Learning in Labor Markets: Models of Discrimination and School Enrollment and Empirical Tests

by

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Abstract

This thesis develops and tests a variety of models of symmetric learning in the labor market. Each model is motivated by a different empirical regularity in labor market data — the wage gap between observationally equivalent blacks and whites, re-enrollment in school after extended interruption in attendance, and transitions from part-time to full-time enrollment in college — for which existing theory offers no accepted explanation. Auxiliary predictions are derived for each of the learning models and are tested using data from the National Longitudinal Survey of Youth (NLSY).

The first essay develops and tests a simple dynamic model of statistical discrimination in the labor market. Previous formulations of the statistical discrimination model, all of which have been static, can rationalize an observed wage differential between groups but typically offer no additional testable predictions. In contrast, the present model has a number of empirical implications. Moreover, it improves upon static versions of the theory by allowing the uncertainty about the productivity of an employment match (a key assumption in all statistical discrimination models) to be resolved as the quality of the match is learned by observing on-the-job performance. The model's predictions are tested using a sample of black and white males from the NLSY. A majority, but not all, of the evidence is consistent with the theoretical predictions. However, the model explains several features of the data that cannot be accounted for by alternative theories. This suggests that the informational disadvantage proposed by the statistical discrimination model — that good job matches are less apparent *ex ante* for blacks than for whites — is a part of the explanation for the different labor market outcomes of black and white males in the early stages of work careers.

The second essay presents evidence from the NLSY that, contrary to the prediction of a basic life cycle model of earnings, the transition from school to work is frequently characterized by extended interruptions in attendance and subsequent re-enrollment. An extension of the life cycle model, in which individuals learn about the value of additional schooling through labor market experience, is developed to explain this pattern of interruption and re-enrollment. An alternative explanation of the phenomenon based on borrowing constraints is also presented. The two models differ in their empirical implications and are tested using data from the NLSY. The data offer little support for a pure borrowing constraints explanation of interruption and re-enrollment, but a combination of the learning and borrowing constraints models is consistent with the findings.

The last essay presents evidence from the NLSY that part-time enrollment in college and simultaneous enrollment and employment among college students are quite common. More importantly, it shows that a significant fraction of part-time enrollment spells end with a return to full-time enrollment. An extended life cycle model of earnings, in which ability is learned through past performance in school, is developed to explain transitions from part-time to full-time enrollment. An alternative explanation based on borrowing constraints is also presented. The two models yield different empirical predictions which are tested using data from the NLSY. The evidence offers support for the learning model, suggesting that part-time college enrollment results, in part, from the combination of uncertain ability, learning about ability over time, and the sequential nature of the enrollment decision.

Thesis Supervisor: Henry S. Farber
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Introduction

This thesis focuses on learning in the labor market. More precisely, it develops and tests a variety of models of symmetric learning in the labor market.[1] Each model seeks to explain a different feature of labor market data. Consequently, while learning is a central idea in each of the models, they differ significantly in their details. Several auxiliary predictions are derived for each of the models and these are tested using data from a sample of young workers.

Symmetric learning models are based on two intuitive ideas. First, some of the fixed characteristics that affect the outcome of labor market exchange are unobservable to the trading parties, at least when the parties first meet. Second, the results of past exchange allow the parties to make inferences about those fixed characteristics that affect the outcome of exchange but are not directly observable. Put more succinctly, not everything is known about an employment match upon its formation, but more is learned with the passage of time. The assumption that learning is symmetric rules out strategic behavior. The fixed characteristic that the parties learn about may be specific to the worker, to the job, or to the match between worker and job. Regardless, the information contained in the observed sequence of past labor market outcomes reduces the uncertainty surrounding future realizations. At the same time, the history of past labor market outcomes causes agents to update their prior beliefs and, potentially, to change their behavior in the future.

[1]Hereafter, I often use the generic phrase "learning models" to refer to models of symmetric learning in the labor market. There also exists a large literature on asymmetric information in the labor market. Asymmetric information leads to strategic behavior that is not present in symmetric learning models. That is, the uninformed party learns by drawing inferences from the behavior of the informed party, and as a result the informed party takes this into account when deciding on an action.

Theoretical work on learning in labor markets was originally motivated by the observed pattern of turnover, job tenure, and wages over the life cycle. Mincer and Jovanovic (1978) showed that the steep decline in job mobility with age is largely a reflection of a similar negative relationship between the probability of turnover and the length of job tenure.[2] Even after attempting to control for unobserved heterogeneity in a sample of workers, the authors found that the negative relationship between job tenure and mobility is strong. At the same time, Mincer and Jovanovic found that there is a positive correlation between wages and job tenure, and that the measured return to labor market experience declines once job tenure is included as an explanatory variable in the estimation of earnings functions.

The learning model proposed by Jovanovic (1979) offers an explanation for these correlations. Jovanovic postulates that the productivity of a match between a worker and a job is unknown initially, but is gradually revealed to both worker and employer as output from the match is generated. Wages rise with tenure in this model because only matches that are revealed to be sufficiently productive survive. Thus, individuals with long tenure are a selected sample of those matches that are unusually productive, other things equal. Job mobility declines with tenure because beliefs settle down as information about the productivity of the match accumulates. At low levels of tenure, new information can significantly alter prior beliefs about the quality of the job match. In particular, many individuals learn that a job that was worth trying is not worth keeping. In contrast, there is little left to learn about jobs that have survived for many periods. Consequently, the probability that it is optimal to leave a match that was optimally continued in the previous period is very small.

The intuitiveness of the basic ideas underlying the learning model has led to application of the theory to other questions in labor economics. For instance, Miller (1984) extends the learning framework to the question of occupational choice and derives predictions about the order in which occupations should be sampled and the pattern of transition between occupations that one would expect to observe. Viscusi

[2]Hall (1982) also analyzes cross-sectional job tenure data and finds that the probability of a job separation declines with job tenure.

(1979) develops a learning model of job safety to analyze the effect of occupational hazards on mobility behavior.

At the same time, evidence from a variety of empirical studies suggests that learning plays a significant role in the labor market. Topel and Ward (1988) analyze wage growth and turnover behavior for a sample of young men and find substantial support for the predictions of the Jovanovic model. Farber and Gibbons (1991) consider a model in which the labor market learns about (worker-specific) ability. Their learning model makes predictions about the evolution of wages and about how earnings function estimates should vary with labor market experience. These predictions receive support in the data set that the authors analyze. Finally, Glaeser (1991) finds that the absolute value of residuals from wage change regressions are strongly and negatively correlated with job tenure. To the extent that these (absolute values of) residuals measure the change in the estimated productivity of a job match, the finding that beliefs are less volatile as tenure on the job increases is consistent with the learning model.

The theoretical appeal and empirical success of the learning model suggests that further application of the approach might be fruitful. The essays in this thesis undertake this task. The first essay expands the learning framework to the question of labor market discrimination. The second and third essays consider school enrollment behavior from a learning perspective. Each essay is motivated by a particular empirical finding and a model consistent with each finding is developed. Additional empirical predictions are derived for each model and these predictions are then tested using data from the National Longitudinal Survey of Youth (NLSY). Since learning models make predictions about dynamic behavior, a panel data set is required to test the theory. Moreover, since learning is apt to be most important among the young, a data source focused on youth is desirable. Thus, the NLSY is probably the best available data set for examining the hypotheses that are derived from the models.

The first essay develops and tests a learning model of labor market discrimination. This effort is motivated by the well-documented empirical finding that blacks earn less than whites, even after controlling for all observable individual and job characteristics. Two general classes of discrimination models have been proposed to explain this finding. The first group of explanations, of which Becker (1971) is the seminal contribution, relies on tastes. In short, if whites have a "taste for discrimination", this drives a wedge between the wages of blacks and whites in (short-run) equilibrium. The problem with this model is that incentives to segregate and/or competitive market pressures should prevent the wage differential from persisting over the long run. This difficulty has led to a second strand of theory that searches for an explanation based on imperfect information. The statistical discrimination model of Aigner and Cain (1977) exemplifies this more recent literature, and the extension proposed by Lundberg and Startz (1983) succeeds in providing a non-tastes explanation of the black-white wage differential. A problem with the Lundberg and Startz model, however, is that it offers no testable predictions beyond the difference in the mean wages of blacks and whites that motivated the modelling effort in the first place.

I develop a dynamic statistical discrimination model that emphasizes learning as a natural extension of the Aigner and Cain model. At the theoretical level, this model is appealing because, in contrast to the implicit assumption in the static model, the uncertainty about the productivity of a job match does not last forever. Instead, uncertainty about the productivity of a match is only present when a job begins (for blacks); after a single period of work, the productivity of the match is learned with certainty. At the empirical level, the model is appealing because it generates a large number of testable predictions, ranging from the absence of a black-white wage differential at labor market entry, to differential measured returns to experience and tenure for blacks and whites, to varying turnover patterns for blacks and whites. These predictions are tested using a sample of males from the NLSY, with the dynamic statistical discrimination model receiving mixed support.

In the other two essays in this thesis, the focus shifts to the school enrollment decision and patterns of school enrollment. Both essays start with the observation that, in a world of full information and no borrowing constraints, life cycle models of earnings make the strong prediction that time allocated to school should decrease monotonically over the life cycle.[3] One corollary of this implication is that long interruptions in schooling, followed by re-enrollment, should not be observed in the data. A second corollary is that transitions from part-time to full-time enrollment should not be observed in the data. I deal with these questions in turn in the second and third essays.

In the second essay, I present evidence that re-enrollment after a lengthy interruption in school is far from rare in the NLSY data. To explain this phenomenon, I develop a stylized learning model in which there are two levels of ability, two levels of education, and two sectors of employment. High education is only attainable for high ability individuals, but individuals do not learn their ability unless they attempt high education. One of the employment sectors requires high ability (or high education) individuals while the other is not selective. Compensation in each sector is the sum of a component reflecting the average value of education in the sector and a component reflecting the quality of the match between the sector and the worker. The sectoral match component is unknown *ex ante*, but is revealed after working in the sector. In each period, individuals choose between school and work to maximize the expected present discounted value of lifetime earnings.

This model generates the prediction that individuals with optimistic beliefs about ability pursue high education immediately, while those with pessimistic beliefs initially work in the low education sector. However, after learning their sector-specific match quality, some low education individuals (those poorly matched to the low education sector) may be enticed to attempt higher education, even though their beliefs about ability are relatively low. This model predicts that those who enroll in school after an interruption should be less likely to succeed in school, all else equal, and that individuals earning less than their expected wage, given their characteristics, should be more likely to return to school, other things equal. These predictions are contrasted with those of a borrowing constraints model and empirical tests are performed using data from the NLSY. The evidence is strongly consistent with the

[3]An increasing and concave earnings function is sufficient to generate this result. An assumption of finite lifetimes reinforces it. See Weiss (1986) for more details.

existence of learning-induced interruption and re-enrollment, although it might be possible to construct a borrowing constraints model that would generate these same predictions.

In the third essay, I show that transitions from part-time to full-time enrollment also are not rare in the NLSY data. I then develop a stylized learning model that is consistent with this behavior. The model assumes that in every period an individual must choose one of three school-work options: full-time work and no school, part-time work and part-time school, or no work and full-time school. Individuals know that the optimal level of education rises with ability, but ability is unknown *ex ante* and is learned only gradually as a by-product of previous enrollment outcomes. That is, individuals update their estimates of ability after each new outcome from enrollment in school. In each period, individuals select the option that maximizes the expected present discounted value of lifetime earnings.

This model implies that it is optimal to increase the time devoted to school as the estimate of ability rises. More importantly, part-time to full-time enrollment transitions can occur if beliefs about ability improve sufficiently after a successful outcome in school. Similarly, full-time to part-time transitions can occur when beliefs become more pessimistic in response to a negative outcome in school. A prediction from this learning model, then, is that stronger school attachment in any period should be indicative of better academic performance in the previous period, all else equal. I then show that, for students who were enrolled full-time in the previous period, a borrowing constraints model predicts that *weaker* school attachment in a given period should be indicative of better academic performance in the previous period, *ceteris paribus*. I test the opposing predictions of the models using data from the NLSY and find support for the predictions of the learning model.

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Chapter 1

Statistical Discrimination and Black-White Differences in Wages and Mobility

1.1 Introduction

Blacks earn less than whites, even after controlling for observable individual and job characteristics. This differential has been observed in a wide variety of data sources, and it remains today, despite the substantial progress towards economic equality made by blacks in the past half-century.[1] Spurred by this empirical regularity, several theories of labor market discrimination have been developed to explain the phenomenon of different average wages for members of presumably equally productive (on average) groups. However, no single explanation has gained general acceptance. In his review of the discrimination literature, Cain (1986) argues that this lack of consensus exists both because these theories offer few unambiguous predictions and (perhaps as a result) because very little of the extensive literature on black-white differences has actually tried to test the theories.

[1]Cain (1986) surveys the extensive work documenting the black-white earnings differential, while Smith and Welch (1986, 1989) and Card and Krueger (1990) review the evidence on the long-run economic progress of blacks.

This essay seeks to address Cain's criticism by developing a modified version of the standard model of "statistical discrimination", deriving several new empirical predictions from this model, and confronting these predictions with data. I modify the traditional statistical discrimination model in two ways. First, I assume that a worker's productivity is match-specific rather than individual-specific. Second, I extend the model by replacing the static framework with a dynamic framework in which match productivity is learned over time. This extension generates endogenous job mobility as optimizing behavior, a realistic feature absent from the static models. Equally important, the model generates several new and testable empirical predictions. I test these predictions using data from the National Longitudinal Survey of Youth (NLSY).

The remainder of the chapter is organized as follows. Section 1.2 considers the original statistical discrimination model and some more recent extensions based upon it. I argue that these static models, although useful, are not fully satisfying at either the empirical or the theoretical level. In Section 1.3, I develop a simple dynamic statistical discrimination model and highlight its empirical predictions. Section 1.4 discusses the data used in the statistical analysis and presents the results. Finally, Section 1.5 evaluates the model in light of the results and considers directions for future research.

1.2 Statistical Discrimination

Most recent theoretical work on discrimination has considered how differential information about members of different groups might generate between-group differences in average wages. Such models represent a departure from Becker's (1971) seminal work on discrimination, in which tastes are the driving force. Becker's model is appealing in several ways, not the least of which is that it is one of the rare economic models of discrimination in which prejudice plays a role. However, as was noted by Arrow (1973), the tastes model has difficulty generating the black-white wage differential which it seeks to explain—at least as a long-run equilibrium in a competitive and fully-informed labor market. Rather, the existence of "tastes for discrimination" gives incentives for segregation in the workforce, and this purposive sorting of workers prevents the discriminatory tastes from manifesting themselves as a racial wage gap. It is this failure of the tastes theory, at least when coupled with the traditional assumption of competitive labor markets, which led to the development of models of discrimination emphasizing the role of information.

