterogeneity among degrees within each nation, most English degrees are completed within three years whereas most Scottish degrees are completed within four years. How-

[14] There are exceptions. For example, students at Cambridge University are accepted to a broad engineering faculty, and students at Keele University are first accepted to a year of "foundation studies."

[15] Again, there are exceptions. Cambridge's system of Tripos allows some flexibility in making changes to courses of study, and the newer universities of Essex, Kent, and Lancaster allow students to study a broader range of subjects. In recent years, even more English universities have introduced course structures that offer more breadth and greater flexibility.

[16] For example, faculties at the University of Glasgow include Arts, Biomedical and Life Sciences, Education, Engineering, Information and Mathematical Sciences, Law, Business and Social Sciences, Medicine, and Physical Sciences.

[17] Note that changing fields is not always possible. Certain professional faculties, such as medicine and law, are more insular. Engineering is usually a separate faculty but changes from the physical sciences are often permitted.

[18] Numerous scholars of British educational systems have noted that Scottish institutions allow for later specialization than English ones. See Evans (1976), Hunter (1971), Osborne (1967), and Squires (1987). Personal conversations and correspondences with university administrators in England and Scotland confirm these observations.

ever, many Scottish students enter university after 6 years of secondary schooling rather than the seven years customary in England. According to this calculation, English and Scottish students who attain a BA degree receive roughly the same number of years of schooling (and this is confirmed in the data by examining the age of graduation). The first year of university in Scotland may be said to correspond to the final year of secondary school in England. But even so, since English students apply to university in the beginning of their final year of secondary school whereas Scottish students make their final choice of field only at the end of their second year of university, there is substantial difference in the timing of specialization.

The difference between English and Scottish universities arose from their respective historical traditions. English universities were largely independent and free to set their curriculum and course structures. Long into the nineteenth century, Oxford and Cambridge maintained their focus on the traditional subjects (classics, Aristotelian philosophy, and mathematics) with less emphasis on modern subjects, such as natural science (Evans 1975). The provincial civic universities established later in urban centers did not substantially depart from the traditions of the "ancient" universities. Even with the introduction of broad faculties and additional courses of study, admissions remained at the departmental level.[19] Conversely, Scottish universities became regulated under the Universities (Scotland) Act of 1858 that set up an executive commission to draw up uniform conditions for courses of study. The Universities (Scotland) Act of 1889 further increased the choice of subjects available in Scottish universities, reflecting the "traditional Scottish preference for a broad general education" (Hunter 1971: 237). In large part, these two Acts of Scottish Parliament determined the distinctive characteristics of universities in Scotland, including the emphasis on late academic specialization.

In addition to differences in higher education, England and Scotland also differ in their system of secondary school education. In England, students need General Certificate of Education (GCE) Advanced-level examinations (A-levels) in 2 or three subjects to gain acceptance into university. In 1989, a new exam, the Advanced Supplementary examination (AS-level) was introduced to broaden the curriculum; it was to be the same standard as an A-level, but half the content. Students were encouraged to substitute two AS-levels for one of their A-levels, but most universities did not regard these examinations as commensurate alternatives and it did little to change the character of English secondary school education. Alternatively, in Scotland, students need Scottish Certificate of Education (SCE) Higher Examinations in five or six subjects to gain acceptance into university. More recently, Advanced Highers and Higher Still certifications have been introduced to provide the opportunity for further specialization in secondary school. However, universities continue to use Highers as the primary basis for admission and there is little doubt that the Scottish system of secondary education provides a broader curriculum than the English one. Again, the reasons for these differences in secondary school curriculum can be traced to historical antecedents. In effect, specialization trickled down from the universities to secondary schools. Moreover, the early influence of English universities on secondary school leaving exams was far stronger than that of Scottish universities since Scottish secondary school leaving certificates had to be approved by the Scottish Education Department.

The difference in the timing of specialization between the English and Scottish systems of undergraduate education does not arise at the graduate level. Graduate degrees in both England and Scotland require admission to a specific field of study. Hence, after accounting for any initial differences due to undergraduate specialization, I compare between England and Scotland at the graduate level as a "placebo test". The discussion above has focused on England and

[19] The main exceptions arise in the (Plate Glass) universities established during the 1960s such as the University of Keele, which implemented an experimental modular curriculum.

Scotland, but Britain also includes Wales, which has a distinct system of higher education. In contrast to Scotland, however, undergraduate students in Wales apply to a specific course of study in similar fashion as in England. Hence, though I exclude Wales from the main empirical analysis, I examine differences between England and Wales at the undergraduate level as another useful "placebo test."

Data and Empirical Strategy

Data

Data for the empirical analysis come from two sources: the Universities Statistical Record (USR) and the 1980 National Survey of Graduates and Diplomates (NSGD). The USR consists of administrative data on all students in British universities undertaking courses of one academic year or longer between 1972–1993: almost 1.9 million undergraduates and more than 1 million graduate students.[20] For the most part, I focus on students who completed their degree in 1980 to correspond with the data from the NSGD. These administrative data include detailed background information on demographic characteristics and entry qualifications in addition to information related to the degree attained. This is supplemented by information on the occupation, industry, and location of the job held in the first year following graduation. The NSGD contains information obtained from a national postal survey of some 8,000 graduates undertaken in 1986–87 by the British Department of Employment. It includes a random sample of one in six university graduates in 1980.[21] The NSGD contains information about their 1980 qualification, their subsequent labor market experience (occupation, industry, and wages for first and current jobs), and further educational pursuits. There is also information about their high school examination results. Although it is not possible to identify specific universities in the NSGD, there is information on whether students took English or Scottish secondary school leaving exams.

Neither dataset is representative of the overall population. Therefore, we might be concerned that the English and Scottish samples of university graduates may not be comparable because of differing participation rates. Using two nationally representative datasets that include all individuals born in Great Britain during one week in 1958 and 1970 (the National Child Development Study and British Cohort Study respectively), I calculated the percentage of individuals who attained a first degree from university by age 26. In both of these datasets, participation rates in university are remarkably similar between England and Scotland: 8% of the 1958 cohort and 12% of the 1970 cohort.[22] For the sample of students used in the regression analysis, almost all successfully complete their degree. This is because NSGD data was only collected for degree recipients and USR data on occupation is missing for most students who drop-out. Based on the full USR sample of university leavers in 1980, the fraction of students who drop out of university is 15.6%. There are differences across nations, with 14.6% of students dropping out in England and 19.5% of students dropping out in Scotland. I account for the bias introduced by differential dropout rates in a robustness check described below.

Table 1 indicates that the average characteristics of those attending English and Scottish universities are quite similar in both the USR and NSGD. Summary statistics are shown for the sample of students used in the regression analysis. There is a slightly larger

[20] Excluded are students enrolled in the Open University, Cranfield University, the independent University of Buckingham, and the former polytechnics and central institutions, which obtained university status from 1992 onwards.

[21] The NSGD also includes one in four graduates from other institutions (polytechnics, colleges of education), but I exclude them from the present analysis. Engineering students in Scottish universities are oversampled in the NSGD. Consequently, it is particularly important to control for fields of study with the NSGD sample.

[22] The oft-mentioned higher participation rate in Scotland usually includes students enrolled in non-university higher education institutions, such as polytechnics and colleges of education.

Table 1. Summary Statistics for 1980 College Graduates

	England			*Scotland*		
	Mean	*SD*	*Obs*	*Mean*	*SD*	*Obs*
Panel A: USR						
Individual characteristics						
Female	0.38	0.48	10,455	0.43	0.50	3,427
Married (during degree)	0.03	0.18	10,455	0.05	0.21	3,427
Average age (upon completion)	22.39	2.40	10,455	22.57	2.78	3,427
High School GPA (out of 30)	20.92	6.39	10,455	19.91	6.06	3,427
Number of high school subjects	3.22	0.71	10,455	4.78	1.27	3,427
Degree characteristics						
Duration	3.33	0.73	10,455	3.97	0.75	3,427
Changed major	0.07	0.25	10,455	0.18	0.39	3,427
Occupation-field switching						
Very broad classification	0.39	0.49	10,455	0.35	0.48	3,427
Broad classification	0.49	0.50	10,455	0.42	0.49	3,427
Narrow classification	0.68	0.47	10,455	0.63	0.48	3,427
Panel A: NSGD						
Individual characteristics						
Female	0.34	0.47	1,242	0.31	0.47	213
Married (6 years after degree)	0.53	0.50	1,242	0.59	0.49	213
Average age (upon completion)	22.01	1.51	1,242	22.26	2.40	213
High School GPA (out of 30)	19.71	5.84	1,242	18.25	5.77	213
Number of high school subjects	3.18	0.69	1,242	5.15	1.04	213
Occupation-field switching						
Very broad classification	0.44	0.50	1,242	0.29	0.45	213
Broad classification	0.50	0.50	1,242	0.34	0.48	213
Narrow classification	0.63	0.48	1,242	0.51	0.50	213

Notes: The base sample for the Universities Statistical Records (USR) includes all individuals who aimed to attain a BA degree in 1980 and were employed in a job during the 1st year following graduation and not pursuing graduate studies. The base sample for the 1980 National Survey of Graduates and Diplomates (NSGD) includes all individuals who attained a BA degree in 1980 and were employed in a job during the 1st year following graduation and not pursuing graduate studies. Median age at the start of the degree is 19 for both nations. GPA is an average measure of the achievement in secondary school leaving exams out of 30 (but standardized by nation in all regressions). Honors is a measure of success at university standardized across nations taking discrete values from 0 (no honors) to 4 (highest honors). Occupation-field switch is defined as 1 if field of study at the undergraduate level is different from the occupational field of first job 6 months following degree and 0 otherwise (see Data Appendix for further discussion of classification groups).

percentage of women and married students in Scottish universities. The average age upon completion of the first degree is almost equivalent in England and Scotland but the average duration of the degree is somewhat longer in Scotland. Further, although the average age that students begin university is slightly lower in Scotland, the median age of students during their first year in university is 19 for both England and Scotland (not shown). The raw high school grade point average (GPA) scores shown in Table 1 are converted from letter grades in the A-level and Scottish Higher school leaving examinations. In the regression analysis, these scores are normalized within each nation so that coefficients represent the effect of a one standard deviation increase in GPA. As expected, there are striking differences in the likelihood that students change their major field of study in university.[23] If I exclude the handful of English universities that allow for changes in major fields, the fraction of English students who change major drops to less than 4%.