Among the informational models of discrimination, the statistical discrimination model is the best known.[2] The standard rendering of this model (Aigner and Cain (1977)) posits two groups (which I will call black and white) with identical known Normal distributions of productivity ($\mu \sim N(m, \sigma^2)$). Productivity, however, is assumed to be unobservable and instead the market observes only an unbiased signal equal to true productivity plus a Normal error ($\epsilon \sim N(0, \sigma_\epsilon^2)$). The assumption that defines this model is that the noise has greater variance for blacks than whites ($\sigma_{\epsilon,B}^2 > \sigma_{\epsilon,W}^2$) so that the signal is less informative for blacks. Assuming individuals are paid the conditional expectation of productivity given the signal, one can show that the worker's wage is

$$w = \left(\frac{\sigma_\epsilon^2}{\sigma^2 + \sigma_\epsilon^2}\right) m + \left(\frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}\right)(\mu + \epsilon).$$

Immediately, two things can be noted. First, because $\sigma_{\epsilon,B}^2 > \sigma_{\epsilon,W}^2$, the individual signal carries less weight (and, hence, group mean productivity is given more weight) in the wage determination process for blacks than for whites. But, second and more importantly, blacks and whites earn the same on average (provided that blacks and whites are on average equally productive) because, for any choice of σ_ϵ^2, $E(w) = m$. Thus, without further adornment, the most basic model of statistical discrimination cannot explain different average wages for different groups.

Various authors have extended the basic model so that it does generate the

[2]This is not to suggest that there are not other informational models of discrimination. Examples include Arrow (1973) and Milgrom and Oster (1987). Interestingly, the sharp dichotomy in the latter paper concerning what the market knows about "Visibles" versus "Invisibles" is very similar in spirit to the informational assumptions made in the model developed in the present paper.

between-group wage differential that is observed empirically. Lundberg and Startz (1983) assume that workers can make an *unobservable* productivity-enhancing investment in human capital prior to entering the labor market. Such an investment raises the worker's signal (and true productivity), but, because a black worker's individual signal receives less weight in the wage setting equation, blacks have less incentive to invest. As a result, blacks invest less, are less productive, and earn lower wages than whites in equilibrium. While the Lundberg-Startz model is an important contribution, convincing tests of the model do not seem possible since the mechanism generating the wage gap is, by assumption, unobservable (to both the market and the econometrician). Thus, as Lang (1986) points out, the most obvious pre-market investment, (years of) education, cannot be the investment since it is observable to employers. More generally, none of the explanatory variables commonly found in an earnings regression can represent the unobservable investment. Furthermore, to the extent that employers can observe, say, school quality and school performance (even if the econometrician does not), these cannot be the unobservable investment either. But, then one is left to conclude only that the investment is "something unobservable". More importantly, the model's only "prediction" — that blacks earn less than observationally equivalent whites — is the very finding which the model was built to explain. Since the model makes no auxiliary predictions, it ultimately is not testable.

Lang (1990) takes a different approach by assuming that a worker's pre-market investment (education) is observable and partially reveals "innate ability". Thus, employers usefully distinguish workers by both race and educational attainment. Labor market productivity now is assumed to be the sum of two terms: a function of schooling and innate ability plus a second term representing the ability component which is unobserved by both the labor market and the individual. Since a worker's schooling choice does not perfectly reveal productivity, wages remain a convex combination of the average productivity of the (race-schooling) group to which the individual belongs and the individual's specific signal. In this model, additional schooling increases pay in two ways: first, by directly increasing productivity and, second, by signalling that the individual belongs to a high productivity group. It turns out that this second effect is larger. Therefore, since average group productivity still receives more weight (and the individual signal correspondingly less weight) in the wage setting equation for blacks than for whites (since $\sigma^2_{\iota,B} > \sigma^2_{\iota,W}$) blacks now have a greater incentive to invest in education than do whites of equal ability.

This model generates two interrelated empirical predictions. First, blacks get more education than equally able whites, and, second, blacks have a lower measured return to education than whites. Thus, at any given level of education, blacks are less able and consequently lower-paid than whites. The evidence regarding these predictions is mixed. Unconditionally, it is well known blacks get less education than whites, but, after controlling for observable family background variables, blacks appear to get more education than equivalent whites (Griliches, Hall, and Hausman, 1978). Conditioning on *observable* background, though, it seems quite plausible that, on average, blacks would be more advantaged in terms of *unobservable* background, since historical barriers must have made it more difficult for blacks to achieve a given level of "success" than otherwise equal whites. Thus, conditional on (observable and unobservable) background, it is not clear whether blacks get more education than whites.

Turning to the returns to education, the recent evidence (Smith and Welch (1986, 1989), Card and Krueger (1990)) suggests that blacks and whites have similar returns. This finding is in contrast to much of the earlier work on this subject (for example, Welch (1967)). The persuasive and well-documented argument that these authors advance to reconcile the disparate evidence is that the lower returns to education that previous cohorts of blacks earned were owe in large part to the lower quality schooling that they received. In recent cohorts, the quality of education received by blacks has converged towards that received by whites with the apparent consequence that blacks no longer have a lower return to education than whites. Thus, while Lang's model of statistical discrimination generates testable predictions, the relevant empirical findings, drawn from elsewhere in the labor economics literature, do not provide definitive evidence, either for the theory or against it.

In summary, then, very few testable models of statistical discrimination have been proposed and no direct tests of the model have been attempted. However, scarcity of empirical content is not the only weakness of this class of models. At the theoretical level, the static formulation of the model is somewhat troubling. The crucial assumption in the model involves information — how much is known about which groups — yet it makes no allowance for the acquisition of information over time. However, in Cain's words, one would expect "that the employer's uncertainty about productivity of workers may be inexpensively reduced by observing the worker's on-the-job performance" (1986, p. 727). More generally, the parties to an employment relationship should learn its quality as time passes and respond to the newly available information. Indeed, recent theoretical work on life cycle wage growth and turnover (Jovanovic (1979a, 1984)) has emphasized exactly this dynamic aspect of the employment relationship. In sympathy with this idea, the model of statistical discrimination that I develop below attempts to address, as simply as possible, this consideration.

1.3 The Model

1.3.1 Assumptions and Discussion

In this section, I set out the model of statistical discrimination upon which the empirical analysis is based. Several features distinguish the model from its predecessors: individuals are infinitely-lived, rather than (implicitly) living for a single period, and maximize expected present discounted lifetime earnings; new job offers arrive randomly over time generating endogenous mobility as optimizing behavior; and, productivity is specific to the worker-job pair ("match quality") rather than worker-specific ("ability"). In this dynamic setting, I modify the classic statistical discrimination assumption in a simple way to allow for learning about match quality over time.

I operationalize the notion that individuals learn the quality of an employment match as time on the job accumulates by assuming that, after working on the job for one period, all individuals know the quality of an employment match with certainty. Thus, uncertainty about match quality is only present when a match is initially formed. Statistical discrimination models posit that this uncertainty is greater for blacks than whites ($\sigma^2_{\epsilon,B} > \sigma^2_{\epsilon,W}$). For the sake of tractability, I make the further assumption that $\sigma^2_{\epsilon,B} = \infty$ and $\sigma^2_{\epsilon,W} = 0$. Thus, for whites, jobs are pure "inspection goods"; the quality of any match is known with certainty (the signal is perfect) immediately upon arrival of an offer. Conversely, for blacks, jobs are pure "experience goods"; nothing can ever be ascertained about match quality *ex ante* (the signal is pure noise) but, after a single period of work on any job, match quality is fully revealed.[3] Given a random stream of offers and the (race-dependent) informational content of those offers, individuals move from job to job so as to maximize the expected present discounted value of lifetime earnings, thereby determining the evolution of observed wages and job tenures.

One might criticize the assumptions on information and learning as both specific and extreme. Nevertheless, they capture two basic features that should be present in any dynamic statistical discrimination model: first, the initial assessment of a worker's productivity is more noise-ridden for blacks than whites, and, second, observing on-the-job performance improves the estimate of (and perhaps ultimately reveals) any worker's productivity. The utility of the specific assumptions made here is that they simplify the analysis considerably. However, the hypotheses which are tested in the empirical section do not appear to hinge on these specific assumptions.[4]

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[3]In terms of the existing literature, the model's informational assumptions are essentially like Burdett (1978) for whites and a simplified (discrete-time, "one-shot" learning) version of Jovanovic (1979a) for blacks.

[4]As will be seen below, the "limiting case" assumptions on σ^2_ϵ lead to very simple mobility rules. In the intermediate case, $0 < \sigma^2_\epsilon < \infty$, with a continuum of match qualities, the mobility rule becomes more complicated. Added complexity arises because (as in the case where $\sigma^2_\epsilon = \infty$) there is uncertainty about the quality of a new offer but, because the offer is now partially informative about the underlying true match quality, an individual's mobility decision depends on both the value of the current match *and* the value of the new offer. Unfortunately, deriving the comparative static implications for observable labor market outcomes of changes in σ^2_ϵ appears exceedingly difficult.

If, however, one is willing to restrict the set of possible true match qualities and signals to be finite (rather than a continuum), then for any given choice of σ^2_ϵ (and the other parameter values) one can determine the optimal mobility decision for each {true match quality on current job, signal for new job offer} pair by iterative techniques on a computer. The solution can be arrived at iteratively because the dynamic programming problem is a contraction mapping and because there are only a finite number of such pairs. In limited experimentation, the empirical predictions (obtained from analyzing data generated by computer simulation) of the intermediate model with a finite number of "states" are qualitatively the same as those that I derive below under the limiting case assumptions.

Before proceeding more formally, it may be useful to discuss the assumption of greater error variance for blacks than for whites ($\sigma^2_{\epsilon,B} > \sigma^2_{\epsilon,W}$) in some detail. As Lang (1990) notes, the statistical discrimination literature has provided little justification for this key assumption. To fill this gap, Lang offers the following two defenses. First, evidence from sociolinguistics (discussed in Lang (1986)) indicates that miscommunication, broadly construed, is more common across (racial) groups than within them. If employers are (disproportionately) white, then this evidence on between-group communication suggests that it makes sense to model the signal as being noisier for blacks than for whites. Of course, if communications difficulties are the source of black workers' disadvantage, they have an incentive to segregate themselves into black-owned or black-managed firms. However, the combined effects of past discrimination and credit market rationing conceivably could have inhibited the emergence of a black managerial and/or entrepreneurial class large enough to employ the population of black workers. In any case, a look at the data suggests that it would be difficult for blacks to fully segregate themselves into black-owned or black-managed firms, even if they wanted to. For instance, Meyer (1990) presents evidence that blacks are much less likely to own businesses than whites, and black-owned businesses tend to have fewer employees. In addition, blacks are disproportionately less likely than whites to be in managerial occupations.[5]

The second defense relies on Holzer's (1987a, 1987b) evidence that blacks are less likely to find their jobs through "connections". It has long been speculated that one role of connections might be to provide up front information about the quality of a prospective match. More recently, Staiger (1990) has found empirical evidence consistent with this conventional wisdom. Taken together, these findings suggest that, on average, there is more initial uncertainty about the quality of new employment matches for blacks than whites. This provides a second justification for the statistical discrimination assumption.

[5]For example, in the NLSY data that I analyze in this paper, the proportion of blacks in managerial occupations is only half as large as the comparable fraction for whites. In the population at large, this difference is probably even larger since older generations of blacks were presumably more disadvantaged than more recent cohorts.

The crucial and distinctive assumptions of the model are those regarding the initial information content of jobs (different for blacks and whites) and learning. The remaining assumptions are quite familiar. It is assumed that individuals are infinitely-lived, discount the future, strictly prefer work to nonemployment, and maximize the expected present discounted value of lifetime earnings. Associated with every potential worker-job match is a distinct match quality, denoted (suppressing subscripts) μ, which reflects the productive capacity of the match. Match qualities are independent and identically distributed for whites and blacks according to the same (stationary over time) distribution, $F(\cdot)$, which has expectation $E(\mu) \equiv m$. The quality of any match is constant over its duration; match-specific human capital accumulation is ignored to highlight the implications of the information and learning assumptions. For each individual in each period, a single new job offer arrives with exogenous probability p, $0 < p \leq 1$.[6] In a period in which an offer is received, mobility occurs or not as maximization of expected lifetime earnings requires.[7]

The final assumption concerns compensation contracts, or, in other words, how match qualities are translated into wages. Following Jovanovic (1979a, 1979b, 1984) and others, I assume that the worker captures all of the rent that the match generates; firms earn zero (expected) profits. This assumption, which guarantees that all job mobility is efficient, relies on either explicit contracts or reputational considerations on the part of the firm as an enforcement mechanism.[8] In Jovanovic's model, this assumption still does not uniquely determine the form of the wage contract. Possi-

[6]Thus, search effort plays no role in the generation of new job offers. This assumption is consistent with the evidence in Clark and Summers (1982) that, for young workers, job-finding is a fairly passive process.

[7]A slightly more general analysis would include mobility costs. Introducing mobility costs complicates the notation and analysis somewhat, without essentially changing any results. Consequently, I proceed with the analysis under the assumption of costless mobility.

[8]At the other extreme, one could assume that firms held all the bargaining power, and presented workers with take-it-or-leave-it offers. This assumption appears to have some different implications. For instance, giving firms all of the bargaining power (and assuming that contingent contracts are not possible), would appear to imply that black workers face a wage ceiling at the mean of the match quality distribution. The reason is that the employer of a well-matched black worker need only pay marginally above average wages to prevent job mobility since any other potential employer (who is completely uninformed about the quality of the prospective match) will be unwilling to offer a wage in excess of the mean.

ble compensation schemes include paying the worker the conditional expectation of productivity given past history ("wages in advance"), paying the worker the value of current period output ("piece rates"), or any weighted average of the two. In the simple model of the present paper, these alternative payment schemes only differ for blacks in the first period on a job. For whites in all periods and for blacks who have been with a job for at least one period, match quality is known with certainty and all of these payment schemes reduce to the worker being paid this known match quality. Nevertheless, certain predictions arise only for a particular contract form. Since the model does not uniquely specify the form of the wage contract for blacks in the first period on a job, I will be interested in those predictions that are robust across the possible wage contracts. As a necessary preliminary to deriving these predictions, I now examine the model's implications for mobility behavior.

1.3.2 Optimal Mobility Rules

Whites

Consider first the mobility decision of a white worker. Because the value of both the current job and any new offer are known up front with certainty, in the absence of mobility costs a white worker moves to a new job if and only if its match quality exceeds match quality on the current job. Thus, a white worker who receives an offer in period $n+1$, observes the following simple mobility rule:

$$\text{Move if and only if } w_n^W < \mu_{n+1},$$

where

$$\begin{aligned} \mu_{n+1} &= \text{realized draw on match quality in period } n+1, \\ w_n^W &= \text{wage earned on job held in period } n \\ &= \text{wage would earn in period } n+1 \text{ if stay on current job} \\ &= \text{maximum of all match quality draws received previously.} \end{aligned}$$

Blacks

Now, consider a given black worker's optimal mobility behavior. In any period (after the initial period in the labor market) in which an offer is received, the worker is faced with the choice between staying on the current job, in which match quality is now known, or moving to a new job of completely unknown quality. The key point to note is that if the worker optimally rejects an offer in the current period, no offer will *ever* be accepted. This result obtains because all offers look identical (since the signal is uninformative) and because the worker's time horizon never changes (since workers are infinitely-lived). Furthermore, it implies that the worker's optimal mobility rule is a reservation wage rule. That is, there exists some unique match quality, μ^*, such that, when the current job pays μ^*, moving and behaving optimally in all future periods yields exactly the same payoff, in expectation, as does staying on the current job forever and collecting μ^* each period. Therefore, if the black worker receives an offer in period $n+1$, the following optimal decision rule is observed:

$$\text{Move if and only if } \mu_n^B < \mu^*,$$

where

μ^* = constant reservation match quality,

μ_n^B = match quality on job held in period n

= wage would earn in period $n+1$ if stay on current job.

Deriving the reservation wage result, and an implicit formula for μ^* for a given worker, is fairly straightforward. Let

$$d = \begin{cases} 1, & \text{if a new offer has ever been rejected while on current job} \\ 0, & \text{otherwise,} \end{cases}$$

$V^S(\mu \mid d)$ = valuation of staying on current job which pays μ, given d,

V^M = valuation of moving to a new job of unknown quality.

Now,

$$V^S(\mu \mid d = 1) = \frac{\mu}{1-\beta}$$

because rejecting an offer once implies that the worker will always reject (identical) future offers. Also,

$$\begin{aligned} V^S(\mu \mid d=0) &= \mu + \beta\{(1-p)V^S(\mu \mid d=0) + p\max(V^S(\mu \mid d=1), V^M)\} \\ &= \frac{\mu}{1-\beta(1-p)} + \frac{\beta p \max(V^S(\mu \mid d=1), V^M)}{1-\beta(1-p)}. \end{aligned}$$

The first term on the right-hand side represents the expected discounted earnings on the current job until a new offer is received. The second term on the right-hand side represents the expected present discounted value of optimal behavior when a new offer is ultimately received. Finally,

$$V^M = m + \beta\{(1-p)\mathrm{E}(V^S(\mu \mid d=0)) + p\mathrm{E}(\max(V^S(\mu \mid d=1), V^M))\}.$$

This term is completely analogous to the expression for $V^S(\mu \mid d=0)$, except that now expectations are taken over the distribution of possible match quality realizations on the new job to which the individual moves. One can see that $V^S(\mu \mid d=1)$ is monotonically increasing in μ, while V^M is a constant. Consequently, a reservation match quality, below which the worker prefers to move to a new job and above which the worker prefers to stay on the current job, must exist. Using the expressions for $V^S(\mu \mid d=0)$, $V^S(\mu \mid d=1)$, and V^M, and working through some algebra, one can show that the reservation match quality, μ^*, solves

$$(1-\beta)(\mu^* - m) - \beta p(1-F(\mu^*))(\mathrm{E}(\mu \mid \mu > \mu^*) - \mu^*) = 0.$$

That a single value of μ^* satisfies this equality can be argued as follows. The term furthest to the left, $(1-\beta)(\mu^* - m)$, is monotonically increasing in μ^*. In contrast, $1 - F(\mu^*)$ is monotonically decreasing in μ^*, with a lower limit of zero. Furthermore, in the usual case, $\mathrm{E}(\mu \mid \mu > \mu^*) - \mu^*$ is also monotonically decreasing in μ^*, again with a lower limit of zero.[9] Therefore, putting these pieces together, the entire term on

[9] The condition which guarantees that $\mathrm{E}(\mu \mid \mu > \mu^*) - \mu^*$ decreases monotonically in μ^* is log-concavity of $F(\cdot)$. All of the standard continuous univariate distributions are log-concave. Heckman

the left-hand side of the equality is monotonically increasing in μ^*. It is also obvious upon inspection that for low enough values of μ^* this term will be negative, while for high enough values it will be positive. Consequently, there exists a unique value of μ^* that solves the above equation.

The previous analysis considers the optimal mobility decision of *a single worker*. While μ^* is unique at the individual level, cross-section variation in β or p will imply a non-degenerate distribution of reservation match qualities *in the population*. In particular, blacks who discount the future less (higher values of β) will be more selective about settling on a "lifetime" job (i.e., will have higher values of μ^*). Similarly, higher offer arrival probabilities (higher values of p) cause workers to be more selective. Such population heterogeneity in μ^* seems quite likely. Nevertheless, to keep the presentation simple, the empirical implications of the model are derived below under the assumption of no heterogeneity. Allowing for heterogeneity does not substantively alter the predictions of the model. I discuss this extension in the Appendix. Finally, it is evident from the above expression that $\mu^* > m$ for all β and p. The intuition for this result is that a black worker could on average earn m per period simply by changing jobs each time an offer was received. Thus, for a black worker to stay on a job permanently, it must pay wages in excess of m.

In summary, then, blacks and whites have distinct mobility rules. Whites change jobs whenever match quality on the current job is less than the match quality of the new job offer. In contrast, blacks move (given the arrival of a new job opportunity) whenever match quality on the current job falls below some constant threshold value. This cutoff value always exceeds the mean of the match quality distribution. These different mobility rules arise because the quality of a prospective match is completely unobservable *ex ante* for blacks, but fully observable for whites. Having determined the optimal mobility rules, I now turn to their empirical implications.

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and Honore (1990) provide an extended discussion on log-concavity and its implications. Note that $E(\mu \mid \mu > \mu^*) - \mu^*$ decreasing monotonically in μ^* is a sufficient, but not a necessary, condition for the existence of a unique reservation match quality, μ^*.

1.3.3 Empirical Implications – Whites

Recall that the optimal mobility rule for a white worker is simply to move if the match quality of a new offer exceeds the match quality of the current job. This mobility rule has implications for a variety of observable labor market outcomes. I now develop these implications in detail.

Wages at Entry

For whites, the average wage in the initial period after labor force entry is simply the expectation of a single draw from the match quality distribution. Thus, the mean wage at entry for whites is just m.

Measured Returns to Experience and Tenure

Consider the wages of a white worker in period $n+1$, or, in other words, with experience n. Because offers arrive each period with probability p and whites are always employed on the highest draw received from the time of entry to the present, the conditional distribution of wages given experience (n) and tenure (τ, $0 \leq \tau \leq n$) is

$$\Pr(w^W \leq w_0 \mid n, \tau) = \frac{F(w_0)\{\sum_{i=0}^{n} \frac{n!}{i!(n-i)!}(pF(w_0))^i(1-p)^{n-i}(\frac{1}{i+1})\}}{\sum_{i=0}^{n} \frac{n!}{i!(n-i)!}p^i(1-p)^{n-i}(\frac{1}{i+1})}.$$

The denominator represents $\Pr(\tau \mid n)$; it takes the same value for all τ, $0 \leq \tau \leq n$, reflecting the fact that the highest offer is equally likely to have arrived in any period. Thus, if i other offers in addition to the current job have arrived since entry, the *ex ante* probability that the offer which arrived τ periods ago (the current job) would turn out to be the highest is $\frac{1}{i+1}$. The numerator, similar in form to the denominator, is the joint probability $\Pr(w, \tau \mid n)$, so that the quotient gives the desired conditional probability.

Given the conditional distribution of wages, the conditional expectation of wages is given by

$$\mathrm{E}(w^W \mid n,\tau) = \frac{\sum_{i=0}^{n} \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i} (\frac{1}{i+1}) \mathrm{E}[\max(\mu_1,\ldots,\mu_{i+1})]}{\sum_{i=0}^{n} \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i} (\frac{1}{i+1})}.$$

Examination of the expression for $\mathrm{E}(w^W \mid n,\tau)$ indicates that conditional expected wages are only a function of experience and *not* a function of tenure.[10] Wages rise with experience because the expected number of offers received (np) rises with experience and the expected value of the maximum draw rises with the number of draws. This is most obvious in the special case when a single offer is received with certainty in every period, $p = 1$. In this case, $\mathrm{E}(w^W \mid n,\tau) = \mathrm{E}[\max(\mu_1,\ldots,\mu_{n+1})]$. Here, it is clear that average wages rise with experience but not tenure. Intuitively, after already conditioning on the number of draws received, knowing when the highest draw occurred (tenure) does not alter the prediction about the value of the highest draw. Thus, in a cross-section, wages rise with experience, but not tenure, for whites.

Wage Growth

Because match quality is known up front and wages on any job are constant through time, wage growth only occurs with job change for whites. Thus, at all levels of experience and tenure, white job stayers have zero wage gains. Conversely, job mobility yields positive returns for whites. In fact, because whites only leave the current job in response to an even better offer, the theory predicts that job mobility should *always* lead to wage growth for whites. Moreover, this prediction holds regardless of the worker's experience or tenure.

Investigating the average wage gain for a white mover is somewhat more complex.

[10]This claim presumes that the worker begins accruing experience immediately upon labor force entry, regardless of whether or not a job is held at the time of entry. If instead one begins counting experience from the time that the first job is held, as is done in the empirical section, then in a cross-section wages actually decline with tenure, after controlling for experience. The reason is that, in this case, longer tenured workers of a given experience level have on average received fewer job offers.

Anticipating the empirical work, though, it should be pointed out that the hypothesis that I test is only that blacks have a higher return to tenure than whites. Since the model predicts that blacks should have a positive return to tenure, the prediction that blacks have a higher return to tenure than whites holds whether the return to tenure for whites is zero or negative.

Let W denote the wage on the job that the worker just left, and let μ be the value of the new match that attracted the worker from the previous job. Thus, W is simply the maximum of all the draws received prior to the most recent draw. Given W, the expected wage gain from moving is simply $E(\mu \mid \mu > W) - W$. So, for any population of white movers, the average wage gain is simply $E(\mu \mid \mu > W) - W$ integrated over the distribution of wages, W, for this population; in other words, the expected wage gain is $E_W(E(\mu \mid \mu > W) - W)$. Except in very special cases, this expectation cannot be calculated analytically because of the complexity of the probability density function for W. Nevertheless, one can say a few things about this expression. First, it is always positive because $E(\mu \mid \mu > W) - W$ is always positive; this just restates the fact that whites always move from worse to better matches. Second, under the mild additional assumption that the match quality distribution is log-concave, an immediate consequence is that $\frac{d(E(\mu|\mu>W)-W)}{dW} < 0$. That is, the expected wage gain from moving declines as the wage on the previous job rises. If instead (as is usual) one conditions on experience and tenure, but not the wage, then the average wage gain for white movers should fall with experience but not tenure. This just follows from the fact that wages rise with experience but not with tenure for whites.

Turnover

Not surprisingly, the simple mobility rule followed by white workers has straightforward empirical implications for turnover. For any given white worker, the probability of turnover before the next period is simply the product of the probability that a new offer arrives in the current period and the probability that the match quality of this new offer exceeds the current wage. Thus, for a worker earning wage w, the probability of turnover is $p(1 - F(w))$. Several things are clear from this expression. First, the probability of turnover declines as the wage on the current job increases. In fact, the probability of turnover is only a (nonlinear) function of the wage; after conditioning on the wage, turnover should be unrelated to experience and tenure. If, on the other hand, one conditions on experience and tenure but not on the wage, then the probability of turnover falls with experience but does not depend on tenure because wages rise with experience but not with tenure. Finally, for a cohort of white new entrants to the labor force, the average frequency of turnover is $\frac{p}{2}$, since $E[1 - F(w)] = \frac{1}{2}$ when the wage, w, is just the outcome of a single draw from the match quality distribution.

Summary of Predictions

Taken as a whole, the model makes the following major predictions for whites.

1. Average wages at entry are m.

2. Wages rise with experience, but not tenure, in a cross-section.

3. Wage growth always accompanies job change.

4. The probability of turnover immediately after entry is $\frac{p}{2}$.

5. Not controlling for the wage, the probability of turnover falls with experience but not tenure.

1.3.4 Empirical Implications – Blacks

Having considered the model's predictions regarding whites, I now analyze the case of blacks. Recall that the black worker's optimal mobility rule is a reservation rule: if the current match quality is less than some cutoff value, μ^*, then mobility occurs as soon as a new offer is received, but if the current match quality exceeds μ^*, then the worker never moves. This rule has several implications. For ease of exposition, these implications are developed in detail only for the case where blacks are paid "piece rate" wages.[11]

[11] All of the predictions which are emphasized in the discussion and which are tested in the empirical section hold whether wage contracts are assumed to pay "piece rates" or "wages in advance". In general, the empirical implications turn out to be very similar for both wage contracting assumptions. Discussion of differences in the implications of the two contracting assumptions, where they arise, is relegated to footnotes.

Wages at Entry

The wage of a black worker, like a white worker, in the first period after entry is just the outcome of a single draw from the match quality distribution. In expectation, this wage is just m, the mean of the match quality distribution.[12]

Measured Returns to Experience and Tenure

For blacks, wages rise with tenure, but not with experience, in a cross-section. This correlation stems from the fact that, for blacks, job tenure is a measure of the probability that match quality on the current job surpasses the reservation value, μ^*. Jobs that do not attain this cutoff value are left at the first opportunity. Since new offers arrive with constant probability independent across periods, the longer a job has lasted the less likely it is that its match quality falls short of the reservation level. Moreover, since every move to a new job represents a return to the same initial state of no information, a black worker's experience level provides no information about the probability that the current match exceeds μ^*, after controlling for tenure. For this reason, expected wages for a black worker rise with tenure but do not vary with experience. Demonstrating this claim formally simply requires deriving the conditional expectation of wages given experience (n) and tenure (τ) for an individual black worker. Letting

$$d = \begin{cases} 1, & \text{if no offers have been received since on current job} \\ 0, & \text{otherwise,} \end{cases}$$

it follows that

$$\begin{aligned} \Pr(d = 1 \mid n, \tau, \mu^*) &= (1-p)^\tau, \\ \Pr(d = 0 \mid n, \tau, \mu^*) &= 1 - (1-p)^\tau, \\ \mathrm{E}(w^B \mid n, \tau, \mu^*) &= \sum_{i=0}^{1} \Pr(d = i \mid n, \tau, \mu^*) \mathrm{E}(w^B \mid n, \tau, \mu^*, d = i) \end{aligned}$$

[12]If blacks are paid "wages in advance", then their wage in the initial period after entry is identically equal to m.

$$= (1-p)^{\tau} m + (1-(1-p)^{\tau})\mathrm{E}(\mu \mid \mu > \mu^*).$$

Clearly, $\mathrm{E}(w^B \mid n, \tau, \mu^*)$ rises with tenure but not with experience.[13]

Wage Growth

Under the assumption that wage contracts pay piece rates, black job stayers, like whites, have zero wage gains. While the strong prediction of zero wage gains with job change is specific to this form of the wage contract, under no wage contract is there a strong prediction of wage growth for black job stayers.[14] Thus, the possibility of wage gains for job stayers depends entirely on arbitrary assumptions about the form of the wage contract.