The model introduces an important distinction between individuals who enter an occupation that is related to their field of study and those who switch to an unrelated occupation. I construct a variable, *SWITCH*, that captures such field switching by grouping fields of study and occupations into categories; I refer to it as an occupation-field switch. As Appendix Table 1 shows, I allow for three levels of classification: narrow (42 categories), broad (12 categories), and very broad (6 categories). Individuals are said to switch to an unrelated occupation when the field of study of their degree and their occupational field are in different categories, subject to the level of classification. Therefore, *SWITCH* is coded as 1 if the occupational field is different from the field of study at university, and 0 otherwise. Broader classifications indicate lower rates of switching since only drastic changes from fields of study to occupational fields will register. But the rate of occupation-field switching is substantially lower in Scotland than in England according to all classifications. For example, in terms of the broad classification, the rate of switching in Scotland is 10 to 20 percentage points lower than the rate of switching in England. Most of the empirical analysis will focus on the broad classification of fields.[24]

Table 2 indicates that the composition of broad fields of study across the two nations is not too dissimilar. Nevertheless, relatively more students in Scotland study life sciences, health sciences, and business and relatively fewer study mathematical and social sciences. The composition of occupations across the two nations is also largely comparable. As expected, the majority of students in both England and Scotland enter employment in the United Kingdom. The lower rate of unemployment among Scottish individuals is a consequence of the over sampling of engineering graduates who are less likely to be unemployed than others. Note that some individuals do work concurrently while pursuing further study in the United Kingdom. Finally, results from the IEA Third International Mathematics and Science Study (TIMSS) in 1994–95 indicate no significant differences between England and Scotland in the mathematics achievement for students in the fourth and eighth grades.[25]

Using data from the USR, Figure 3 plots the rates of occupation-field switching, unemployment, and the continuation of further studies following graduation from 1973–1993 as well as the proportion of students who change a major field of study while in university. The raw differential in switching between England and Scotland is persistent over time. Conversely, the rates of unemployment and further study are similar across England and Scotland for most years. It is worth noting that the recessions in the early 1980s and early 1990s appear to be associated with an increase in the rate of occupation-field switching.

Empirical Strategy

The base sample includes all individuals aiming to attain a BA degree in 1980 and employed full-time in the first year following completion of their qualification. I exclude individuals pursuing graduate studies while working because this may select for weaker students who need to work while pursuing higher degrees. Using the USR, I verify that the main results hold for other years as well. Using the NSGD, I check whether the main results continue to hold 6 years after entry into the labor market. Furthermore, I explore a variety of alternative sampling

[23] In Scotland, students are coded according to a broad code associated with a faculty or school or on the basis of a provisional field of study, which changes when they select a specific field. See the Data Appendix for more details.

[24] These include Math/Computer Sciences, Physical Sciences, Architecture, Engineering, Biological Sciences, Health, Social Services, Social Sciences, Business, Law, Education, and Arts.

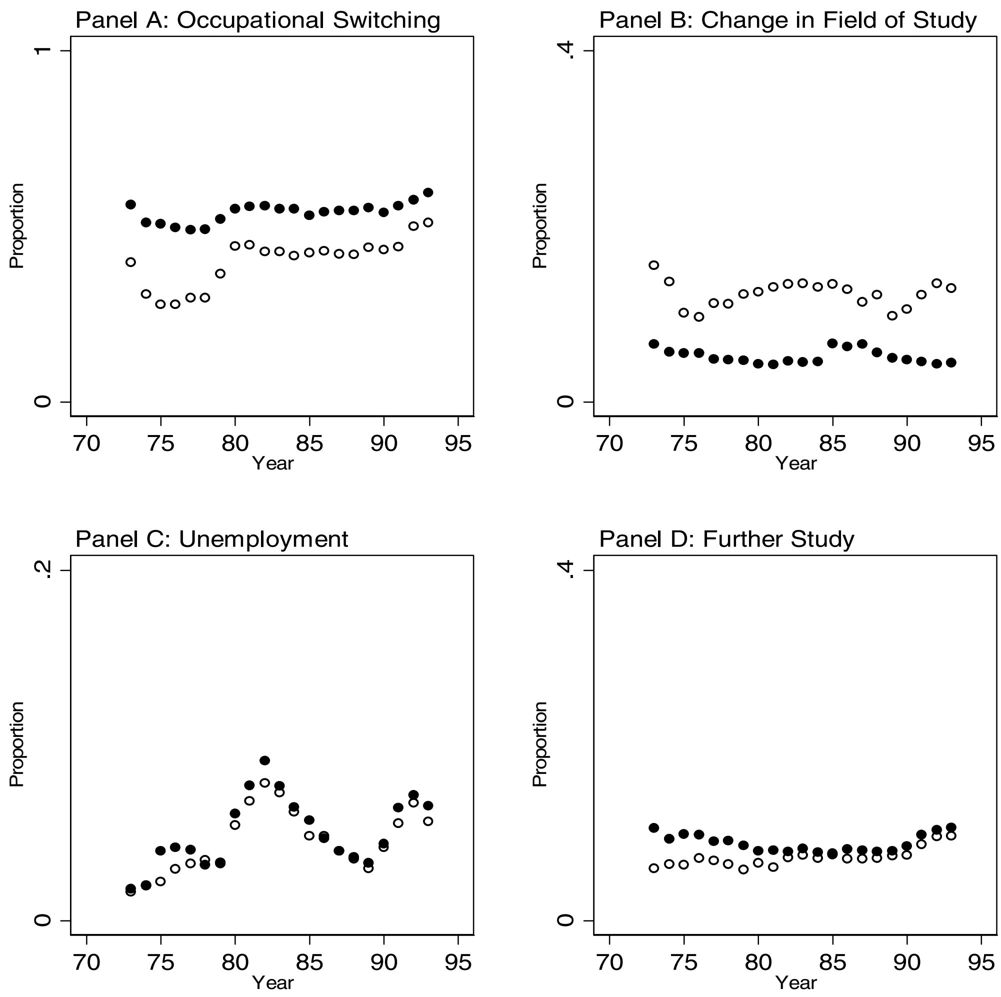
[25] There are, however, some differences in the science achievement scores. English students in the eighth grade do somewhat better than their Scottish counterparts, but there is no significant difference for fourth graders.

Table 2. Further Summary Statistics on Degrees and Destinations for 1980 College Graduates

	USR		*NSGD*	
	England	*Scotland*	*England*	*Scotland*
Degree Field Composition (%)				
Math and Computer Sciences	6.44	4.20	7.57	3.76
Physical Sciences	9.52	9.22	14.65	7.51
Architecture	1.56	1.31	1.77	2.35
Engineering	11.41	8.70	21.18	30.05
Life Sciences	5.96	7.56	6.76	7.98
Health Sciences	16.15	19.67	4.27	5.16
Social Services and Welfare	2.94	3.68	2.98	1.88
Social Sciences	16.06	16.72	18.92	15.49
Business/Accounting	3.59	5.52	4.43	6.10
Law	8.13	6.45	1.29	9.86
Education	1.23	1.28	3.14	4.23
Art	17.03	15.70	13.04	5.63
Occupational Field Composition (%)				
Math and Computer Scientists	5.23	4.64	11.19	6.10
Physical Scientists	6.74	6.36	6.04	4.23
Architects/Planners	1.43	1.69	2.74	3.29
Engineers	10.13	7.76	21.42	30.52
Life Scientists	0.39	0.50	2.17	3.76
Medical Professionals	16.56	20.51	5.56	4.69
Social Services Professionals	1.71	2.63	3.22	2.35
Social Scientists	2.09	2.92	1.85	2.82
Accountants/Managers	27.69	29.00	34.78	24.88
Lawyers/Judges	7.55	6.07	0.24	7.51
Educators/Teachers	17.24	15.76	7.89	7.98
Artists/Journalists/Entertainers	3.24	2.16	2.90	1.88
Post-BA Activity (%)[a]				
Entering employment	76.74	79.28	61.86	64.13
Further Study	11.64	10.11	27.65	29.00
Unemployed	11.63	10.61	10.48	6.88
Region of Work (%)				
England	87.17	32.59	87.36	25.35
Scotland	1.15	61.04	1.77	70.89
Wales	1.90	1.02	3.38	0.47
Northern Ireland	0.37	0.50	0.32	0.00
Abroad	9.40	4.84	7.17	3.29
Region of Prior Residence (%)				
England	91.91	15.61		
Scotland	0.61	81.27		
Wales	4.75	0.35		
Northern Ireland	1.19	1.69		
Abroad	1.54	1.08		

Notes: Composition of fields of study and occupational fields are based on a broad classification (other classifications are discussed in the Data Appendix). Occupational field represents the field of employment in the 1st year after completing degree. Foreign students returning overseas are excluded from counts of Post-BA activity.
[a] is out of the unrestricted sample including unemployed and graduate students.

Figure 3. Outcomes by Year of Graduation (USR sample)



Notes: Closed and open circles represent England and Scotland averages, respectively. Outcomes based on USR samples of undergraduates from 1973–1993. Occupation-Field switching is calculated with the broad classification (see Appendix Table 1). Change of field of study is determined by students who receive a degree in a field different from the one they applied for. Unemployment and Further study occur during the 1st year following graduation.

restrictions: (a) including graduate students who have occupation data; (b) including unclassified occupations such as manual and clerical occupations instead of coding them as switches since individuals in one nation may be more likely to end up in nonprofessional occupations; (c) coding individuals who end up unemployed as switches since this may be the result of a differential macroeconomic shock across the two nations; (d) excluding the fields of education and business or coding individuals who study them as non-switches since they are particularly subject to misclassification (and similarly with combined fields); and (e) coding students who dropped out as switches. Additional robustness checks restrict the sample to students with top high school grades who are clearly free to choose their fields, unconstrained by admissions requirements and the availability of slots. Finally, I also focus on the sample of English students from northern England since they are probably most similar to individuals from Scotland.