For black job switchers, the model yields somewhat crisper predictions. Black movers are a selected sample of those matches revealed to fall short of μ^*, the reservation match quality. However, unlike whites, who only move to better matches, a black mover just takes a job drawn at random from the match quality distribution, $F(\cdot)$. Sometimes these random draws will turn out to be worse than the previous job, in which case the worker will have a negative wage change. Thus, the model's clearest prediction for black movers is that some of them receive negative (non-positive) wage changes, regardless of experience or tenure.[15]

While the model predicts that some black movers will experience wage declines,

[13]A relevant issue at this point is that $\mathrm{E}(w^B \mid n, \tau)$, and not $\mathrm{E}(w^B \mid n, \tau, \mu^*)$, is the expectation of interest. If blacks are heterogeneous in μ^* (because of, say, heterogeneity in discount rates), then these two expectations will not generally be equal. The effects of introducing heterogeneity are considered in the Appendix. The basic conclusion is that the empirical implications of the model which are ultimately tested do not change when one allows for heterogeneity.

[14]If wage contracts pay wages in advance, then black job stayers can experience a one-time wage change. On average, this wage change will be positive because stayers are composed of two groups: (i) those who did not receive an offer, stay because they have no alternative, and on average receive zero wage gains, and (ii) those who did receive a wage offer, stay because the current match exceeds the cutoff level, and receive wage increases. Still, these wage gains from staying could be quite small (if stayers are predominantly of the first type), and, in any case, are a one-time phenomenon.

[15]This prediction holds when blacks are paid wages in advance as well. In this case, wages on the new job are always m, but since $\mu^* > m$, some black movers leave above average matches and therefore experience wage declines. Even consecutive period movers, who receive m in both periods, receive zero wage gains. This contrasts sharply with the positive wage changes with job change which the model predicts for whites.

on average blacks will have positive returns to mobility. Since each mover is leaving a job with match quality less than that individual's reservation match quality in favor of a randomly drawn job, the expected wage gain for a black mover with reservation match quality μ^* is $m - \mathrm{E}(\mu \mid \mu < \mu^*)$, which is clearly nonnegative.[16] This expression is not, in general, directly comparable to the expression (derived earlier) for average wage gains for white movers. Nevertheless, it is not hard to come up with examples (distributions) where one expects the average wage gain to be smaller for blacks than for whites. The results of computer simulations also indicate that the average wage gain for white movers exceeds that of blacks. This is hardly unexpected since the theory predicts that whites always move to better matches while blacks often do not. Furthermore, it is clear that the expression for the average wage change with job change for blacks is not a function of experience or tenure. The intuition for this result is that, at every experience-tenure combination, job change indicates the same thing—that the old job did not attain the cutoff match quality.

Turnover

The probability of turnover for an individual black worker follows directly from the mobility rule. In particular, the probability of turnover for a black worker with current wage w is

$$\begin{cases} p, & \text{if } w < \mu^*, \\ 0, & \text{otherwise.} \end{cases}$$

Thus, as is true for whites, for any single black worker the probability of turnover is solely a function of the wage (match quality) on the current job, albeit a highly nonlinear function (specifically, a step function, with a discontinuous drop in the probability of turnover at $w = \mu^*$).[17] However, it is clear that at entry (tenure =

[16]If one allows heterogeneity in μ^*, then for the population of movers the average wage gain is $\mathrm{E}_{\mu^*}(m - \mathrm{E}(\mu \mid \mu < \mu^*))$ which is simply $m - \mathrm{E}(\mu \mid \mu < \mu^*)$ integrated over the distribution of μ^* for movers.

[17]The result that the quit probability should depend only on the current wage is not unfamiliar in matching models. See MacDonald (1988).

experience = 0), the average frequency of turnover among blacks should exceed $\frac{p}{2}$, the average frequency for whites at entry. For all blacks, $\mu^* > m$, but match quality on the initial job is, on average, only m. Thus, most (in particular, more than half) who receive offers in the second period (a proportion p of the population) change jobs. Finally, if one conditions on experience and tenure, but not the wage, the probability of turnover falls with tenure but not experience, since wages rise with tenure but not experience.

Summary of Predictions

Taken as a whole, the model makes the following major predictions for blacks.

1. Average wages at entry are m.

2. Wages rise with tenure, but not experience, in a cross-section.

3. Wage declines sometimes accompany job change.

4. The probability of turnover immediately after entry exceeds $\frac{p}{2}$.

5. Not controlling for the wage, the probability of turnover falls with tenure but not experience.

1.3.5 Empirical Implications – Blacks and Whites Together

The two previous sections outline the model's separate predictions for blacks and whites. In testing the model, however, I examine the predictions in "differenced" form. For instance, rather than separately test whether the measured return to experience is zero for blacks and positive for whites, I simply focus on whether blacks have a lower measured return to experience than whites. Similarly, I look at the other predictions in differences. There are at least three justifications for this strategy.

First, to the extent that the model leaves out factors that affect the outcomes of blacks and whites similarly, looking at the predictions in differenced form will net out these factors. Of course, if the left out factors affect the two groups differently, then differencing will not remove the influence of these factors. Second, retreating from the extreme assumptions on information ($\sigma^2_{\epsilon,B} = \infty$ and $\sigma^2_{\epsilon,W} = 0$) to the more general case ($0 < \sigma^2_{\epsilon,W} < \sigma^2_{\epsilon,B} = \infty$) would appear to deliver the predictions in differenced form directly, although the complexity of the problem in the more general case precludes a full analysis of the comparative static properties.[18]

Third, and perhaps most compelling, if one generalizes the model in simple and natural ways even within the current informational structure, the predictions arise in differenced form. So far, I have assumed that all job endings result from optimal mobility decisions. Also, I have assumed that all individuals are alike in their underlying characteristics, apart from race. It would be natural, however, to allow for the possibility that matches dissolve for exogenous reasons. Likewise, allowing for individual heterogeneity in the key parameters of the model (discount factors, offer arrival probabilities, match dissolution probabilities) would be a reasonable extension. I explore the effects of these theoretical extensions in detail in the Appendix. The key finding is that, in this richer setting, the model's predictions naturally emerge in differenced form. The strong predictions derived separately for blacks and whites above depend on specific assumptions. In contrast, the predictions in differenced form appear to be robust to (indeed, appear to be the predictions which flow directly from) a variety of natural extensions of the model.

Having offerred a justification for looking at the predictions of the model in differences, a catalog of these predictions now follows:

1. Blacks and whites should earn the same wages at labor force entry.

2. Blacks should have a lower measured return to experience than whites.

3. Blacks should have a higher measured return to job tenure than whites.

4. Blacks should have lower average wage gains with job change than whites.

[18]If σ^2_ϵ is positive but finite, then the worker's reservation match quality depends on both the value of the current match and the value of the new offer. However, the greater is σ^2_ϵ, the greater is the worker's option value from moving. One consequence of this fact is that, given the value of the current match, higher values of σ^2_ϵ make it more likely that a worker takes a chance on a job that looks worse than the current job. But this just says that workers with high σ^2_ϵ (blacks) are more likely to have negative wage changes, which is the current model's prediction in differenced form.

5. Negative (non-positive) wage changes with job change should be more common for blacks than whites.

6. Blacks should turn over more frequently than whites at labor force entry.

7. If one does not control for the wage, the negative effect of experience on turnover should be weaker for blacks than for whites.

8. If one does not control for the wage, the negative effect of tenure on turnover should be stronger for blacks than for whites.

These predictions are examined in the empirical analysis which follows.

1.4 Data and Empirical Analysis

1.4.1 Sample Composition

To test the predictions of the theory, I analyze a data set constructed from the National Longitudinal Survey of Youth (NLSY). The NLSY contains labor market panel data, collected on an annual basis, for a sample of 12,686 individuals who were aged 14-21 on January 1, 1979. The data set that I use spans the period 1979-1988. For a variety of reasons, the NLSY is a particularly useful data source for examining the questions suggested by the theory developed in Section 1.3. Recall that the theory predicts that, at the time of labor force entry, observationally identical blacks and whites should earn the same wages. Any black-white wage differential should only emerge over time. Additionally, the theory predicts that blacks and whites should have different measured returns to experience and tenure. Finally, the model has implications for wage changes with job mobility. Examining these questions, then, requires accurate dating of labor force entry, longitudinal data covering the post-entry period, and reliable measures of experience and tenure.

Because the NLSY is a longitudinal data set focused on youth, it is uniquely suited to addressing these questions. The availability of detailed data on essentially all jobs that each sample member ever held allows one to date (at least approximately) the point of transition to full-time participation in the labor market. This same information also enables one to construct more accurate measures of labor market experience and job tenure than those that are usually available. Both the panel structure of the data source and the focus on youth are essential. The typical cross-section data set does not afford the opportunity to examine the strength of a worker's labor force attachment at a point in time by retrospective analysis of his past work history. Furthermore, only a panel that follows individuals from the start of their work life allows the construction of actual measures of experience and tenure. In contrast, researchers using cross-sections, or panels other than the NLSY, typically must use a potential measure of experience (age − education − 6), while reliable measures of job tenure are often unavailable. Finally, a cross-section data set makes an analysis of wage changes impossible.

Despite the advantages that the NLSY offers for the present purposes, one still faces several sample construction decisions in taking the model to the data. First, one must decide which individuals to include in the analysis. To sharply focus on black-white differentials, I restrict the sample to black and white males from the civilian (representative and low-income supplemental) subsamples of the NLSY. The military sample is dropped both because the available data for this group is more limited and because these individuals are likely to differ significantly (both in observables and unobservables) from the rest of the sample. Dropping women from the sample places attention squarely on racial differences, at the expense of differences by gender. Gender-based differentials, while significant and much-studied, seem less well-fitted to the statistical discrimination story. At the least, other theoretical explanations for the gender differential, usually emphasizing the differential importance of the non-market sector for men and women, already exist. Analogous explanations for wage differentials by race seem less plausible. While one could compare black and white females to examine racial wage differentials, it still would be necessary to deal with questions concerning the importance (possibly different across races) of the non-market sector. To avoid these issues, I focus exclusively on black and white males. Finally, I exclude Hispanics from the sample, both because a Hispanic could be either black or white, and because including Hispanics could conceivably introduce complicating issues of immigration and language. Making these cuts leaves panel data on 4,632 individuals from which to fashion a data set.

Given the model's predictions, it is clear that the empirical analysis should focus on the initial period of work immediately following labor force entry. While standard economic theory suggests that this transition to work should be unambiguously identifiable, the empirical reality is more complex. As a result, one must adopt some criterion for deciding what constitutes the point of transition to "full-time labor force participation". Of course, any such rule for identifying this transition point is, in the end, arbitrary. Determining the date of entry only can be done retrospectively, after observing a "sufficient" amount of continuous "strong" labor force attachment. In this study, I define strong labor force attachment in an "interview year"[19] as working in at least half the weeks since the date of the previous interview and averaging at least 30 hours of work per week in those weeks. The start of the first three consecutive interview year period of strong labor force attachment, following at least one observed interview year in which the individual was not strongly attached to the labor force, is marked as the date of transition.[20] Thus, this criterion rejects individuals who never had three consecutive interview years of strong attachment during the sample period (1979-1988). Also rejected are individuals who had strong labor force attachment in the first year in which they were observed. Members of this latter group are dropped because there is no way to tell how long this period of strong attachment had been ongoing.

It should be noted that this sample qualification rule (i.e., the definition of transition to full-time labor force participation) tends to eliminate blacks and whites from the sample for different reasons. Table 1.1 highlights this point. Although blacks and whites are about equally likely to qualify for the sample, blacks are much more likely

[19]An "interview year" is the time elapsed between consecutive year interviews.

[20]Both the definition of strong attachment and the rule for dating full-time transition are identical to those used by Farber and Gibbons (1991) in their analysis using this same data source. The authors also present evidence that the make-up of the sample is not highly sensitive to changes in either the definition of strong attachment or the rule for dating full-time transition, provided that the changes are not "too large".

than whites to be rejected for never having a spell of three consecutive years of strong attachment. By implication, blacks are much less likely to be disqualified for having had strong labor force attachment in the first year in which labor market data was available.[21] While, among NLSY males, whites are very slightly older than blacks on average, the primary explanation for Table 1.1 is that, especially among youths, blacks have much lower employment rates than whites (see, for example, Ballen and Freeman (1986)). Because young blacks have significantly weaker labor force attachment than their white counterparts, the blacks who do qualify for the sample may be more "exceptional" than the whites, potentially raising issues of sample selection. If anything, though, by selecting the most exceptional blacks the qualification rule tends to understate black-white differences. Furthermore, since the qualification rule only admits individuals with strong employment histories, one can be sure that any average differences between blacks and whites are not attributable to between-group differences in the use of "temporary" jobs or in the rate and stability of employment.

These cuts reduce the sample of individuals to its final size of 566 blacks and 1321 whites. In addition, because the empirical implications of the model are strongest for the early years following labor force entry, I restrict attention to just the first five years of labor force experience. Thus, the number of observations per sample individual ranges between three and five. As a result of the definition of transition to full-time labor force participation, the initial year of data for the individuals who qualified for the sample ranges between 1980 and 1986. Summary statistics on key variables for the final sample are presented in Table 1.2.

1.4.2 Estimation Strategy

The approach which I employ to test the model is straightforward. To test the hypotheses concerning initial wage levels and the returns to experience and tenure, I estimate (by OLS in levels and random effects GLS) standard cross-section log wage equations. The hypotheses about wage change from job mobility are examined in

[21] In the NLSY, labor market data is first available either in 1979 or in the year that the individual turns 16 years of age, whichever comes later.

two ways. First, I estimate log wage change regressions to explain the wage changes of movers. Second, to investigate the probability of positive wage change with job change, I estimate logit equations for movers. For both sets of equations, the specification is derived by taking first differences of the log wage equation. Finally, I test the model's turnover predictions by estimating logit equations for the probability of job change. In all of these equations, the explanatory variables of primary interest are the black dummy variable and its interactions with experience and job tenure.

In any econometric study using micro data on a cross-section of individuals, the possible presence of unobservable individual effects becomes an issue. If these unobservables are correlated with the explanatory variables, then the estimates obtained from standard cross-section techniques will not be consistent for the parameters of interest. A major advantage of panel data is that it offers a solution to this problem. In a linear regression setting, the well-known solution is to estimate the model in deviations-from-means form (or some other differenced form). A solution exists for the logit estimation problem as well, as shown by Chamberlain (1980). In this case, the remedy is to estimate the parameters of the likelihood function conditional on a sufficient statistic for the unobservable heterogeneity. Unfortunately, in both of these settings, the transformed estimation problem does not allow one to obtain estimates of the parameters on any time-invariant explanatory variables.[22] This is a particularly serious deficiency for the present paper, since the coefficient on the black dummy variable is of major interest. Thus, usual methods for dealing with the unobservable individual effects are not without drawbacks.

At the same time, it is at least possible that, even in the presence of unobserved individual effects correlated with the explanatory variables, the coefficients on the key variables — the black dummy and its interactions — will be estimated consistently by standard techniques. For instance, consider the cross-section linear regression

[22]Actually, for the linear regression problem, Hausman and Taylor (1981) propose identifying restrictions that allow consistent estimation of the parameters on both the time-varying and the time-invariant right-hand side variables. The identification strategy relies on there being a sufficient number of time-varying right-hand side variables that are uncorrelated with the individual fixed effect. It is far from clear, however, what restrictions of this sort could be considered reasonable for identifying the wage equation.

equation

$$y_{ijt} = Z_{ijt}\gamma + X_{ijt}\beta_j + \alpha_{ij} + \epsilon_{ijt}$$

where i indexes the individual, j indexes race (W or B), and t indexes the time-period. Thus the coefficients on Z are constrained to be the same for whites and blacks while the coefficients on X can vary across the two groups. The α represent unobserved fixed effects and the ϵ are well-behaved error terms. Then, one can show that the *difference*, $\beta_B - \beta_W$, which is what the interaction terms estimate, is consistently estimated so long as $\mathrm{E}(\alpha_W \mid Z_W, X_W) = \mathrm{E}(\alpha_B \mid Z_B, X_B)$ and the second moments of the explanatory variables are the same for blacks and whites. While there is no guarantee that these conditions hold, they are much weaker than the usual necessary conditions for parameter consistency ($\mathrm{E}(\alpha \mid Z, W) = 0$) when unobserved individual effects are present.

On the other hand, the results from Table 1.1 indicate that the sample qualification rule tends to reject blacks and whites for different reasons. This might lead one to doubt whether $\mathrm{E}(\alpha_W \mid Z_W, X_W) = \mathrm{E}(\alpha_B \mid Z_B, X_B)$. For example, suppose that the generally more tenuous labor force attachment of blacks is, to some extent, exogenous (e.g., an "environment effect"), but that there is an unobservable individual component to labor force attachment. In this case, the sample qualification rule selects partly on the unobservable individual fixed effect. Furthermore, if one imposes the same sample qualification rule for blacks and whites, there will tend to be systematic differences in these unobservable fixed effects across the two groups. As a result, parameter estimates for the black dummy and/or its interaction terms from a "levels equation" will be biased. As a specific example, suppose that blacks tend to have weaker labor force attachment than whites for exogenous reasons, and that, for both whites and blacks, strong labor force attachment is negatively correlated with (unobservable) propensity to change jobs. Then, even if (as the theory predicts) blacks turn over more than whites at labor force entry, the sample selection criteria will tend to mask this effect by selecting blacks who are on average more "stable" than whites.

In summary, then, to the extent that there are unobserved fixed effects correlated with the explanatory variables, there may be no fully satisfactory way to obtain coefficient estimates on the time-invariant variables in the levels relationships (log wage regressions and job change logits). Fortunately, the theory makes predictions about changes (specifically, wage changes with job change) as well as levels. Because the wage change specifications are derived from first differences of the cross-section wage equations, any unobservable fixed individual effect should be eliminated. Thus, the parameter estimates from the change equations should be consistent whether or not there are unobservable individual fixed effects in the levels equations.

1.4.3 Results

Wages at Entry and Returns to Experience and Tenure

Regression-based tests of the model's predictions begin with Table 1.3, which presents cross-section wage equation estimates using the entire panel. These estimates are intended to provide evidence as to whether (i) observationally equivalent blacks and whites earn the same wages at entry, and (ii) blacks and whites have different measured returns to experience and tenure in the direction predicted by the theory. Thus, the coefficients of primary interest are those associated with the black dummy variable and its interactions. I report both OLS estimates for the pooled sample and random effects GLS estimates.

Table 1.3 shows the estimated coefficients from the cross-section log wage regressions for a variety of different specifications. The specifications differ in how the effect of race is constrained to enter the equation, with more constrained specifications appearing first. All of the explanatory variables typically found in wage equations are included in the specifications, but, for convenience, only the coefficients of major interest from the standpoint of the theory are reported. None of the coefficient estimates for the other control variables are unusual.

Column 1 shows that blacks earn roughly 6.7 percent less than observationally equivalent whites when the effect of race is constrained to be a common intercept for all education categories. Column 2 allows for different returns to education for blacks and whites in addition to an intercept effect. The point estimates suggest that blacks earn a lower return to education than whites although the estimated effect is not significant at conventional levels. The black dummy, however, remains strongly significant and of large negative magnitude, indicating that in general blacks earn less than otherwise similar whites at each education level.

The next two columns allow the estimated return to experience and tenure to differ for blacks and whites. Since the model developed in Section 1.3 made specific predictions about such differences, and about the wages at entry for both groups, the estimates in these columns bear directly on the theory. Column 3 allows different returns to experience and tenure across racial groups, but constrains the return to education to be the same for blacks and whites. Column 4 loosens up the specification in Column 3 by allowing the return to education to vary between blacks and whites. Both columns tell the same story. First, after allowing blacks and whites to have different returns to experience and tenure, the black dummy is nowhere near significant. Also, in column 4 one cannot reject the joint hypothesis that the black dummy and the black-education interaction are zero (p-value = .321). Thus, the data cannot reject the hypothesis that, at labor force entry (experience = tenure = 0), blacks and whites earn the same wages. This finding agrees with the prediction of the model.

Second, blacks have a dramatically lower measured return to experience than do whites. This difference is highly significant (p-value = .014 in both columns).[23] This finding also offers support for the theory. On the other hand, focusing on returns to tenure, blacks and whites do not appear to earn different returns. This finding opposes the theoretical prediction.

In column 5, random effects GLS estimates of the specification in column 4 are presented. These estimates assume that the error covariance matrix has the classic random effects form.[24] In contrast, the OLS estimates assume that the errors are

[23]These findings remain if one allows experience to enter the specification quadratically. However, given the low values of experience for this sample of new entrants, experience and its square are highly collinear, and including the square term makes the results less stable. For this reason, I only report the results from the linear specification.

[24]In the case of a balanced panel (N individuals, T observations per individual), the form of

uncorrelated both across individuals and within individuals over time. If the random effects assumption is correct, then the estimated standard errors will not be consistent when estimated by OLS, but will be consistent when estimated by GLS. Inspection of the estimates in column 5 reveals them to be qualitatively identical to those in column 4.[25]

Of course, it is quite possible that the returns to experience and tenure vary depending on one's educational attainment. For instance, the jobs held by highly educated workers might tend to offer higher wage growth. If this is true, then the estimation should not constrain these returns to be the same for all educational levels. To account for this possibility in a parsimonious way, I run the same regressions for the subset of workers with exactly 12 years of education.[26] These results are reported in the last 3 columns of Table 1.3. None of the conclusions from the previous analysis change. Once one allows for different returns to experience and tenure by race, the black dummy is again insignificant. The strongly negative and significant black-experience interaction and the insignificant black-tenure interaction also echo the full sample findings.

The finding that blacks have lower returns to experience than whites, though hardly new, deserves comment. Typically, this result is derived from a cross-section analysis in which years of experience ranges from zero to upwards of 40. In their

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the covariance matrix of the stacked $(NT \times 1)$ error vector in a random effects setting is $\Omega = I_N \otimes (\sigma_\epsilon^2 I_T + \sigma_u^2 l_T l_T')$, where σ_u^2 is the individual-level variance component, σ_ϵ^2 is the idiosyncratic variance component, and l_T is a $T \times 1$ vector of ones. The covariance matrix in the unbalanced panel case is a straightforward extension, but one that defies compact notation.

[25]The consistency of both the OLS and GLS estimates relies on the individual effects being uncorrelated with the explanatory variables. In contrast, fixed effect estimates will be consistent even if these individual effects are correlated with the explanatory variables (so long as the individual effects are not time-varying), but do not yield estimates of the coefficients of time-invariant explanatory variables. If one estimates the cross-section log wage equation by fixed effects methods, and then performs a Hausman test of the hypothesis that the GLS and fixed effects estimates are the same, one rejects the null. One interpretation of this rejection is that the orthogonality assumption is violated, in which case the OLS and GLS estimates are inconsistent. Still, the coefficients on the black-experience and black-tenure interactions from the fixed effects estimation are qualitatively identical to those from OLS and GLS: the black-experience interaction is strongly negative, while the black-tenure interaction is insignificantly different from zero. Thus, the results concerning returns to experience and tenure appear quite robust.

[26]Exactly 12 years of education is by far the most common level of educational attainment in the sample.

important work, Smith and Welch (1986, 1989) argue persuasively that results from such regressions should not be interpreted as evidence that blacks have slower wage growth than whites as careers unfold. Instead, they claim that the cross-section findings are merely a statistical illusion; the presence of multiple cohorts in a single cross-section, coupled with the convergence of black and white earnings in more recent cohorts, makes it appear as though blacks earn lower returns to experience. Smith and Welch document this assertion by constructing synthetic cohorts using decennial census data from 1940-1980 and observing that, within cohorts, black-white earnings ratios do not decline with experience.

However, the results found here are not susceptible to this line of criticism, since the age range of the sample is very narrow. Moreover, the present results agree with those found in the main previous investigation of black-white earnings differentials exploiting longitudinal data. Using data from the Panel Study of Income Dynamics, Hoffman (1979) finds that blacks have slower wage growth than whites over the first five to ten years of work experience. In a methodologically distinct study, but one focused on youth, Lazear (1979) also finds that blacks have flatter wage-experience profiles than whites. Even Smith (1989) finds that black-white earnings ratios declined with experience for young workers in the 1980's, and he concludes that, regarding the question of lower returns to experience for blacks, "the remaining issue of legitimate debate should concentrate on the first five years of work." Thus, a significant body of work suggests that blacks earn a lower return to experience than whites during the early stages work careers. An additional contribution of the present paper is that it offers a theoretical explanation for this finding as well.

Wage Changes for Movers

The next two tables investigate wage changes for individuals who change jobs. Recall that an analysis of wage changes, since it uses the data in differenced form, eliminates any unobserved individual fixed effects that might bias the estimates from the levels equation. Table 1.4 presents estimates of the determinants of the change in the log real wage between interviews. The specification for the log wage change equation is strictly derived as a first-difference of the cross-section log wage specification of Table 1.3. In accordance with the theory, the analysis is restricted to just the sample of movers. By taking differences, the linear experience term is absorbed by the constant term while the black-experience interaction becomes a black dummy. Since the sample is restricted to movers, tenure and the black-tenure interaction still enter the specification, although now in the form of change in tenure variables. Higher tenure on the previous job implies a lower (possibly negative) value for the change in tenure variable. All of the other explanatory variables from the levels specification are included (in first-differenced form) in the wage change estimations, but I only report the estimates for the main variables of interest.

Column 1 presents estimates for the full sample of movers. The black dummy is negative, large in magnitude, and highly significant at conventional levels (p-value = .025). However, it also appears that, for whites but not for blacks, wage growth with job change falls as tenure on the previous job increases. Thus, the evidence is very strong that, at least among movers with low levels of tenure on the previous job, blacks receive much smaller wage gains than whites. In the sample of movers, however, only 8% of the observations have values of the change in tenure variable smaller than −2, and only 20% of the observations have values of the change in tenure variable less than −1. Thus, almost all movers in the sample have very low tenures on the old job at the time when mobility occurs. Consequently, consistent with the theory, the evidence strongly suggests that, in general, black movers receive smaller wage gains than whites. Moreover, there is no evidence that wage gains with job change for blacks vary with tenure on the old job (p-value = .379). This, too, agrees with the theory. The finding that wage gains with job change fall with tenure on the old job for whites does not follow directly from the theory. However, the theory does predict that these wage gains will fall as experience rises. Thus, one possible explanation of this finding for whites is that the change in tenure variable is correlated with experience (since tenure and experience are correlated), and that the change in tenure variable is picking up the experience effect. On the whole, the evidence in support of the model is quite strong in Table 1.4. The results when the sample is restricted to those with exactly a high school degree (column 2) are qualitatively identical; the black dummy loses some significance but is not insignificant at conventional levels (p-value = .073).

Of course, the strongest prediction of the model concerning wage change with job change is that such wage changes should be negative (non-positive) for blacks more frequently than for whites. To test this hypothesis, I estimate, for the sample of movers, logit equations in which the dependent variable takes the value 1 if the wage change is positive, and zero otherwise. The explanatory variables are identical to those used in the log wage change equation. The estimation results are available in Table 1.5. Column 1 shows that, for the full sample (all education categories), blacks do appear more likely to have wage declines with job change (p-value = .080). The results are stronger in column 2, where the sample is restricted to individuals with exactly 12 years of education; the estimated coefficient on the black dummy more than doubles in magnitude and becomes highly significant (p-value = .015). Analogous to the results from Table 1.4, the point estimates suggest that higher tenure on the previous job reduces the probability of positive wage change for whites but not for blacks, although even for whites these results are only borderline significant. However, since "high" tenure on the previous job is quite rare in the sample of movers, the evidence is again quite strong that blacks are generally less likely to have real wage gains with job change than whites. This finding agrees with the model's predictions. Furthermore, to the extent that the tenure effects are not significantly different from zero, the lack of an effect of tenure on the probability of wage gain with job change is also supportive of the theory. The estimates indicate that, for workers who change jobs in between survey years but are the same in all other observables (job tenure, industry and occupational affiliation, union status, part-time status, marital status) in both survey years, blacks are 5 to 11 percent more likely than whites to experience real wage declines.

Probability of Turnover and the Effects of Experience and Tenure

Finally, I examine the model's predictions about different mobility patterns of blacks and whites. Recall that the model has three implications regarding turnover. First, at least at labor force entry, blacks should be more mobile than whites. Second, if one does not control for the wage, the negative effect of experience on turnover should be weaker for blacks than for whites. Third, if one does not control for the wage, the negative effect of tenure on turnover should be stronger for blacks than for whites.

Table 1.6 shows the relationship between tenure on the current job and the probability that the worker has left this job by the next interview. It is clear that for both blacks and whites the probability of turnover declines markedly with tenure. This finding is well-known and a large body of work has attempted to determine how much of this apparent negative duration dependence is structural (resulting, say, from investment in specific human capital) and how much is spurious (induced by "mover-stayer heterogeneity"). The effect of tenure that the current model proposes is distinct from both of these stories. In the present model, tenure is negatively correlated with turnover, for blacks only, because it is an indicator of whether the job exceeds the cutoff match quality. Thus, the present model cannot explain the very strong tenure effects found for both blacks and whites in Table 1.6. In the estimations presented in Table 1.7, I allow for a very unconstrained effect of tenure, by controlling for tenure with a series of dummy variables corresponding to the tenure categories in Table 1.6. By imposing little structure on the shape of the tenure effect, I hope to minimize the chance of bias which might result from a too restrictive specification of the tenure effect if tenure is a proxy for unobserved heterogeneity and is correlated with other explanatory variables.