The effect of a Scottish degree on the probability of switching is captured by λ in the following regression equation:

$$(1) \qquad SWITCH_{ij} = \beta' X_{ij} + \lambda SCOT_{ij} + \phi_j + \varepsilon_{ij}$$

where $SWITCH_{ij}$ is a dummy variable for an occupation-field switch for individual i in field j, $SCOT_{ij}$ is a dummy variable indicating the individual received a Scottish degree and therefore specialized late, ϕ_j is a set of field of study fixed effects, X_{ij} are demographic characteristics, and ε_{ij} is a disturbance term. The primary demographic controls include sex, age, marital status, high school GPA, and parents' socioeconomic status (SES). In further robustness checks, I show results from two "placebo tests" in which $WALES_{ij}$ or $SCOTGRAD_{ij}$ are used in place of $SCOT_{ij}$ to explore comparisons between England and Wales or between England and Scotland at the graduate level. The identifying assumption for the main regression equation is that students in England and Scotland are no different on unobservable characteristics, that is, $Cov(\varepsilon_{ij}, SCOT_{ij}) = 0$.

Note, however, that attainment of a Scottish or English degree is not randomly assigned. Rather, once they complete their secondary education, individuals can choose to attend universities in either England or Scotland. Table 2 shows the national breakdown of individuals studying in England and Scotland. The migration patterns from prior residence to university indicate that 3.3% of individuals with English prior residence choose to study in Scotland whereas 7.4% of individuals with Scottish prior residence choose to study in England. There may be systematic differences between those individuals who decide to attend university in the other system. If these differences are uncorrelated with the probability of switching, this should not pose a problem. However, if individuals who migrate to university have a different likelihood of switching, OLS estimates will be biased. This might arise because individuals who migrate have unobserved characteristics that are correlated with the likelihood of switching. Or more directly, individuals might choose the university system based on their own expected likelihood of switching. For example, individuals from England that have less precise priors on match quality may decide to attend universities in Scotland where academic specialization is postponed. Hence, I will also consider regressions in which I instrument for the attainment of a Scottish or English degree with the region of prior residence. Since the type of degree and region of prior residence are not available in the NSGD, I use the type of school leaving examinations (whether Scottish or English) to estimate a reduced form equation of the probability of switching.[26]

Results

In Tables 3, 4 and 5, the main predictions on occupation-field switching with both the USR and NSGD are tested. Across almost all specifications, the probability of a switch is significantly lower for individuals with Scottish degrees than for their English counterparts. The estimated difference in occupation-field switching between England and Scotland from the preferred 2SLS specification is approximately 6 percentage points, which is substantial considering that the rate of switching in Scotland is about .42. Indeed, the coefficient on *SCOT* from equation 1 is negative and significant in almost every year between 1973 and 1993 (results not shown, but Panel A of Figure 3 displays the raw differences over time). According to the model, these findings indicate that the return to match quality is high relative to the return to specific skills. That we observe more occupation-field switches in England, a system with early specialization, implies that the benefits to increased match quality are substantial, and, indeed, large enough to outweigh the greater loss of skills.

[26] There is some choice available with the type of secondary school, but the correlation between Scottish residence and attendance in Scottish high school is .96. Furthermore, the correlation between attendance in a Scottish high school and sitting Scottish leaving examinations is .98.

Main Findings

Using data from the USR, Table 3 shows the pattern of occupation-field switching for students who graduated in 1980. As a baseline, Panel A includes all English students. All regressions include controls for gender, marital status, age, high school GPA, and parental SES. In column (1), I estimate the difference in the probability of switching between England and Scotland without controlling for fields of study or region of work. Once I control for the composition of fields across nations in column (2), the estimated differential in occupation-field switching declines substantially. In other words, not only do individuals in Scotland switch less, but they also tend to study fields that are associated with less switching.[27] In column (3), I add controls for region of work and the coefficient on *SCOT* becomes smaller still, suggesting that there may be less switching among Scottish employers who prefer to hire individuals with related qualifications. This specification needs to be interpreted with care, however, since the decision to work in England or Scotland is probably endogenous; individuals who decide to switch may also make systematically different decisions about where they wish to work.

In columns (4), (5) and (6), I instrument for the attainment of a Scottish degree with the region of prior residence.[28] 2SLS estimates of the difference in occupation-field switching between England and Scotland increase substantially and lend support to the hypothesis of non-random selection. If individuals who are less focused and hence more likely to switch decide to earn their degrees in Scotland, OLS estimates of switching in Scotland will be biased towards more switching. Similarly, if individuals who are more focused and less likely to switch decide to earn their degrees in England, OLS estimates of switching in England will be biased towards less switching. Since individuals with Scottish degrees are, in fact, less likely to switch than their English counterparts, 2SLS estimates should *and do* indicate an even greater differential in switching. Panel B uses information from the USR to restrict the sample of English students to those from northern England since they are the most similar comparison group to individuals from Scotland.[29] The pattern of occupation-field switches between Scotland and northern England appears to be even stronger than the one found when all students from England are included.

These findings are robust to alternative (broader and narrower) classifications, as well as to the sampling restrictions described in the previous section. In particular, results are similar when assuming that any student who dropped out would have switched to an occupation that was unrelated to his or her field of study (since this would otherwise bias towards finding a lower rate of switching in Scotland than England). Moreover, the findings remain unchanged when restricting to the sample of students with top high school GPAs and when excluding students at Oxford and Cambridge. Interestingly, the main results do appear to be slightly stronger for women than for men, but there is not much heterogeneity by age and parental SES. A full set of robustness results is available upon request.

Table 4 presents evidence on the determinants of occupation-field switching within the field of engineering. A degree in engineering is associated with a well defined occupation, and the content of such degrees is extremely similar across the two nations. Using the narrow classification, I can identify switches by subfield, such as from study-

[27] In fact, English students may be endogenously choosing broader fields that facilitate switching to avoid specializing in an excessively narrow field. Much of the variation in field switching is explained by differences across fields of study (the R^2 increases from .03 to .39 once controls for fields of study are included).

[28] Coefficient estimates are almost equivalent when instrumenting for attainment of a Scottish degree with the type of secondary school leaving exams completed or with the location of secondary school.

[29] I have also considered reweighting the Scottish and English samples to resemble one another using the methods developed by DiNardo, Fortin, and Lemieux (1996). The coefficients from regressions using the DFL weights are very similar to those from the unweighted specifications presented in the paper (available by request).

Table 3. Effect of Scottish Degree on Occupation-Field Switching for 1980 Graduates (USR)

	Dependent variable: switched to occupation unrelated to field of study					
	OLS			*2SLS*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A: Scotland vs. England						
SCOT	−0.079**	−0.064**	−0.048*	−0.107**	−0.089**	−0.099**
	[0.016]	[0.017]	[0.023]	[0.034]	[0.019]	[0.029]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R2	0.03	0.39	0.39	0.03	0.39	0.39
Observations	13,882	13,882	13,882	13,882	13,882	13,882
Mean of dep. Variable	0.47	0.47	0.47	0.47	0.47	0.47
Panel B: Scotland vs. Northern England						
SCOT	−0.086*	−0.079**	−0.079**	−0.093	−0.101**	−0.128**
	[0.029]	[0.023]	[0.023]	[0.047]	[0.025]	[0.031]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R^2	0.03	0.37	0.37	0.03	0.37	0.37
Observations	4,921	4,921	4,921	4,921	4,921	4,921
Mean of dep. Variable	0.42	0.42	0.42	0.42	0.42	0.42

Notes: Huber-White standard errors, clustered by university in brackets. Sample includes all students who aimed to attain a first degree in England and Scotland with occupation data and were not pursing further studies. Dependent variable is defined as 1 if broad field of study at the undergraduate level is different from the broad occupational field of the first job in the 1st year following degree and 0 otherwise. SCOT is defined as 1 for Scottish degree and 0 for English degree. SCOT is instrumented with nation of prior residence in columns 4, 5, and 6. Main controls include sex, marital status, age, high school GPA, and parent SES. Panel B is restricted to students in England whose region of prior residence was northern England (including North East and Tyne, and all of Yorkshire).
*Statistically significant at the .05 level; **at the .01 level.

ing mechanical engineering to becoming an electrical engineer. In order to increase precision, I pool the USR data on engineers from 1980 to 1992.[30] The main results are confirmed in this setting—individuals who study engineering in Scotland are generally less likely to switch to an unrelated occupation than their counterparts who study engineering in England. Pooling USR data from 1980 to 1992, I also examined the likelihood of switching for each field of study separately (results available upon request). The coefficient on *SCOT* for social sciences and the arts is negative and significant, indicating that this differential is also associated with fields outside the hard sciences. There are no significant differences in switching across England and Scotland for certain fields such as health, business, and education.[31] More generally, these effects may vary across fields because of differences in the relative returns

[30] Note that I exclude 1973–1979 and 1993 because there is no information on parental SES. The results are similar if I include these years and drop the measures of SES.

[31] A degree in medicine is an extremely specialized course in both English and Scottish institutions. A degree in business may provide a broad set of skills that dampens the differences that arise from early versus late specialization.