Table 1.7 presents estimates of probability of job change logit equations. In contrast to the wage estimations, categorical education is used rather than linear education because it fits the data better. The first three columns focus on the full sample, with race allowed to enter in progressively less constrained ways moving from left to right. From the point of view of testing the model, the third column is of primary interest; the first two columns are provided merely for the sake of comparison. The results indicate that, contrary to the theoretical prediction, blacks are not more prone than whites to change jobs at the time of labor force entry. In column 1, one can come nowhere close to rejecting the hypothesis that blacks and whites are equally likely to change jobs upon joining the full-time labor force. In contrast, in columns 2 and 3, one can overwhelmingly reject the joint hypothesis that, for all education categories, blacks and whites have the same turnover frequency at entry. However, the point estimates suggest that, at least among some educational categories, blacks turn over less frequently than whites. While these results are at odds with the theory, they confirm the finding of Blau and Kahn (1981). The results concerning the effect of experience are more favorable for the model. In column 3, the black-experience interaction is positive and statistically significant. The estimated coefficients for the sequence of tenure dummies (not reported) indicate a strong negative effect of tenure, consistent with the raw frequency data in Table 1.6. However, the effect of tenure on the probability of turnover does not appear to differ between blacks and whites.

Of course, as with the cross-section log wage equations, it could be that experience and tenure affect the probability of job change differently for different education categories. To investigate this possibility in a tractable manner, I narrow the focus to those with exactly a high school degree in columns 4 and 5. Once again, the results are qualitatively identical to those for the full sample. On the whole, the analysis of turnover patterns yields at best mixed evidence for the theory.

Apart from the predictions of the theory, Table 1.7 contains one other rather striking correlation. While turnover propensity falls markedly with educational attainment for whites, the hypothesis that turnover propensity is the same across all educational categories for blacks comes nowhere close to being rejected. While the theory developed above offers no insight about this last finding, it is nonetheless provocative and merits further investigation.[27]

[27]This finding would be consistent with a version of the "connections" story of statistical discrimination in which whites are able to use education as a connections network but blacks are not. Of course, the model in this paper does not address this issue, and no corroborating evidence for this story is provided.

1.5 Conclusion

Most models of discrimination offer few, if any, easily testable predictions. As a result, very little of the voluminous literature on black-white earnings differences has been aimed at testing the models. In contrast, this essay developed an empirically testable model of statistical discrimination, and confronted the model with data from the NLSY. A number of the model's predictions received strong confirmation.

1. Blacks and whites do not earn significantly different wages at the time of labor force entry.

2. Blacks have a lower measured return to labor market experience than whites.

3. Blacks receive smaller average wage gains with job change than whites.

4. Blacks are more likely to experience real wage declines with job change than whites.

5. The probability of turnover falls more slowly with experience for blacks than for whites (in fact, it rises with experience for blacks).

A few predictions, however, are not borne out by the data.

1. Blacks do not have higher measured returns to job tenure than whites.

2. Blacks are not more likely than whites to change jobs at the time of entry to the labor force.

3. The probability of turnover does not appear to fall more rapidly with tenure for blacks than for whites.

On the whole, then, a majority of the evidence is consistent with the theoretical model. Moreover, although the present model cannot account for the full range of findings, it does account for certain features of the data which alternative models fail to explain. For instance, in a standard tastes model of discrimination, one would expect to observe a black-white wage gap even among new entrants (although it might grow with experience). Similarly, a wage differential should exist at entry in static statistical discrimination models. However, in the data analyzed here, there is no evidence of a wage differential among new entrants; rather, the wage gap develops only as time in the labor force accrues.

Lazear (1979) proposes a modified tastes theory in which antidiscrimination laws prevent employers from paying blacks and whites different wages at entry. As a result, employers exercise their taste for discrimination by providing less on-the-job training to black workers, with the result that blacks experience slower wage growth over time. This story would appear to be consistent with the findings reported above. However, Lazear's theory suggests that blacks should have lower *within-job* wage growth than whites. The model of the present paper made no robust predictions about within-job wage growth, but this question can be examined by estimating log wage change regressions on the sample of job *stayers*. The results from such estimation, presented in Table 1.4a, show no strong evidence that blacks suffer slower within-job wage growth than whites, in contrast to what the modified tastes model would predict.[28] Finally, while the model of the present paper cannot successfully account for the turnover patterns in the data, none of the other theories that have been articulated shed any light on turnover behavior at all.

In short, many of the predictions of the model developed here receive support in the data. Given the difficulty that alternative theories face in trying to explain even these findings, the overall results seem to provide some measure of support for the (dynamic) statistical discrimination model. However, since the evidence does not support all of the model's predictions, a more definitive conclusion must await further work.

[28]The estimated coefficient on the black dummy from this regression is small (−.012) and not statistically significant. The black dummy is the only relevant coefficient because, for a sample of stayers, the change in tenure is equal to the change in experience, and both are absorbed by the constant term. Combined with the results from Table 1.4, the evidence suggests that black movers experience smaller wage gains than white movers, but that there is no such difference for stayers. Loprest (1990) observes the same pattern of wage growth differences for men and women using a similar data set from the NLSY.

On the empirical side, this additional work might include spelling out more clearly what mechanism underlies the statistical discrimination assumption, and devising tests of the proposed mechanism. For example, this essay cites two rationales for the statistical discrimination assumption from the discrimination literature. The first one emphasized the role of "connections" and the different frequency with which blacks and whites use these personal referrals to find jobs. Assuming that a referral provides up front information about a match, the connections story suggests that blacks who get jobs by referral should have labor force outcomes more similar to whites than blacks who get jobs through other means. The second rationale for the statistical discrimination assumption emphasized "communication". Specifically, the statistical discrimination assumption was justified by noting that, first, most employers are white, and second, "miscommunication" is more likely to occur between members of different groups. This story suggests that blacks who work for black employers should have predictably different patterns of labor force outcomes than blacks who work for white employers. In principle, then, the implications of both stories can be examined empirically, so that a direct test of the statistical discrimination model should be possible. Actually carrying out the analysis, though, will require labor market data beyond what is available in the standard sources.[29]

The work can be extended on the theoretical side as well. Indeed, a richer model might be capable of explaining the full range of findings reported in Section 1.4. For instance, consider a model in which a worker can allocate time to work, job search, and investment in specific human capital. Work generates output and information about the quality of the current match. Job search generates new offers. Investment raises the value of the current match. Such a model represents a melding of the ideas contained in two influential papers by Jovanovic (1979a, 1979b). In this setting, if black workers have less initial information about the quality of a match, then it seems probable that initially they will spend most of their time working to learn about match quality. But, if blacks allocate less time than whites to both search and investment

[29]The NLSY has limited data on job finding method, but an effort to use this data to examine the connections story yielded only miniscule samples.

early on, then there is no longer any reason to expect that blacks will have higher returns to tenure or higher probability of turnover immediately after entry. Thus, reasonable extensions of the present model could perhaps account for the findings that currently appear anomalous.

In summary, the present work represents only the first attempt at testing the statistical discrimination model. The results, while not unanimously supportive, are fairly consistent with many of the theoretical predictions. Moreover, there is no coherent alternative explanation for all of the findings. This suggests that the informational disadvantage posited by the statistical discrimination model — that good matches are less apparent *ex ante* for blacks than whites — is a likely part of the explanation for the different labor market outcomes of blacks and whites in the early stages of work careers. While it is perhaps unlikely that any single model is the true explanation for all of the differences in the labor market outcomes of blacks and whites, it seems clear that subsequent work on discrimination, "statistical" or otherwise, should concentrate on developing testable models and subjecting them to empirical scrutiny.

Appendix

This appendix considers two generalizations of the model developed in Section 1.3. First, the possibility of exogenous job endings (e.g., permanent layoffs) is introduced. Second, the effects of population heterogeneity in the basic parameters of the model (discount factors, offer arrival probabilities, job death probabilities) are considered.

The possibility of job death is modelled as a constant, exogenous probability, q, in each period, independent across periods. The possibility that jobs can die reduces any worker's expected present discounted value of lifetime earnings because there is no longer any guarantee that a good match, once located, will last forever. Still, the possibility of job death does not alter the mobility rule of a white worker at all. For a white worker, it is still optimal to move to any match which is better than the current match.

Similarly, for blacks the decision rule remains a reservation rule. The reservation rule is derived from the value functions describing the payoff from each possible decision. A worker's action in any period can be classified into one of three categories: (1) stay on current job, although other job offers have been received (and rejected) while on the current job, (2) stay on current job, although no other job offers have been received while on the current job, and (3) move to a new job. By assumption, a worker who has rejected a previous offer while on the current job will never leave the current job voluntarily. Also by assumption, a worker will never voluntarily move to unemployment from employment. Letting d be an indicator for whether a new job offer has ever been received while on the current job, the value functions for each of these three decisions are given by

$$\begin{aligned}
V^S(\mu \mid d=1) &= \mu + \beta\{pqV^M + (1-p)qV^U + (1-q)V^S(\mu \mid d=1)\}, \\
V^S(\mu \mid d=0) &= \mu + \beta\{pqV^M + (1-p)qV^U + (1-p)(1-q)V^S(\mu \mid d=0) \\
&\quad + p(1-q)\max(V^S(\mu \mid d=1), V^M)\}, \\
V^M &= \mu + \beta\{pqV^M + (1-p)qV^U + (1-p)(1-q)\mathrm{E}(V^S(\mu \mid d=0)) \\
&\quad + p(1-q)\mathrm{E}(\max(V^S(\mu \mid d=1), V^M))\},
\end{aligned}$$

where

$$V^U = \beta\{pV^M + (1-p)V^U\} = \frac{\beta p V^M}{1-\beta(1-p)}.$$

After a lot of algebra, one finds that the reservation match quality, μ^*, is implicitly defined by

$$(1-\beta(1-q))(\mu^* - m) - \beta p(1-q)(1-F(\mu^*))(\mathrm{E}(\mu \mid \mu > \mu^*) - \mu^*) = 0.$$

If one chooses $q = 0$, this equation reduces to the same formula derived in Section 1.3 under the assumption that there are no exogenous job deaths. One can see that as q increases, μ^* decreases. Workers become less selective about settling on a job as the probability of job death rises because they realize that, in expectation, they will reap the rewards from any match for a shorter period of time. Still, $\mu^* > m$, because the worker could earn m on average (in the periods of employment) simply by changing jobs at every opportunity. Thus, a job must pay more than m to entice a worker to stay with it.

While the decision rules are essentially unchanged, the empirical predictions now arise only in differenced form. For instance, both groups now have positive returns to tenure because, for both blacks and whites, jobs that have lasted a long time tend to be good matches that have been spared exogenous termination. Similarly, both groups now sometimes experience wage declines with job change because some job change results from involuntary displacement from good matches. It is not immediately apparent from this discussion what the relative magnitude of the effects for blacks and whites are. However, extensive computer simulations indicate that the empirical predictions that flow from this augmented model are exactly the differenced predictions discussed in Section 1.3.

The simulations were performed by generating artificial "5-year" work histories for a sample of 1000 "blacks" and 1000 "whites". For the "blacks", match quality was assumed to be unobservable *ex ante*, and voluntary job mobility was enforced as specified by the optimal mobility rule for blacks. For the "whites", match quality was assumed to be perfectly observable *ex ante*, and voluntary job mobility was enforced as required by the optimal mobility rule for whites. Both groups were assumed to draw matches at random from the same Normal distribution. After specifying values for the parameters β (the discount factor), p (the offer arrival probability), and q (the job death probability), artificial work histories were created as follows:

1. A series of random draws from the assumed match quality distribution was generated for every individual in every period.

2. A series of random Bernoulli trials (with "success" probabilities p and q) was generated in every period to determine whether an individual actually received a new offer and/or lost his current job.

3. Voluntary job mobility was enforced as specified by the optimal mobility rules.

Heterogeneity was incorporated by allowing variation across individuals in the values of β, p, and q. The distributions describing the heterogeneity were assumed to be the same for blacks and whites. Two population distributions were considered for the parameter β. The first "distribution" was degenerate: all individuals were assumed to have $\beta = 0.9$. The second distribution for β was assumed to be a truncated Normal distribution — specifically a Normal distribution with expectation 0.9 and standard deviation 0.1, doubly truncated so that all realizations lie in the interval (0,1). This truncated distribution has a modal discount factor of 0.9, with 92 percent of the population having a discount factor in excess of 0.75.

Three distributions were considered for both of the parameters p and q. For p, one choice of the distribution was $p = 0.8$ for all individuals. A second choice was $p = 0.5$ for all individuals. The final choice was a two mass point distribution with $p = 0.8$ with probability $\frac{1}{2}$, and $p = 0.5$ probability $\frac{1}{2}$. The distributions which were considered for q were similar. One choice of the distribution of was $q = 0$ for all individuals. A second choice was $q = 0.3$ for all individuals. The final choice was a two mass point distribution with $q = 0$ with probability $\frac{1}{2}$, and $q = 0.3$ probability $\frac{1}{2}$.

For all 18 combinations of these distributions for β, p, and q, simulated work history data was generated and analyzed by performing regressions analogous to those performed on the actual NLSY data. In all of these cases, the predictions that came from this analysis were the differenced predictions outlined in Section 1.3 of the paper. In general, however, the strong separate predictions for blacks and whites derived in Section 1.3 did not hold in the simulated data. Thus, I conclude that these separate predictions are quite fragile, while the differenced predictions are the robust predictions of the model.

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Table 1.1: Effect of Sample Qualification Rule

		Blacks	Whites
Initial Population:		1451	3181
Proportion Qualified:		.390	.415
Proportion Rejected:	Working in First Year	.196	.304
	Never Made Full-Time Entry	.414	.281

The first row of the table indicates the total number of black and white males in the NLSY. Individuals can be rejected from the sample either because they were "primarily working" (worked in over half of the weeks and averaged 30 or more hours in those weeks) in the first year in which data was available or because they never made the transition to full-time participation in the labor force during the sample period (never had three consecutive sample years in which they were "primarily working").

Table 1.2: Summary Statistics

		Blacks	Whites
Entry Year:	1980	.134	.167
	1981	.106	.124
	1982	.143	.169
	1983	.131	.141
	1984	.170	.146
	1985	.171	.144
	1986	.145	.110
Education:	$<$ 12 years	.276	.209
	12 years	.424	.363
	13-15 years	.205	.187
	$\geq$ 16 years	.095	.241
Married		.187	.302
Occupation:	Prof/Mgmt	.123	.244
	Sales/Clerical	.136	.146
	Craftsmen	.136	.195
	Operatives	.394	.311
	Service	.211	.104
Wages Set by Collective Bargaining		.275	.142
Experience (Months)		33.96	34.26
		(16.94)	(16.95)
Job Tenure (Months)		18.26	18.66
		(15.24)	(15.36)
Real Hourly Wage		6.19	7.10
		(3.07)	(3.85)
Job Change Frequency		.408	.375

Summary statistics are derived from the pooled time-series cross-section of observations in the final sample from the NLSY. As a result, the summary statistics reflect multiple observations for each individual. For those variables that are not binary, standard deviations appear in parentheses.