Table 4. Effect of a Scottish Degree on Occupation-Field Switching for Engineers (USR, 1980–1992)

	Dependent variable: switched to occupation unrelated to engineering subfield					
	OLS			*2SLS*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
SCOT	−0.062	−0.037*	−0.034*	−0.064*	−0.047**	−0.049**
	[0.032]	[0.014]	[0.016]	[0.032]	[0.012]	[0.015]
Main controls	X	X	X	X	X	X
Sub-field effects		X	X		X	X
Region of work effects			X			X
R^2	0.02	0.29	0.29	0.02	0.29	0.29
Observations	21,819	22,320	22,320	22,320	22,320	22,320
Mean of dep. variable	0.28	0.28	0.28	0.28	0.28	0.28

Notes: Huber-White standard errors, clustered by university in brackets (that the standard errors are larger for OLS than 2SLS may occur because of the strong first stage and the cross-correlations within the clustered groups). Sample includes all students who aimed to attain a first engineering degree in England and Scotland with occupation data and were not pursing further studies. Dependent variable is defined as 1 if the engineering subfield at the undergraduate level is different from the engineering subfield of the first job in the 1st year following degree and 0 otherwise. SCOT is defined as 1 for Scottish degree and 0 for English degree. SCOT is instrumented with nation of prior residence in columns (4), (5), and (6). Main controls include sex, marital status, age, high school GPA, parent SES and year fixed effects.
*Statistically significant at the .05 level; **at the .01 level.

to match quality; learning about match quality may be more important in certain fields than in others.

Table 5 presents data from the NSGD to show occupation-field switching between England and Scotland. I estimate a reduced-form equation in which *SCOT* is a dummy variable identifying whether students took English or Scottish secondary school leaving exams, because that is the only indicator available in the NSGD. As a result, I cannot restrict the sample to individuals from northern England. Again, all regressions include controls for gender, marital status, age, high school GPA, and parental SES. Columns (1), (2) and (3) show the reduced-form effect of having completed school leaving exams in Scotland on the likelihood of working in an occupation unrelated to the chosen field of study in the first year following graduation. Confirming our results from the USR, most specifications show that students from England are more likely to switch than their counterparts from Scotland. However, the NSGD also contains information on student outcomes six years following the completion of their degree. Columns (4), (5), and (6) indicate that the differential in switching between England and Scotland remains after six years. Note that the coefficient on *SCOT* becomes insignificant when controlling for region of work.[32] Stronger results are obtained if I consider all individuals employed six years following completion of the BA degree by including those who were not employed in the first year after completing their degree (results not shown).

Placebo Experiments

In addition to the various robustness checks discussed above, Table 6 presents two

[32] The NSGD data contain somewhat more detailed categories for region of work than the USR data, with locations in England classified as London, Midlands, East Anglia, and Southern and Northern England. As mentioned above, the decision to work in these more specific regions (such as London) may well be endogenous to occupational switching.

Table 5. Effect of Scottish Degree on Occupation-Field Switching for 1980 Graduates (NSGD)

	Dependent variable: switched to occupation unrelated to field of study					
	1st year after completing degree			*6th year after completing degree*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
SCOT	−0.151**	−0.086**	0.014	−0.174**	−0.110**	−0.053
	[0.035]	[0.028]	[0.045]	[0.036]	[0.029]	[0.046]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R^2	0.03	0.35	0.36	0.03	0.30	0.31
Observations	1,455	1,455	1,455	1,455	1,455	1,455
Mean of dep. variable	0.48	0.48	0.48	0.52	0.52	0.52

Notes: Huber-White standard errors, clustered by university in brackets. Sample includes all students who aimed to attain a first degree in England and Scotland with occupation data and were not pursing further studies. Dependent variable is defined as 1 if field of study at the undergraduate level is different from the broad occupational field of the first job in the 1st year following the degree and 0 otherwise. SCOT is defined as 1 for having completed Scottish school leaving exams and 0 for having completed English school leaving exams. Main controls include sex, marital status, age, high school GPA, and parent SES.
*Statistically significant at the .05 level; **at the .01 level.

"placebo tests" to verify that the differential in occupation-field switching between England and Scotland is not due to differences in unobserved characteristics across the two nations. Panel A examines the difference in switching between England and Wales for 1980 college graduates using data from the USR where I can identify whether individuals attended university in Wales. Since undergraduate students in both England and Wales generally apply to a specific field of study in university, we would expect no difference in switching between England and Wales. The specifications are analogous to those in Panel A of Table 3. Columns (1), (2), and (3) present the results from OLS regressions in which *WALES* is a dummy variable indicating whether individuals completed university in Wales. Columns (4), (5), and (6) show the results from the 2SLS regressions in which the attainment of a Welsh degree is instrumented with the region of prior residence. None of the specifications indicates any significant difference in switching between England and Wales. Since the timing of academic specialization in Wales is similar to that in England, the absence of a difference in switching between England and Wales is reassuring and supports the contention that the difference between England and Scotland is a consequence of the timing of specialization.

Panel B examines the difference in occupation-field switching between England and Scotland, but at the graduate level. As mentioned, the USR has separate files containing information on students with graduate degress. Since graduate degrees in both England and Scotland are similar in terms of specialization—both require admission to a very specific field of study—we expect to see no difference in switching at the graduate level. Of course, I control for undergraduate degree since the model itself predicts that students who complete an undergraduate degree in Scotland will have higher match quality and lower levels of specific skills than those in England. I focus on the sample of students who completed their studies in 1980 and entered the labor market at the same time as the undergraduate students analyzed above. Columns (1), (2), and (3) display results from the OLS regressions in which *SCOTGRAD* is a dummy variable

Table 6. Placebo Tests

Panel A: Occupation-Field Switching in Wales vs. England (USR sample)

	OLS			*2SLS*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
WALES	0.094	–0.001	–0.003	–0.08	–0.02	–0.034
	[0.051]	[0.019]	[0.020]	[0.120]	[0.036]	[0.048]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R2	0.03	0.40	0.41	0.03	0.40	0.40
Observations	12,082	12,082	12,082	12,082	12,082	12,082
Mean of dep. variable	0.51	0.51	0.51	0.51	0.51	0.51

Panel B: Graduate-level Occupation-Field Switching in Scotland vs. England

	USR Sample (OLS)			*NSGD sample (reduced form)*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
SCOTGRAD	0.005	0.029	0.019	0.040	0.048	–0.048
	[0.036]	[0.042]	[0.040]	[0.050]	[0.047]	[0.070]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R2	0.01	0.19	0.19	0.03	0.11	0.13
Observations	4,400	4,400	4,400	760	760	760
Mean of dep. variable	0. 50	0.50	0. 50	0.32	0.32	0.32

Panel C: Academic Switching in Scotland vs. England

	USR Sample (OLS)			*NSGD sample (reduced form)*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
SCOT	0.038	0.050**	0.002	0.020	0.037	0.005
	[0.030]	[0.024]	[0.017]	[0.046]	[0.040]	[0.070]
Main controls	X	X	X	X	X	X
Field of study effects		X	X		X	X
Region of work effects			X			X
R2	0.01	0.23	0.24	0.01	0.21	0.23
Observations	15,038	15,038	15,038	1,100	1,100	1,100
Mean of dep. variable	0.37	0.37	0.37	0.61	0.61	0.61

Notes: Huber-White standard errors, clustered by university in brackets. Dependent variable in Panel A is defined as 1 if the broad field of study at the undergraduate level is different from broad occupational field. WALES is defined as 1 for Welsh degree and 0 for English degree, and instrumented with nation of prior residence in columns 4, 5, and 6 of Panel A. Main controls include sex, marital status, age, high school GPA, and parent SES. Dependent variable in Panel B is defined as 1 if the broad field of study at the graduate level is different from broad occupational field. SCOTGRAD is defined as 1 for graduate Scottish degree and 0 for graduate English degree. Columns 4, 5, and 6 of Panel B show the reduced form using Scottish school leaving exams as a proxy for a Scottish graduate degree. Main controls for the USR in Panel B include sex, marital status, and type of undergraduate degree, while the corresponding main controls for the NSGD include sex, marital status, age, high school GPA, and parent SES. Dependent variable in Panel C is defined as 1 if the broad field of study at the graduate level is different from broad field of study at the undergraduate level. Main controls for the USR in Panel C include sex and marital status, whereas the corresponding main controls for the NSGD include sex, marital status, age, high school GPA, and parent SES. The USR regressions in Panel C use students graduating in 1990 (due to the absence of undergraduate field for 1980 graduates); all other regressions are restricted to students graduating in 1980.
*Statistically significant at the .05 level; **at the .01 level.

indicating whether individuals completed their graduate degrees in Scotland.[33] Controlling for undergraduate degree, there is no significant difference in the probability of an occupation-field switch between England and Scotland at the graduate level. The NSGD includes students who graduated from college in 1980 and completed their graduate degrees some years later. Columns (4), (5), and (6) report results from the reduced form regression where the completion of graduate degrees in Scotland is proxied by whether students took English or Scottish secondary school leaving exams (I cannot control for undergraduate degree in these regressions). Still, there is no significant difference in switching between England and Scotland at the graduate level. These results further support the argument that the difference in occupation-field switching between England and Scotland derives from the timing of specialization in undergraduate education and not from some other characteristic inherent to English and Scottish individuals, or from labor market conditions particular to England and Scotland.

Finally, I examine the probability of switching to a graduate degree in a field that is unrelated to the undergraduate field of study—"academic field switching"—in Panel C. The probability of switching to an unrelated graduate degree is not significantly different for individuals with a Scottish undergraduate degree than for individuals with an English undergraduate degree for most specifications. Indeed, the sign is actually positive in all cases. One possible explanation is that the relative return to match quality for success in further study is different than for wages in the labor market. If further study at the graduate level depends more on the specific skills acquired at the undergraduate level, the benefits from switching may no longer exceed the greater loss of skills in the early system. In other words, the relative return to academic skills in graduate education may be substantially larger than in the job market.

Alternative Explanations for Switching

Occupation-field switching may arise for reasons other than those described by my model of academic specialization.[34] If certain individuals are particularly indecisive, they may be more likely to switch. Other individuals may simply be more adept at making changes and are therefore more likely to switch to an occupation unrelated to their field of study. Although these characteristics are generally unobservable, I can examine whether such switching is correlated with other decisions, such as a change in major field of study in university. Regression analysis confirms that individuals who change fields of study *during* university are also significantly more likely to experience an occupation-field switch (not shown). However, as mentioned previously, 18% of Scottish students change their field of study during university compared to just 7% of the English students. That students from Scotland are less likely to switch to an occupational field unrelated to their field of study despite being more likely to change their declared field of study after entry into university provides some suggestive evidence that this differential in switching between England and Scotland is not driven by such unobservables.

Occupation-field switching may also be driven by the availability of jobs in different occupational fields. If certain sectors experience negative shocks to labor demand, recent graduates may be forced to switch to a different occupational field from the one they studied. Appendix Table 2 shows the percentage of individuals employed in different occupational fields by field of study in 1980. As expected, certain fields of study have substantial outflows into unrelated occupational fields (social sciences, physical sciences, and arts). Other occupational

[33] The USR does not contain information on birth region, so I cannot instrument for whether an individual attained a Scottish degree with their place of birth or place of residence prior to commencing their studies.

[34] For this reason, simply observing that switching takes place is not sufficient evidence that education provides valuable information about match quality, and we need to test the comparative static predictions from the model.

fields have substantial inflows from unrelated field of study (business, engineering, education). However, evidence for flows in both directions—for example, from math/computer sciences to physical sciences *and* vice versa—suggests that field switching is not driven solely by the availability of jobs in different occupational fields.

Variation in Switching across Universities

A comparison of labor market outcomes across England and Scotland has the disadvantage of including only two nations. An alternative empirical approach would have been to compare student outcomes across universities. The theoretical model assumes that the cost of changing majors in university following specialization is infinite and identical across all universities within each system. But in fact, there is some variation across institutions. In England, although most universities require students to apply to a specific field prior to entry, there are differences in the penalty to changing fields of study once students are enrolled in a specific course. In Scotland, students are either required to write down their expected field of study or they are coded with a broad faculty to begin with, which is then changed appropriately when they select a specific field. Since these penalties are difficult to quantify, we might consider using the actual proportion of students changing fields as a proxy for the penalty.

Any comparison across universities, however, will suffer from selection bias since students choose from among the many universities available to them. We expect that individuals who are unsure about what to study would be more likely to choose a university with less stringent penalties and be more likely to switch to an unrelated occupation upon entering the labor force. Moreover, using the actual proportion of students who change fields as a proxy may well confound the actual penalty with student characteristics that are correlated with these changes and other labor market outcomes. Indeed, if students who change majors are also more likely to switch to unrelated occupations, then any unequal distribution of students across universities will yield this correlation. Figure 4 plots the proportion of individuals who switch to an unrelated occupation by the proportion of students who change fields of study while in university.[35] The pattern of occupational switching *between* England and Scotland confirms the main findings of this paper and demonstrates that the propensity to switch fields in English universities is higher than in Scottish universities with comparable proportions of students who change majors. However, the positive correlation between changes in major and occupational switching *within* both England and Scotland would mistakenly suggest that students attending universities with less stringent penalties for specializing later are also more likely to switch to an unrelated occupation—a rather different result from the one reached by comparing across nations.[36] Thus, the presence of selection bias may present serious problems if we don't focus on exogenous differences in the timing of specialization.

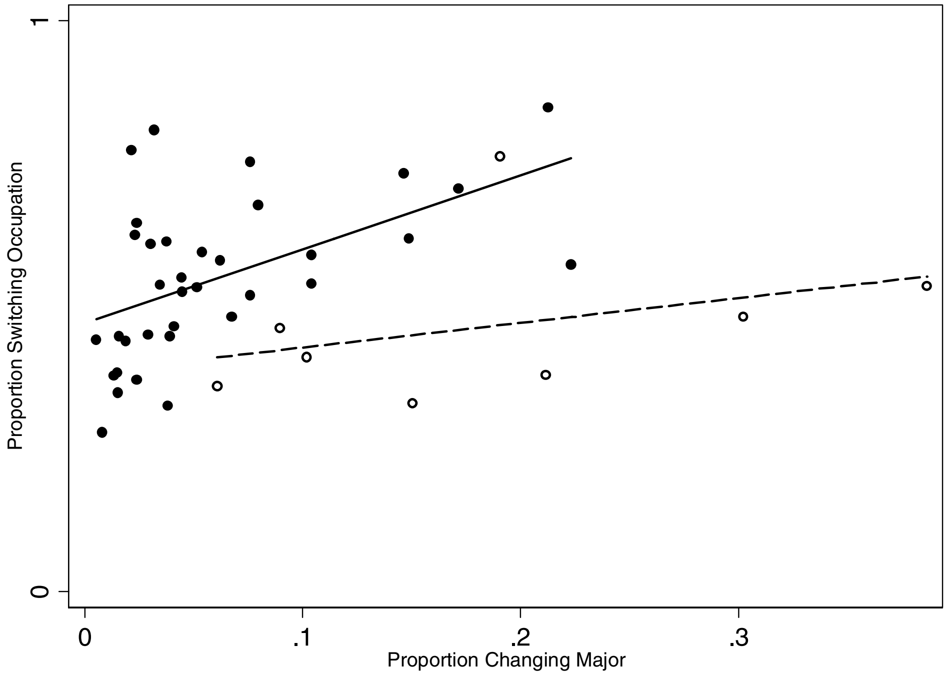
Conclusion

Substantial research has examined the effect of education on labor market outcomes. Recent work has confirmed that the relationship between education and outcomes such as wages is indeed causal (Card 1999). However, there has been less progress in understanding *why* education affects labor market outcomes. Education is often thought to provide certain skills that make workers more productive in performing tasks that are valued in the labor market (Neal and Johnson 1996; Cascio and Lewis 2006). Alternatively, education may enhance workers' ability to deal with disequilibria, which may

[35] A similar pattern arises when plotting the residuals in occupational switching and changes in major after controlling for observable differences in the main control variables.

[36] This positive correlation is borne out in regression analysis, which compares occupational switching across English universities with high and low rates of switches across fields of study.

Figure 4. Changes in Major and Occupation-Field Switching by University (USR)



Notes: Closed and open circles represent English and Scottish university averages, respectively. Outcomes are based on USR samples of undergraduates from 1980. Occupation-field switching is calculated on the basis of the broad classification (see Appendix Table 1). Change of field of study is determined by students who receive a degree in a field different from the first field of study.

result from technological change (Nelson and Phelps, 1966; Bowles 1970). In this paper, I have examined another important mechanism for why education might improve labor market outcomes. By providing valuable information about tastes and talents for different fields of study, I have shown how education can help individuals match more successfully to different fields in university and in the labor market.

In order to examine this mechanism, I developed a model of *academic* specialization in which individuals, by taking courses in different fields of study, accumulate field-specific skills and receive noisy signals of match quality in these fields. Distinguishing between educational systems with early and late specialization, I derived a comparative static prediction regarding the probability of switching to an occupation unrelated to one's field of study. If higher education serves mainly to provide specific skills, the model predicts more switching in a system with late specialization because the cost of switching is lower in terms of foregone skills. Alternatively, if higher education serves mainly to provide valuable information about match quality, switching may be higher in a system with early specialization because the benefits from higher expected match quality due to switching will outweigh the greater loss of specific skills.

University administrative data and survey data on college graduates show that individuals from Scotland, who specialize relatively late, are less likely to switch to an unrelated occupation than their counterparts from England. The pattern is even more striking when instrumenting for English and Scottish degrees with region of prior residence. In contrast, there is no difference in the probability of switching between England and Wales where the timing of academic specialization is similar, or between England and Scotland at the *graduate level*, where the timing of specialization is also similar. These findings indicate that the return to match quality is high relative to the return to specific skills. In other words, the fact that England—a system with early specialization—exhibits a higher incidence of switching implies that the benefits to increased match quality are substantial, and, indeed, large enough to outweigh the greater loss of skills. The data thus confirm that undergraduate education has an important role in helping students discover their tastes and talents about different fields of study.

The finding that education provides valuable information about tastes and talents also has implications for the timing of academic specialization. Later specialization, which allows students more time to learn about their match quality in different fields of study, may be preferable when there are large returns to being well matched to a particular field. Although I have focused on the differences in the timing of specialization between England and Scotland, there is also substantial variation in the difficulty of changing majors across college in the United States. Moreover, there are some countries that require students to specialize while still in elementary or secondary school. In this paper, I have suggested that these structural differences in the timing of specialization may have important consequences for efficiency and welfare.

A. Data Appendix

Complete documentation for the Universities' Statistical Record, 1972–73—1993–94: Undergraduate Records, Postgraduate Records and the National Survey of 1980 Graduates and Diplomates, 1986–1987 are available from the UK Data Archive: http://www.data-archive.ac.uk (Department of Employment 1988). Details of the variables constructed for this study are described as follows:

Occupation-Field Switch: An occupation-field switch is defined as a binary variable that takes on a value of 1 if individuals are employed in an occupation unrelated to their major field of study at the undergraduate level, and 0 otherwise. In order to determine whether individuals are employed in an occupation that is related or unrelated to their field of study, I group fields of study and occupations into categories. As shown in Appendix Table 1, I allow for three gradations of classification: narrow (42 categories), broad (12 categories), and very broad (6 categories). Occupations and fields of study are coded according to each of the alternative classifications. Where the occupation and field of study are classified in different categories, the field switch variable takes on a value of 1. For example, individuals studying physics at university will have their field of study coded as "physics" according the narrow classification, "physical sciences" according to the broad classification, and "mathematical, computer, and physical sciences" according to the very broad classification. If they are employed as computer programmers, the field switch variable will take on a value of 1 according to the narrow and broad classifications and a value of 0 according to the very broad classification. Combined fields are considered switches if the individuals are not employed in any of the fields mentioned.

Change in Major Field of Study: Using the USR, I record changes to the major field of study by observing when the field of study upon entering university is different from the field of study in the degree awarded based on the appropriate classification. In Scotland, students are coded according to a broader code representing the combination of fields in a faculty or school or on the basis of a provisional field of study, and subsequently change when they select a specific field.