Table 1.3: Cross-Section Log Wage Equations

	All Education Levels					Exactly 12 Years Education		
	OLS	OLS	OLS	OLS	GLS	OLS	OLS	GLS
education	.0531 (.0022)	.0544 (.0024)	.0530 (.0022)	.0543 (.0024)	.0650 (.0035)			
experience	.0437 (.0039)	.0437 (.0039)	.0489 (.0045)	.0489 (.0045)	.0482 (.0052)	.0519 (.0062)	.0596 (.0071)	.0962 (.0078)
tenure	.0299 (.0037)	.0298 (.0037)	.0304 (.0044)	.0301 (.0044)	.0180 (.0043)	.0234 (.0057)	.0241 (.0068)	.0127 (.0068)
black	-.0668 (.0106)	-.0646 (.0107)	-.0139 (.0208)	-.0123 (.0208)	.0242 (.0226)	-.0862 (.0166)	-.0162 (.0315)	.0422 (.0349)
black* education		-.0061 (.0043)		-.0058 (.0043)	-.0046 (.0070)			
black* experience			-.0175 (.0071)	-.0176 (.0071)	-.0231 (.0059)		-.0229 (.0107)	-.0338 (.0090)
black* tenure			-.0023 (.0079)	-.0017 (.0079)	-.0040 (.0079)		-.0031 (.0120)	-.0004 (.0119)
R^2	.3532	.3534	.3539	.3541	.2617	.2699	.2715	.2357
N	7986	7986	7986	7986	7986	3038	3038	3038

Data is from the NLSY, 1979-1988. The dependent variable is the log of the real hourly wage. The education variable is: completed years of education−12. Thus, the black dummy measures the mean wage difference between black and white new entrants with 12 years of education. Other regressors, which are not reported, are (1-digit) industry and occupation dummies, a dummy for marital status, a dummy for whether wages are set by collective bargaining, a dummy for whether the individual works part-time hours on the job, year dummies, a dummy indicating whether the respondent is from the Supplemental ("poverty") Civilian Sample of the NLSY, and a constant term. Standard errors are in parentheses. The GLS estimates are derived under the assumption that the within-individual error covariance structure has the standard random effects (two error component) form.

Table 1.4: Log Wage Change Equations for Movers

	All Education Levels	Exactly 12 Years Education
constant	.1049	.1024
	(.0125)	(.0205)
change in tenure	.0352	.0390
	(.0114)	(.0179)
black	-.0479	-.0588
	(.0213)	(.0328)
black* change in tenure	-.0199	-.0422
	(.0205)	(.0311)
R^2	.1041	.1652
N	2262	837

Data is from the NLSY, 1979-1988. The estimated equation is derived by first-differencing the levels specification in Table 1.3, and restricting the sample to job changers only. The dependent variable is the change in the log real hourly wage. The change in linear experience is absorbed by the constant term; the change in linear tenure is simply $\text{tenure}_t - \text{tenure}_{t-1}$, so that higher values of this variable correspond to lower tenure on the previous job. Other regressors, which are not reported, are a constant term and first differences of the following dummy variables: (1-digit) industry and occupation dummies, a dummy for marital status, a dummy for whether wages are set by collective bargaining, a dummy for whether the individual works part-time hours on the job, and year dummies. Standard errors are in parentheses.

Table 1.4a: Log Wage Change Equations for Stayers

	All Education Levels	Exactly 12 Years Education
constant	.0741	.0708
	(.0058)	(.0090)
black	-.0117	-.0121
	(.0098)	(.0151)
R^2	.0115	.0173
N	3752	1475

Data is from the NLSY, 1979-1988. The estimated equation is derived by first-differencing the levels specification in Table 1.3, and restricting the sample to job stayers only. The dependent variable is the change in the log real hourly wage. The change in linear experience and the change in linear tenure (which are the same for job stayers) are both absorbed by the constant term. Other regressors, which are not reported, are a constant term and first differences of the following dummy variables: (1-digit) industry and occupation dummies, a dummy for marital status, a dummy for whether wages are set by collective bargaining, a dummy for whether the individual works part-time hours on the job, and year dummies. Standard errors are in parentheses.

Table 1.5: Logit Estimates for Probability of Wage Gain with Job Change

	All Education Levels	Exactly 12 Years Education
constant	.5299	.6347
	(.0637)	(.1128)
change in tenure	.0977	.1424
	(.0578)	(.0969)
black	-.1905	-.4321
	(.1086)	(.1778)
black*	-.0271	-.1334
change in tenure	(.1028)	(.1671)
log L	-1419.6	-506.9
N	2262	837

Data is from the NLSY, 1979-1988. The dependent variable takes the value 1 if the change in the real hourly wage is positive, and zero otherwise. The included explanatory variables are the same as in Table 1.4; see the note following Table 1.4 for a full explanation. Standard errors are in parentheses.

Table 1.6: Current Job Tenure and the Probability of Moving from Current Job

	Blacks		Whites	
Tenure Category (in Months)	Proportion Movers	Total in Category	Proportion Movers	Total in Category
0 – 3	.684	272	.644	669
3 – 6	.536	248	.493	594
6 – 9	.508	254	.438	578
9 – 12	.390	292	.382	757
12 – 18	.381	236	.363	562
18 – 24	.253	237	.267	671
24 – 30	.245	139	.223	291
30 – 36	.278	144	.230	370
36 – 42	.241	79	.186	183
42 – 48	.154	78	.203	202
48 +	.303	89	.179	234
Total	.408	2068	.375	5111

Data is from the NLSY, 1979-1988. Each cell represents the proportion of individuals in the corresponding tenure category at the interview in year t who leave the current job by the time of the year $t+1$ interview. Because an observation is a person-year, and not a person-job, long jobs show up multiple times in the table. For this same reason, there is no reason why the "Total in Category" must decline monotonically as tenure increases.

Table 1.7: Logit Estimates for Probability of Moving from Current Job

	All Education Levels			Exactly 12 Years Education	
< 12 yrs ed	.3271 (.0672)	.4686 (.0829)	.4654 (.0827)		
13-15 yrs ed	.1353 (.0709)	.1812 (.0855)	.1801 (.0853)		
≥ 16 yrs ed	-.3899 (.0774)	-.3930 (.0864)	-.4000 (.0863)		
experience	.0692 (.0252)	.0698 (.0252)	.0292 (.0289)	.0470 (.0409)	-.0137 (.0478)
black	-.0144 (.0666)	.1096 (.0951)	-.0958 (.3870)	.1424 (.1077)	-.2840 (.5838)
black* (< 12 yrs ed)		-.4103 (.1409)	-.4067 (.1421)		
black* (13-15 yrs ed)		-.1384 (.1527)	-.1358 (.1539)		
black* (≥ 16 yrs ed)		.1833 (.1960)	.1895 (.1980)		
black* experience			.1464 (.0506)		.1911 (.0786)
log L	-4385.6	-4379.7	-4370.5	-1701.9	-1693.3
N	7179	7179	7179	2787	2787

Data is from the NLSY, 1979-1988. The dependent variable equals 1 if the individual's most recent job at the time of the next interview is different from the most recent job at the time of the current interview, and zero otherwise; quits are not distinguished from other job mobility (e.g., layoffs). The effect of tenure on the probability of turnover is controlled for by a series of dummy variables corresponding to the tenure categories in Table 1.6. Other explanatory variables, which are not reported, are a marital status dummy, year dummies, and a dummy indicating whether the respondent is from the Supplemental ("poverty") Civilian Sample of the NLSY, and a constant term. Standard errors are in parentheses.

Chapter 2

Uncertain Returns to Education and Multiple Transitions from School to Work

2.1 Introduction

People attend school early in the life cycle. While school attendance at the earliest ages is compulsory, voluntary attendance beyond the required minimum level still occurs mainly among the young. Life cycle models of earnings and human capital accumulation, in which schooling is viewed as an investment that increases future earnings power, predict just such a pattern. But, in fact, the standard life cycle model makes an even stronger prediction: the period in which a worker devotes all of her time to acquiring human capital (namely, full-time schooling) should occur only at the start of the working life[1]. An implication of this basic model, then, is that for any worker the transition from school to work should be unique and well-defined. While an interim period during which an individual both attends school and works in the labor market is not inconsistent with the theory, the life cycle model *does* predict that individuals who have made a long-term break with formal schooling should not

[1]See Weiss (1986) for a survey of the theoretical literature on life cycle earnings, and for a discussion of this implication of the model in particular.

return.

In view of this strong implication of the life cycle model, it is somewhat surprising that the time pattern of school enrollment and the transition from school to work has not been the subject of much empirical investigation in labor economics. If the actual patterns are substantially at odds with those predicted by the simple life cycle model, it then might be worthwhile to explore generalizations of the basic model. Although Weiss (1986) notes that "outside the scope of the model there are potential causes for delayed investment [in schooling] such as changing market conditions, unknown ability (tastes) and borrowing constraints", there has been very little development of these themes in the literature.[2] Of course, distinguishing between these possible explanations would be desirable since they presumably have different policy implications.

This essay provides both an empirical and theoretical analysis of school enrollment behavior. In the next section, I review the small amount of existing evidence on school to work transitions, and then I present new evidence from the National Longitudinal Survey of Youth (NLSY). It turns out that re-enrollment in school after a significant break from schooling, though not the typical pattern, is far from rare. Furthermore, among individuals who return to school after such a break, the distribution of educational attainments prior to re-enrollment is quite spread out; thus, the individuals who return to school are not all, say, high school dropouts. Finally, among individuals in school, those who previously have taken an extended break from school differ from those who have not both in their progress in school (i.e., grade advancement) and in their employment status.

After documenting the basic phenomenon, I develop some models which can explain it in Section 2.3. One, perhaps the leading, explanation for an enrollment pattern marked by interruption is borrowing constraints. Thus, I analyze several variants of the borrowing constraints model and determine their empirical implications. However, even in a world with no borrowing constraints, one might observe

[2] Manski (1989) and Altonji (1991) both introduce uncertainty into the educational choice problem, but neither focuses on uncertainty as a possible explanation for re-enrollment in school after an extended break from schooling.

school interruption and re-enrollment. In particular, I show that a richer life cycle model, in which individuals are initially uncertain about various determinants of their labor market productivity but learn about these characteristics through work experience, can generate re-enrollment in school after extended interruption in school attendance as optimal behavior.

The basic idea in the model is that some jobs have higher educational requirements than others, so that additional education enlarges the pool of occupations available to an individual. Jobs that require more education pay more on average, but, *ex ante*, individuals are uncertain about the return to further education for two reasons. First, individuals are unsure whether they have the requisite ability to successfully complete the next level of schooling. In addition, individuals do not know how well-suited they are to either the occupations that are accessible given their current education or the occupations that additional education (if successfully completed) will make available, before actually working in these occupations.[3] Thus, individuals are uncertain both about whether they can complete additional education and about what benefits successful completion of further education will yield. In this setting, those who are likely to succeed in further schooling find it optimal to continue in school uninterrupted, but those with only a low probability of success at the next level of school optimally leave school and begin work in the sector requiring only low education. As a by product of work, each member of this latter group learns the quality of the match with the low education sector. For those who discover that the match is poor, it might be optimal to reconsider the exit from school and attempt further education, even though the probability of successfully completing this additional education is relatively low.

Section 2.4 returns to the NLSY data to evaluate the models. The general strategy is to see whether the data can be explained by a pure borrowing constraints model of school interruption and re-enrollment, or whether there exists evidence for learning-induced re-enrollment as well. I begin with an informal look at responses to survey questions on reason for school exit and desired level of education, and follow this with

[3]For example, a worker's productivity may have an occupation-specific component that is only revealed after working in that occupation. See Miller (1984) and McCall (1990) for models of this type.

tests of the models derived directly from the theory. Section 2.5 concludes.

2.2 The Transition from School to Work

2.2.1 Previous Work

Not much evidence exists on the transition from school to work, but what evidence there is suggests that the transition is more complex than the life cycle model would predict. Coleman (1984) finds substantial differences between the distribution of "age at first exit from full-time education" and the distribution of "age at first full-time job after last full-time education".[4] Both concepts represent possible definitions for the date of transition from school to work, and it is clear that "transition" under the second definition always occurs at least as late as does "transition" under the first definition. If individuals immediately took up full-time work upon leaving school, and never returned to school thereafter, the date of transition would be the same under either definition.

In fact, the empirical distribution of age at transition looks quite different under the two alternative definitions. In particular, for the median individual in Coleman's sample, the first exit from full-time education occurs nearly one year before the start of the first full-time job after last full-time education. At higher percentiles of the distribution (i.e., individuals for whom the transition from school to work occurs much later than average), the first full-time job after last full-time education begins more than two years after the the first exit from full-time education. These findings, while highly suggestive, do not unequivocally establish the importance of school re-enrollment, however, since other phenomena (for example, significant periods of nonemployment between the exit from school and the start of full-time work) could account for the difference.

Meyer and Wise (1982, 1984) and Manski and Wise (1983) also consider the transition from school to work. However, in none of these works is the pattern of

[4]Coleman defines "first exit from full-time education" as the start of the first out of school spell lasting 16 months or more.

transition the primary focus of the analysis. Meyer and Wise are mainly interested in the effect of work experience while in high school on subsequent labor market performance, while Manski and Wise are interested in the decision to apply to, attend, and complete college. Nevertheless, their work provides evidence of more complex school enrollment histories than would be predicted by the standard life cycle model.[5]

Table 2.1 reproduces Table 3.6 from Manski and Wise. Each 5-digit sequence describes a possible schooling sequence over the period 1972-76, with the digit furthest to the left corresponding to 1972, the digit second from the left corresponding to 1973, and so forth up to the digit furthest right which corresponds to 1976. For each digit in the sequence, a "1" indicates that the individual was "in school full-time" in the first week of October of the appropriate year, while a "0" indicates that this was not the case. The simple life cycle model suggests that a zero should always be followed by an uninterrupted string of zeros. In fact, for a substantial minority of the sample — 24% — this is not the case, and this understates the number of individuals who eventually return to school, since undoubtedly some individuals returned for the first time only after 1976. This data is not ideal for identifying long spells of non-enrollment, however, since it only refers to school status in the first week of October in each year. It is possible that an individual was essentially steadily in school, but happened not to be in school in one October, thus creating the appearance of a break. On the other hand, it is also possible that some individuals who actually had significant breaks from school were nevertheless in school in consecutive Octobers so that they appear to have been continuously enrolled. Obviously, one needs retrospective data on school attendance over the entire year to obtain convincing evidence on the frequency of extended interruptions in school enrollment.

[5]Indeed, in their concluding chapter, Manski and Wise suggest examination of the determinants of these "nontraditional" enrollment patterns as a topic for future research. Other work which finds that re-enrollment in school after an extended interruption is not uncommon includes Griliches (1980) and Marcus (1986).