High school GPA: Scores on secondary school leaving exams are officially coded as letter grades (A, B, C, and so on). These are converted into numerical scores where A = 10, B = 8, C = 6, D = 4, and E = 2. Average scores are then standardized by nation and combined so that the overall distribution of high school GPA has mean 0 and standard deviation 1.

SES: SES is coded based on parental occupations. It is represented by a series of dummy variables corresponding to the following categories: 0–unstated, retired, or unknown, 1–professionals workers, 2–intermediate workers, 3–skilled non-manual, 4–skilled manual, 5–partially skilled, 6–unskilled, and 7–unemployed.

Region of Work: Region of work is classified as England, Scotland, Wales, Northern Ireland or abroad in the USR. Region of work is classified as London, Southern England, Midlands, East Anglia, Northern England, Wales, Scotland, Northern Ireland or abroad in the NSGD.

B. Mathematical Appendix

The mathematical appendix provides a formal treatment of the model of academic specialization presented in the main text. For ease of exposition, the structure of the appendix and most of the notation parallels the main text.

Formal Setup

Suppose N courses are taken in $k \geq 2$ fields of study. Let $F_1, \ldots, F_k$ be normal populations associated with fields of study $i = 1, \ldots, k$, each with unknown mean $\theta_1, \ldots, \theta_k$ and a common known variance $\sigma^2 > 0$. The unknown means $\theta_1, \ldots, \theta_k$ represent unobserved match quality in each field.

Sequence of observations

In Stage 1, n observations from each population F_i are observed. These correspond to observations on match quality from courses taken in each field of study prior to specialization. The sample means of these observations, X_i, are independent and distributed $N(\theta_i, p^{-1})$ with $p = n\sigma^{-2}$. In Stage 2, one population, i^*, is selected for further sampling and $(N - nk)$ additional observations are observed from this population. These correspond to observations on match quality in the chosen field from courses taken following specialization. The sample mean of the second set of observations, Y, is distributed $N(\theta_{i^*}, q^{-1})$ with $q = (N - nk)\sigma^{-2}$ and where θ_{i^*} is the (unknown) mean of the population chosen after Stage 1.[37]

Beliefs on match quality

Beliefs about match quality $\theta_1, \ldots, \theta_k$ are represented by the parameters $\hat{\theta}, \ldots, \hat{\theta}_k$. These parameters are random and follow independent and identical prior distributions assumed to have $\hat{\theta}_i \sim N(\ \ , \nu^{-1})$ with $\nu = \sigma_0^{-2}$. The conditional distribution of $\hat{\theta}$ at each stage can be expressed as follows:

$$\hat{\theta}_i \mid \mathbf{X} = \mathbf{x} \sim N\left(\frac{px_i + \nu}{p + \nu}, (p + \nu)^{-1}\right),$$
$$i = 1, \ldots, k \text{ independent}$$
$$\hat{\theta}_i \mid \mathbf{X} = \mathbf{x},\ Y = y \sim N\left(\frac{\pi\ \ _i(\mathbf{x}) + q_i y}{\pi + q}, (\pi + q_i)^{-1}\right),$$
$$q_{i^*} = q \text{ and } 0 \text{ otherwise}$$

where $\pi = p + \nu$ represents the relative combined (prior plus sampling) information gained from field F_i, and where $\ _i(\mathbf{x}) = (px_i + \nu\ \ )/(p + \nu)$ represents the estimated mean of field F_i after Stage 1. In terms of the notation in the main text, $\ '_i = \ _i(\mathbf{x})$ and $\ '_i = \ _i(\mathbf{x}, y)$.[38]

Payoffs

The returns associated with field F_i are denoted by $u_i = \alpha\theta_i + \beta s_i$ where s_i is the cumulative number of observations from field F_i. This return represents the wage received in field i upon entering the labor market. In terms of the model of academic specialization, α is the return to match quality and β is the return to specific skills. Note that we can express the loss function associated with population F_i as $L_i(\theta, s) = \alpha\theta_i + \beta s_i$.[39]

Decision Rules

After $\mathbf{X} = \mathbf{x}$ has been observed at Stage 1, the Bayes selection rule $i^* = d_1^*(\mathbf{x})$ can be found by minimizing the posterior expected loss (or in our framework, maximizing posterior expected returns):

$$\begin{aligned} & E_X\left(L\left(\hat{\theta}, d_1^*(\mathbf{X})\right) \mid \mathbf{X} = \mathbf{x}\right) \\ & \quad = \max_{i=1,\ldots,k} E_X\left(\alpha\hat{\theta}_i + \beta s_i \mid \mathbf{X} = \mathbf{x}\right) \\ & \quad = \alpha \max_{i=1,\ldots,k} E_X\left(\hat{\theta}_i \mid \mathbf{X} = \mathbf{x}\right) + \beta s \\ & \quad = \alpha \max_{i=1,\ldots,k}\ \ _i(\mathbf{X}) + \beta s \\ & \quad = \alpha\left(\frac{p\left(\max_{i=1,\ldots,k}\right) + \nu}{p + \nu}\right) + \beta s \end{aligned}$$

where s corresponds to the specific skills in each field which are equivalent across fields. The optimal selection, i^*, at Stage 1 will therefore be the population with the largest observed sample mean after Stage 1 since $d_1^*(\mathbf{x}) = \arg\max_{i=1,\ldots,k} x_i$. This is intuitive since, with identical prior distributions on match quality, the only distinguishing feature of each population is the information received in Stage 1. Let $x_{[1]} < x_{[2]} < \ldots x_{[k]}$ denote the order sample means from Stage 1 and $\ _{[1]}(\mathbf{x}) < \ _{[2]}(\mathbf{x}) < \ldots \ _{[k]}(\mathbf{x})$ denote the ordered posterior means from Stage 1. Note that, in terms of the notation in the main text, $\ '_{i^*} = \ _{[k]}(\mathbf{x})$ and $\ '_{i^*} = \ _{[k-1]}(\mathbf{x})$.

Similarly, after $Y = y$ has been observed at Stage 2, the Bayes selection rule $i^{**} = d_2^*(\mathbf{x}, y)$ will satisfy

$$\begin{aligned} & E\left(L\left(\hat{\theta}, d_2^*(\mathbf{X}, \mathbf{Y})\right) \mid \mathbf{X} = \mathbf{x}, Y = y\right) \\ & \quad = \max_{i=1,\ldots,k} E\left(\alpha\hat{\theta}_i + \beta s_i \mid \mathbf{X} = \mathbf{x}, Y = y\right) \end{aligned}$$

These Bayes selection rules yield the maximum posterior expected returns, or Bayes risk, of their respective problems in Stages 1 and 2. Let $\ ''_{i^*} = \ _{[k]}(\mathbf{x}, y)$ denote the posterior mean of field, i^*, after Stage 2. An important feature of this decision problem is that the selection

[37] Since X_i and Y_{i^*} already correspond to the mean of the samples, we will use x_i and Y_{i^*} instead of $\bar{x}_i$ and $\bar{y}_{i^*}$.

[38] Note also that the conditional distribution of Y given $\mathbf{X} = \mathbf{x}$ is distributed $\mathrm{N}(\ _\mathrm{i}(\mathbf{x}), w)$ with $w = (\pi + q)\pi q$.

[39] This corresponds to a linear loss function, $L_i(\theta, s) = \theta_{[k]}, = \max\{\theta_{1,\ldots,}\theta_k\}$ where is normalized to zero and with an additional negative cost associated with the amount of sampling from the population i.

Appendix Table 1
Classification of Fields and Occupations

Fields	*Subject codes (NSGD/USR-1980)*	*Occupational Codes (NSGD)*	*Occupational Codes (USR-1980)*
111 Math/Comp. Science			
1111 Math Sciences	Mathematics (81)	Mathematician (444); Statistician (242). . .	Operational research (441); Statistician (452)
1112 Computer Sciences	Computer Science (82); Math/Comp. Science (31)	Computer Programmer (244); Analyst/ programmer (246). . .	Systems analysis (442); Computer programming (443). . .
112 Physical Sciences			
1121 Chemistry	Chemistry (34); Environmental Science (36)	Chemical scientist (442)	Scientist (510) + Chemical and allied industries (240–247)
1122 Geology	Geology (35)	Geological scientist (445)	Scientist (510) + Oil, mining industries (230–235)
1123 Physics	Physics (33); Mathematics/Physics (32)	Physical scientist (443)	Scientist (510) + Atomic energy (284); Other manufacturing
121 Architecture			
1210 Architecture	Architecture (51); Town plan (52); Surveying (17)	Architect (511); Town planning (514); Draughtsman (490). . .	Architect (551); Town planning (553); Surveying (554). . .
122 Engineering			
1221 Mechanical	Mechanical engineering (12)	Mechanical or aeronautical engineer (461)	Engineer (520) + Automotive industry (253)
1222 Chemical	Chemical Engineering (9)	Chemical engineer (481)	Engineer (520) + Chemical and allied industries (240–247)
1223 Civil	Civil Engineering (10)	Civil, municipal or structural engineer (451). . .	Engineer (520) + Civil engineering contractors (220–225). . .
1224 Electrical	Electrical Engineering (11)	Electrical engineer (471); Electronic engineer (472,473)	Engineer (520) + Electronic (256); Computers (257). . .
1225 Industrial	Production engineering (13)	Production engineer (482); Planning engineer (483). . .	Engineer (520) + Food (261); Drink (262); Textiles (271). . .
1226 Materials	Mining (14); Metallurgy (15)	Mining engineer (452); Metallurgist (485)	Engineer (520) + Oil, mining industries (230–235)
1227 Aeronautical	Aeronautical engineer. (8)	Mechanical or aeronautical engineer (461)	Engineer (520) + Aircraft, aerospace industry (254)

continued

Appendix Table 1
Classification of Fields and Occupations Continued

Fields	*Subject codes (NSGD/USR-1980)*	*Occupational Codes (NSGD)*	*Occupational Codes (USR-1980)*
131 Life Sciences			
1311 Agriculture	Agriculture (20); Forestry (23). . .	Farmer, farm manager, horticulturist (600)	Scientist (510) + Agriculture, horticulture, forestry(210–214)
1312 Biology	Biology (25); Botany (26); Zoology (27). . .	Biological scientist, biochemist (441)	Scientist (510) + Health authorities (154)
132 Health Sciences			
1321 Physicians	Medicine (3)	Medical practitioner (351)	Medicine (631); Medical & para-medical services (630)
1322 Dentists/Vets/ Pharm	Dentistry (4); Veterinary (24); Pharmacology (5,6)	Dentist (352); Veterinarian (382); Pharmacist (371). . .	Dentistry (632); Veterinary (640); Pharmacy (634). . .
1323 Nursing/Related	Studies allied to medicine/health (7)	Nurse (360); Physiotherapist (374). . .	Nursing (633); Physio-occupational, speech & therapy (636)
211 Social Service			
2111 Psychology	Psychology (46)	Psychologist (324)	Psychology (623); Occupational guidance (624)
2112 Sociology/Social Work	Sociology (47)	Sociologist (323); Welfare worker (333)...	Social, welfare, religious (620); Social/ welfare (621). . .
212 Social Sciences			
2121 Economics	Economics (41)	Economist (241)	Economic (450); Economist (451)
2122 History/Geography	History (69); Archeology (70); Geography (42)	Librarian, information officer (294)	Librarian (721) Archivist (722)
2123 Govt., Public Admin.	Government and public administration (44)	Inspector (263); General administration (local govít) (280). . .	Consumer protection, environmental health, safety (653). . .
2124 Other Social	Social anthropology (48)	Social or behavioural scientist (325)	Non-scientific research (730); Information research (700). . .
221 Business			
2211 Accounting, Finance	Accountancy (43)	Accountant (221); Investment analyst (228). . .	Financial (460); Accountancy (461); Banking (462). . .
2212 Management	Business, management studies (40, 53)	Management consultant (296); Manager (561). . .	Management & supporting occupations (400). . .
2213 Sales	Business, management studies (40, 53)	Advertising executive (252); Buying and selling (255). . .	Purchasing (431); Selling (432); Marketing (434). . .
2214 Related Business	Secretarial studies (84)	Office manager (572); Personal assistant (297). . .	Clerical, secretarial & related (930). . .

continued

Appendix Table 1
Classification of Fields and Occupations Continued

Fields	*Subject codes (NSGD/USR-1980)*	*Occupational Codes (NSGD)*	*Occupational Codes (USR-1980)*
222 Law			
2220 Law	Law (45)	Judge (211); Advocate, barrister (212); Solicitor (213). . .	Barrister (471); Solicitor (472); Trusts (473). . .
231 Education			
2310 Education	Education (1)	Teacher (secondary) (311); Teacher (primary) (312). . .	Primary (611); Middle school (612); Secondary (613). . .
232 Arts			
2321 English/Languages	English (55); French (57); German (59). . .	Author, writer, journalist, editor (391)	Journalist (811); Technical writer (711); Translator (712). . .
2322 Art	Art (73)	Artist, commercial artist (401); Designer (402–406)	Art, sculpture, design (820); Fashion & textiles (823). . .
2323 Performing arts	Drama (74); Music (75)	Actor, entertainer, musician, singer, stage manager (411). . .	Acting, music, sport (830); Broadcasting/stage/film (840). . .
2324 Religion/Philosophy	Religion (72); Philosophy (71)	Clergy, minister of religion (340)	Pastoral (622)

Notes: Subject codes for USR are correct for 1972-1984 (different codes for 1985-1993) and occupational codes for the USR are correct from 1980-1993 (different codes for 1973-1979). Occupational codes omit some categories for brevity and indicated with ì. . .î when excluded. Engineers and scientist in the USR are matched with industry codes in order to identify particular specializations within each category. Further details are available from the author. Broad fields are in bold. Very broad fields are expressed by the 2-digit codes.

Appendix Table 2
Percentage Employment in Different Occupational Fields by Field of Study in 1980 BA Degree (USR)

	Occupational Field												
Field of Study	*unclassified*	*Math/Comp*	*Physical*	*Architect*	*Engineer*	*Bio*	*Health*	*Social Serv.*	*Social Sci.*	*Business*	*Law*	*Educ*	*Arts*
ENGLAND													
Math/Comp	2.7	**38.3**	7.2	0.1	5.7	0.0	0.1	0.8	0.4	27.9	0.1	15.8	0.8
Physical Sci.	6.8	11.2	**31.3**	0.8	9.8	0.3	0.9	1.1	2.5	18.6	0.6	14.6	1.3
Architecture	10.0	0.2	1.5	**57.1**	0.0	0.2	0.0	0.2	0.4	28.6	0.2	0.9	0.7
Engineering	5.8	2.6	7.1	1.1	**71.3**	0.1	0.2	0.5	0.3	8.9	0.1	1.5	0.6
Biology	12.0	3.9	25.8	0.4	0.8	**3.4**	5.0	1.4	2.3	25.8	0.4	17.4	1.5
Health	0.3	0.1	2.2	0.0	0.1	0.2	**94.4**	0.1	1.0	1.0	0.0	0.6	0.1
Social Serv	11.0	2.9	1.3	0.2	0.2	0.4	7.6	**24.2**	4.1	23.6	1.0	21.4	2.0
Social Sci.	13.2	3.0	0.6	1.6	0.2	0.0	0.9	2.5	**6.0**	47.5	2.5	18.8	3.4
Business	3.9	3.3	0.2	0.4	0.8	0.0	0.2	0.3	0.9	**87.6**	0.4	1.9	0.3
Law	2.0	0.2	0.1	0.0	0.1	0.0	0.1	0.5	1.8	11.8	**81.8**	0.9	0.7
Education	5.9	0.8	0.2	0.0	0.3	0.0	5.6	2.2	0.0	7.0	0.3	**76.9**	0.8
Arts	16.6	1.6	0.1	0.1	0.1	0.0	1.5	2.2	4.0	26.5	1.5	34.7	**11.3**
SCOTLAND													
Math/Comp	1.6	**49.8**	6.2	0.0	2.3	0.0	0.0	0.0	0.4	24.1	0.0	15.6	0.0
Physical Sci.	6.5	7.4	**31.7**	0.3	14.8	0.9	0.3	0.0	0.6	15.1	0.0	21.5	0.9
Architecture	10.1	0.9	0.0	**74.3**	0.9	0.0	0.0	1.8	1.8	10.1	0.0	0.0	0.0
Engineering	4.3	2.1	5.7	0.3	**74.1**	0.0	0.2	0.2	0.3	9.9	0.0	2.9	0.0
Biology	14.6	1.7	24.9	0.9	0.9	**3.5**	4.7	1.2	3.1	25.2	0.2	17.9	1.2
Health	0.0	0.0	0.5	0.0	0.0	0.1	**97.4**	0.0	0.9	0.8	0.0	0.2	0.1
Social Serv.	13.1	5.0	2.3	0.5	0.0	0.0	4.5	**26.7**	2.7	28.5	0.9	14.5	1.4
Social Sci.	9.6	2.7	0.7	3.7	0.2	0.2	0.7	4.5	**8.4**	44.6	1.3	19.6	3.9
Business	2.7	0.3	0.0	0.0	0.3	0.0	0.9	0.0	0.0	**94.7**	0.6	0.3	0.3
Law	1.1	0.0	0.0	0.0	0.2	0.0	0.2	0.4	1.3	8.7	**88.1**	0.0	0.0
Education	6.6	0.0	0.0	0.0	0.0	0.0	19.7	0.8	0.0	4.9	0.0	**68.0**	0.0
Arts	12.8	0.8	0.0	0.0	0.3	0.0	0.9	2.2	4.5	24.5	0.9	38.8	**14.3**

Notes: Occupation and field of study are categorized according to the broad field classification. Fraction employed is calculated using all individuals who aimed to attain a BA degree in 1980 and were employed in a job during the 1st year following graduation and not pursuing graduate studies.

$i^{**} = d_2^*(\mathbf{x}, y)$ after Stage 2 may differ from the selection $i^* = d_1^*(\mathbf{x})$ after Stage 1 since further observations in Stage 2 may reveal that the initial choice was not as good as initially thought. This corresponds precisely to the possibility of switching fields expressed in the main theoretical framework.

Proof of Proposition 1: The probability of switching can be expressed as follows:

$$\Pr\ (switch) = \Pr\left(u\left(\ '_{i^a}, s\right) > u\left(\ ''_{i^*}, s\right)\right) \text{ or}$$
$$\Pr\left(u\left(\ _{[k-1]}(\mathbf{x}), s\right) > u\left(\ _{[k]}(\mathbf{x}, y), s\right)\right)$$

where $u\left(\ ''_{i^*}, s\right) = u\left(\ _{[k]}(x, y), s\right)$ is the wage expected in the chosen field based on the beliefs after Stage 2 and $u\left(\ '_{i''}, s\right) = u\left(\ _{[k-1]}(\mathbf{x}), s\right)$ is the wage expected in the second-best field based on the beliefs after Stage 1. Using the latter notation and since individuals are assumed to be risk-neutral, we can write the probability of switching in terms of skills and beliefs about the mean of match quality: $\Pr(\alpha\ _{[k-1]}(\mathbf{x}) + \beta n > \alpha\ _{[k]}(\mathbf{x}, y) + \beta(n + (N - nk)))$. We can further decompose $_{[k]}(\mathbf{x}, y)$, into the mean of match quality in the chosen field after Stage 1, $_{[k]}(\mathrm{x})$, and the mean of the observations taken from the chosen field in Stage 2, $Y^{[k]}$:[40]

$$\Pr\ (switch) = \Pr\begin{pmatrix} \alpha\left[\ _{[k-1]}(\mathbf{x}) - \ _{[k]}(\mathbf{x}, y)\right] \\ > \beta(N - nk) \end{pmatrix}$$
$$= \Pr\begin{pmatrix} _{[k-1]}(\mathbf{x}) - \ _{[k]}(\mathbf{x}) - \\ \left(\dfrac{q}{\pi(\pi + q)}\right)^{1/2} \\ Y^{[k]} > \dfrac{\beta}{\alpha}(N - nk) \end{pmatrix}$$
$$= \Pr\begin{pmatrix} \left(\dfrac{q}{\pi(\pi + q)}\right)^{1/2} Y^{[k]} \\ < -\dfrac{p}{p + \nu}\left(x_{[k]} - x_{[k-1]}\right) \\ -\dfrac{\beta}{\alpha}(N - nk) \end{pmatrix}$$

$$\text{Where } \frac{d}{dn}\left(\frac{q_i}{\pi + (\pi + q_i)}\right) < 0,$$
$$\frac{d}{dn}\left(\frac{p}{p + \nu}\right) > 0 \quad \text{and} \frac{d}{dn}\left(\frac{\beta}{\alpha}(N - nk)\right) < 0.$$

The left-hand side term represents new information about match quality in the chosen field revealed in Stage 2; the first term on the right-hand side represents the loss in match quality from switching based on beliefs from Stage 1. The second term on the right-hand side represents the loss in skills from switching to the second-best field. Individuals will switch fields when the new information about match quality is sufficiently negative so as to outweigh the loss in match quality and skills from switching.

Later specialization corresponds to more observations in Stage 1 that decreases the relative importance of new information in Stage 2, increases the relative importance of information in Stage 1, and raises the loss in skills associated with switching. When β is large relative to α, the loss in skills associated with switching will dominate and $(d/dn)\Pr(switch) > 0$.[41] When α is large relative to β, the loss in match quality associated with switching will dominate and $(d/dn)\Pr(switch) < 0$.[42] Using numerical methods, we can always find a unique constant $C > 0$, so that a system with early specialization, n^E, will have a higher probability of switching than a system with late specialization, n^L, if $\alpha/\beta > C$ and a system with late specialization, n^L, will have a higher probability of switching than a system with late specialization, n^L, if $\alpha/\beta < C$.

Proof of Corollary 1: Suppose now that $u(\theta_i, s_i) = \alpha\theta_i + \beta s_i + \varepsilon_i$ where $\varepsilon_i \sim N(0, \tau^2)$. Then, if the return to match quality is equal to zero, $\alpha = 0$, we can express the probability of switching as follows:

$$\Pr(switch) = \Pr\begin{pmatrix} \alpha\ _{[k-1]}(\mathbf{x}) + \beta n + \varepsilon_{[k-1]} > \alpha\ _{[k]}(\mathbf{x}, y) \\ + \beta\left(n + (N - nk)\right) + \varepsilon_{[k]} \end{pmatrix}$$
$$= \Pr\begin{pmatrix} \beta n + \varepsilon_{[k-1]} \\ > \beta\left(n + (N - nk)\right) + \varepsilon_{[k]} \end{pmatrix}$$
$$= \Pr\left(\varepsilon_{[k-1]} - \varepsilon_{[k]} < -\beta(N - nk)\right)$$
$$= \Phi\left(\frac{\beta(nk - N)}{\sqrt{2\tau^2}}\right) \quad \text{since } \varepsilon_{[k-1]}$$
$$-\varepsilon_{[k-1]} \sim N\left(0, 2\tau^2\right).$$

Assume that $\sigma^2 = \infty$ yields the same expression since $p = n\sigma^{-2} = 0$ and $q = (N - nk)\sigma^{-2} = 0$. Hence, in either case, a larger n causes the probability of switching to increase. Therefore, if $\alpha = 0$ or $\sigma^2 = \infty$, a system with early specialization will have a lower probability of switching than a system with late specialization.

[40] So $Y^{[k]}$ is a random variable representing observations from an extreme value distribution. See Gupta and Miescke (1994, 1996) and Miescke (1999) for similar decompositions.

[41] This holds so long as switching continues to take place (that is, β is not too large relative to α).

[42] This is clear if $\beta = 0$ and there is no loss in skills from switching. In this case, a larger n will make $((q/\pi(\pi + q)))^{1/2} Y[k]$ less negative and $-(p)/(p + \nu)(x_{[k]} - x_{[k-1]})$ more negative, reducing the probability of a switch.

REFERENCES

Altonji, Joseph G. 1993. "The Demand for and Return to Education When Education Outcomes Are Uncertain." *Journal of Labor Economics*, Vol. 11, No. 1, pp. 48–83.

Arcidiacono, Peter. 2004. "Ability Sorting and the Returns to College Major." *Journal of Econometrics*, Vol. 121, No. 1–2, pp. 343–75.

Bowles, Samuel. 1970. "Migration as Investment: Empirical Tests of the Human Investment Approach to Geographical Mobility." *The Review of Economics and Statistics*, Vol. 52, No. 4, pp. 356–62.

Briggs, Asa. 1980. "System, Diversity, and Choice." In *Higher Education in the United Kingdom 1980–82: A Handbook for Students and their Advisors* (18th edition), pp. 17–18. New York: Longman Group Limited.

Card, David. 1999. "The Causal Effect of Education on Earnings." *Handbook of Labor Economics*, Vol. 3, pp. 1801–63.

Cascio, Elizabeth, and Ethan Lewis. 2006. "Schooling and the Armed Forces Qualifying Test: Evidence from School-Entry Laws." *Journal of Human Resources*, Vol. 41, No. 2, pp. 294–318.

DeGroot, Morris H. 1970. *Optimal Statistical Decisions.* McGraw-Hill Company.

Department of Employment. 1988. National Survey of 1980 Graduates and Diplomates, 1986–1987 [computer file]. Colchester, Essex: UK Data Archive [distributor], SN: 2314.

DiNardo, John, Nicole Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and The Distribution of Wages, 1973–1993: A Semi-Parametric Approach." *Econometrica*, Vol. 64, No. 5, pp. 1001–45.

Evans, Keith. 1975. *The Development and Structure of the English School System.* University of London Press.

Gupta, Shanti S., and Klaus J. Miescke. 1996. "Bayesian Look Ahead One-Stage Sampling Allocations for Selection of the Best Population." *Journal of Statistical Planning and Inference*, Vol. 54, pp. 229–244.

____, and ____. 1994. "Bayesian Look Ahead One-Stage Sampling Allocations for Selecting of Largest Normal Mean." *Statistical Papers*, Vol. 35, pp. 169–77.

Hunter, S. Leslie. 1971. *The Scottish Educational System.* Oxford: Pergamon Press.

Hvide, Hans K. 2003. "Education and the Allocation of Talent." *Journal of Labor Economics*, Vol. 21, No. 4, pp. 945–76.

Johnson, William R. 1978. "A Theory of Job Shopping." *Quarterly Journal of Economics*, Vol. 92, No. 2, pp. 261–78.

Jovanovic, Boyan. 1979. "Job Matching and the Theory of Turnover." *Journal of Political Economy*, Vol. 87, No. 5, pp. 972–90.

____, and Yaw Nyarko. 1997. "Stepping Stone Mobility." In *Carnegie-Rochester Conference Series on Public Policy* 46, pp. 289–326.

Malamud, Ofer (2010). "Breadth versus Depth: The Timing of Specialization in Higher Education." *Labour*, Vol. 24, No. 4, pp. 359–90.

McCall, Brian. 1990. "Occupational Matching: A Test of Sorts," *Journal of Political Economy*, Vol. 98, No. 1, pp. 45–69.

Miescke, Klaus J. 1999. "Bayes Sampling Designs for Selection Procedures." In S. Ghosh, ed., *Multivariate, Design, and Sampling*, pp. 93–117. M. Dekker: New York.

Miller, Robert. 1984. "Job Matching and Occupational Choice." *Journal of Political Economy*, Vol. 92, No. 6, pp. 1086–1120.

Neal, Derek. 1999. "Complexity of Job Mobility among Young Men." *Journal of Labor Economics*, Vol. 17, No. 2, pp. 237–261.

Neal, Derek and William R. Johnson. 1996. "The Role of Premarket Factors in Black-White Wage Differences." *Journal of Political Economy*, Vol. 104, No. 5, pp. 869–895.

Nelson, Richard R. and Edmund S. Phelps. 1966. "Investment in Humans, Technological Diffusion, and Economic Growth." *American Economic Review*, Vol. 56, No. 1/2, pp. 69–75.

Osborne, G.S. 1967. *Scottish and English Schools: A Comparative Survey of the Past Fifty Years.* University of Pittsburgh Press.

Schultz, Theodore W. 1968. "Resources for Higher Education: An Economist's View." *Journal of Political Economy*, Vol. 67, No. 3, pp. 327–47.

Shaw, Kathryn L. 1987. "Occupational Change, Employer Change, and the Transferability of Skills." *Southern Economic Journal*, Vol. 53, No. 3, pp. 702–19.

Spence, Michael. 1973. "Job Market Signaling." *Quarterly Journal of Economics*, Vol. 87, No. 3, pp. 355–74.

Squires, Geoffrey. 1987. "The Curriculum." In Tony Becher, ed., *British Higher Education*, pp. 155–77. London: Allen & Unwin.

Stange, Kevin. 2009. "An Empirical Examination of the Option Value of College Enrollment." Unpublished paper, University of Michigan.

Stinebrickner, Ralph, and Todd R. Stinebrickner. 2009. "Learning about Academic Ability and the College Drop-out Decision." NBER Working Paper 14810, March.

Trow, Martin. 2000. "From Mass Higher Education to Universal Access: The American Advantage." *Minerva*, Vol. 37, No. 4, pp. 1–26.

University of Edinburgh. 2003. *Undergraduate Prospectus.* Communications and Public Affairs for The University of Edinburgh. Edinburgh, UK.