2.2.2 Evidence from the NLSY

Detailed evidence on school-to-work transition patterns can be obtained from the National Longitudinal Survey of Youth (NLSY). The NLSY is an annual survey of 12,686 youths who were between the ages of 14 and 21 on January 1, 1979. It is composed of three subsamples: a civilian sample representative of the youth population in the United States, a supplementary civilian sample of poor and minority youths, and a sample of youths in the military. I have data through the 1988 interview, and I follow each individual until the end of the sample period or the first noninterview year, if one occurs.[6] In all of the empirical analysis in this paper, I limit the sample to males from the civilian subsamples. The military sample is discarded both on theoretical grounds (members of the military sample are likely to differ significantly from those in the civilian sample, in both observable and unobservable dimensions) and on practical grounds (the military sample is followed for a shorter time and asked fewer questions than the civilian sample). Women are dropped from the sample because, at least over this sample period, it is quite plausible that the primary forces behind interruption and re-enrollment were different for women and men.[7]

As a starting point, I follow Manski and Wise and create binary sequences representing the school enrollment history of each individual in the sample. Since my interest is in the frequency of re-enrollment in school for individuals who have been out of school for a "significant" period of time, I restrict attention to the enrollment history of individuals after their first lengthy break from school. In particular, the variable I use to construct schooling histories, and as an indicator of an extended interruption in schooling, is whether the respondent has *ever been in school since the*

[6]Over the full sample period, 1979-88, nearly 80% of the sample never missed an interview.

[7]For instance, there was a dramatic secular increase in women's college enrollment over the sample period (see Clotfelter, et. al., (1991) for details). This upward surge in women's college enrollment probably represents a permanent upward shift in the steady state level of college enrollment among women. At the same time, it is probable that part of this total increase in college enrollment was accounted for by increased re-enrollment after interruption among women. If this is the case, then much of the re-enrollment among women over the sample period represents a transitory phenomenon caused by the shift in steady states. In contrast, the theory of interruption and re-enrollment presented below is a theory of behavior *in steady state*. Thus, in testing the theory, it makes sense to use data on men's enrollment, which was much more stable over the sample period.

previous year's interview. Thus, a zero indicates that the individual has been out of school continuously since the last interview. Since consecutive NLSY interviews usually occur at roughly twelve month intervals, it is approximately correct to think of the period between interviews as one year.[8] For the set of individuals for whom I ever observe a zero, I am interested in how many of them eventually re-enter school. There is perhaps some deficiency in my measure of being in school, since it does not distinguish very brief returns to school from those of longer duration. However, very brief periods in school, if classified as full-time enrollment by the respondent, are also counted by the variable used by Manski and Wise. Moreover, even very brief returns to school after a significant break in school attendance run counter to the predictions of the basic life cycle model. In any case, any drawback of the variable that I use is outweighed by the fact that it unambiguously identifies long periods away from school.

Because different individuals leave school for the first time at different times, and because I stop following individuals after their first noninterview year (if one occurs), the length of the enrollment history after the first exit from school varies across individuals. Tables 2.2a and 2.2b show the frequency of the various possible enrollment histories after the initial exit from school for those individuals who I continue to observe for 3, 4, 5, and 6 or more years, respectively. Each of these histories begins with a zero, which marks the first extended break in school attendance

[8]The average period between interviews in the full sample is 55 weeks, and for 90% of the observations the time between interviews is at least 48 weeks. However, for about 1% of the observations, the elapsed time between interviews is 40 or fewer weeks. Still, the percentage of observations with spells between interviews of much less than a year is very small. More importantly, for individuals who have never been in school since the previous interview, the elapsed time since the last interview must understate the time since school exit, possibly by as much as one year. Thus, non-enrollment for the entire period between interviews can reasonably be taken as evidence of an extended interruption in enrollment.

It should be noted that the definition of extended interruption used here is not the only possible one. Beginning with the 1981 interview, data was collected on enrollment status in every month since the previous interview, allowing (beginning in this year) for the creation of monthly enrollment histories and identification of all breaks in enrollment of any arbitrary length. For instance, if one wished to define extended interruption as all breaks of six months or more, one could select all such periods. Constructing the monthly enrollment history would be very involved, however, and it is not obvious that alternative definitions of "extended interruption" in schooling are superior, for the present purposes, to the simple definition used above.

in the data. If the life cycle model were strictly correct, the only history that one would observe would be a string of zeros. While this is by far the most common pattern, a significant number of individuals eventually re-enroll in school: 16.3% of those observed for 3 years, 22.9% of those observed for 4 years, 20.9% of those observed for 5 years, and 22.1% of those observed for 6 or more years.[9]

Table 2.3 summarizes the frequency of re-enrollment in school after a long interruption somewhat more concisely. The columns represent the total number of remaining years in the sample starting with the first year in which the individual reports that he was never in school since the last interview.[10] The column marked "0" indicates that the respondent was continuously in school up through the final interview. The column marked "1" indicates that the respondent's first year completely out of school since the previous interview was his last year in the sample. The column marked "2" indicates that the respondent's first year completely out of school since the previous interview was his second to last year in the sample, and so on. The rows indicate the number of consecutive survey years in which the individual was never in school before returning to school. Thus, the row marked "1" indicates that the respondent had one survey year in which he was never in school since the previous interview before returning some time in the next survey year.[11] The row marked "2" indicates that the respondent had two consecutive survey years in which he was never in school since the previous interview before returning in the next year, and so on.

As before, one sees that a substantial minority of the sample returns to school after a lengthy spell away from school. By construction, only individuals who make a break with school, and do so before their final year in the sample, can be observed to return to school.[12] There are 4,716 such individuals in the sample and 1,120 of them, or 23.7%, re-enroll within the remaining sample period. As one would expect,

[9]The percentage for the individuals observed for 6 or more years is the number who return to school within the first six years after and including the first interview year in which the respondent was never in school since the last interview.

[10]For the first survey year, 1979, the beginning of the time period obviously is not the date of the previous interview, but is instead January 1, 1978.

[11]Thus, this row corresponds to all individuals who have a schooling history after initial school exit beginning with "01".

[12]This corresponds to the columns marked 2 through 10 in Table 2.3.

the proportion of individuals who have returned to school sometime after their initial exit generally rises as the number of available years after the initial exit rises. For instance, for individuals who are observed for only one year beyond the initial exit year (the column marked "2") the percentage who return to school during the remaining sample period is 14.7%. On the other hand, for respondents who are observed for eight years after the initial exit year (the column marked "9") the percentage who go back to school sometime during the remaining sample period is 30.2%. It may seem somewhat surprising, then, that the percentage of respondents who are observed for nine years after the initial year with no school (the column marked "10") that go back to school is only 22.6%. However, this column represents individuals who, in the 1979 interview, reported that they had never been in school since January 1, 1978. In fact, many had not been in school since long before January 1, 1978. Thus, the lower frequency of school re-enrollment in this column suggests that individuals who do not return to school "soon" after leaving are much less likely to ever re-enroll.

Having established that re-enrollment in school after an extended interruption is far from rare, a natural next step is to examine the characteristics of the individuals who do re-enroll. Indeed, the characteristics of these individuals might suggest an explanation for the re-enrollment phenomenon. Table 2.4 considers the time until return to school after a gap of at least one interview year by racial group. The numbers are very similar for all three groups, and a χ^2 test of independence does not reject at conventional levels of significance (p-value = 0.286).

Table 2.5 presents the distribution of educational attainments for three distinct groups. The first column shows the distribution of highest grade completed at the time of exit from school for individuals who leave school and never re-enter school during the sample period. The second column shows the distribution of highest grade completed *at the time of first exit from school* for individuals who leave school during the sample period but who return to school later in the sample period. Finally, the third column shows the distribution of highest grade completed *at the end of the sample period* for the same group of individuals as in the second column.

Several interesting findings emerge from the table. First, individuals who return to school after a significant period away come from all parts of the education distribution. Indeed, the distribution of educational attainments prior to returning to school for those who do return (Column 2) looks quite similar to the distribution for those who leave school and do not return during the sample period (Column 1), although a χ^2 test of independence rejects the hypothesis that the distributions are the same at virtually any level of significance (p-value ≈ 0). Those who re-enroll are somewhat more likely to be just short of a high school diploma (11 years of education) or have some college but less than a bachelor's degree (13-15 years of education) than those who do not return to school. In contrast, in comparison to those who re-enroll, those who never re-enroll are a bit more likely to have completed only the tenth grade or less, or have exactly a high school diploma. The large number of returners who have less than a high school degree (over 30% of all returners) suggests that borrowing constraints may not be the entire explanation for the re-enrollment phenomenon.[13] Finally, comparing the second and third columns, one sees that by the end of the sample period the individuals who re-enroll augment their education by nearly a full year, on average.

Table 2.6 examines the progress that individuals make through school, for the sample of observations (person-years) in which the individual reports having been enrolled in school since the last interview. The table shows the rate of progress (the proportion of observations with grade advance) separately by various categories of prior educational attainment and by whether or not the individual had previously had an extended interruption in schooling. The clear finding is that, conditional on enrollment in school during the survey year, individuals who have previously had a long interruption in schooling are much less likely to actually advance in school than those who have had no such interruption. This result holds at all levels of prior educational attainment, with the difference in percentage who advance ranging

[13]This is not to suggest that financial constraints must be the primary explanation for the break in schooling for those who have completed high school when the break occurs. However, borrowing constraints are more likely to hamper a student who wishes to enroll in college, since post-secondary education often requires a significant tuition payment. In contrast, because the only cost of attending a public secondary school is the student's opportunity wage, borrowing constraints should only prevent secondary school enrollment for students from the most underprivileged backgrounds.

between 19% and 41%. For instance, for those who already had exactly a high school degree at the time of the previous interview, the percentage of person-years with grade advance, conditional on school enrollment during the survey year, is 71% for individuals who have been continuously enrolled in school (i.e., enrolled in every previous year during the sample) but only 30% for individuals who have had a long interruption in school. Regardless of whether there has been a previous break in schooling, though, the probability of grade advance given school enrollment is highest for those with less than a high school degree and lowest for those with exactly a college degree. The results are qualitatively similar, although the percentages with grade advance are somewhat higher, if one restricts the sample to those who attended school in at least nine of the months since the previous interview.

Table 2.7 examines how an individual's employment experience in a given interview year varies with prior educational attainment and the enrollment history. Employment is measured by weeks worked and average hours per week since the previous year's interview. Comparing the rows of the table, one sees that higher educational attainment is associated with working both more weeks and more hours.[14] For my purposes, though, it is more interesting to compare the columns in the table. Each of the three column pairs considers employment behavior for a different group: the lefthand columns look at individuals enrolled in school sometime since the last interview who have never had an extended interruption in schooling; the center columns focus on individuals enrolled in school during the survey year who previously have had an extended interruption in their schooling; and the rightmost columns examine individuals who were never enrolled in school during the survey year. Individuals enrolled in school during the survey year who had no previous interruptions in school enrollment clearly have the weakest attachment to work, while those who are never enrolled during the survey year have the strongest work attachment. Those who are enrolled in school during the survey year, but who previously had a break in their schooling, fall in between. This is true both for weeks worked since the last inter-

[14]Undoubtedly this simple correlation partly represents a true effect of education and partly merely reflects the fact that older youths, who work more, also tend to have completed more education.

view and for average weekly hours. The employment behavior of individuals enrolled during the survey year but with prior breaks in enrollment bears most similarity to the employment experience of the continuously enrolled at lower levels of educational attainment.

To summarize, then, the actual pattern of school enrollment differs substantially from the stark prediction of standard models of educational choice. Re-enrollment in school after a lengthy interruption, though not typical, is far from rare; nearly one-quarter of a sample of civilian males from the NLSY follow this pattern during the sample period. A richer model of educational choice is needed to account for such behavior. In addition, several other features stand out in the data: the re-enrollment hazard rate appears to decline as the length of the interruption increases; individuals who re-enroll come from all across the educational spectrum; those who re-enroll make slower progress in school after returning than individuals who have never left school; and those who re-enroll after an interruption have stronger attachments to work than those who have been continuously enrolled but weaker attachments than those who are not enrolled in school at all. In short, the phenomenon of school re-enrollment after significant breaks in attendance is clearly observable in the data. The following section considers some models that can account for re-enrollment behavior.

2.3 Some Models of School Re-enrollment

As was noted in the introduction, several possible explanations for the re-enrollment phenomenon exist. The most obvious explanation is borrowing constraints. Indeed, there is a widespread belief that financial constraints are a significant impediment to optimal human capital investment, and a variety of government programs offering need-based financial assistance for education have been created to address this concern. In a borrowing constraints model, some individuals do not have sufficient access to capital markets to finance as much education as they desire. When the constraint binds, these individuals are forced to leave school. Presumably, these individuals will begin work, but some of them might wish to return to school at a later date. In particular, some might find it worthwhile to build up savings from which to finance additional education in the future. Re-enrollment occurs when enough income to finance the additional educational investment has been saved. In addition, there is no reason why an individual must be permanently constrained in the credit market. If borrowing constraints ease at a later date, then re-enrollment after an extended break from school could occur even if the individual had accumulated no savings for this purpose. Thus, it is easy to see how borrowing constraints could lead to the complex school enrollment patterns that are observed in the data.

In the borrowing constraints story, some people are forced to leave school earlier than they would absent the constraint. Individuals who eventually re-enroll come from the constrained group. However, in principle, one can explain re-enrollment without appealing to borrowing constraints. Suppose instead that individuals have only imperfect information about the appropriate level of education at the time that they initially must decide between further school and work, but that additional information arrives *ex post*. Clearly, for those who choose work and only later discover that additional education is worthwhile, one could observe the pattern of interruption and subsequent re-enrollment. The key element in this story is that some determinants of schooling — ability, tastes, etc. — are not fully known to an individual initially, but are learned over time. I develop a simple model along these lines below and trace out its empirical implications.

2.3.1 A Learning Model of School Re-enrollment

Consider a model in which there are two ability levels, two education levels, and two sectors (occupations). Individuals are either of low ability or high ability, $\eta \in \{\eta_L, \eta_H\}$. Similarly, there are two levels of education, $S \in \{S_L, S_H\}$. Only high ability individuals can successfully complete the requirements for education level S_H, but ability is not known with certainty when the decision to pursue further education is made. Rather, individuals have only a prior probability (which varies across the population), p, that they are of high ability. Ability is only revealed for certain as part of the educational process; successful completion of the requirements for S_H indicates an ability level of η_H. Finally, there are two sectors, A and B. Sector A requires workers with high education and therefore employs only high ability workers.[15] Sector B has no such requirement.

In either sector, (net) wages are the sum of a general (sector-specific) component and a component specific to the match between the individual and the sector. The general component, $Y_j(S)$, $j \in \{A, B\}$, describes how education is related to productivity in sector j. The match component, θ_{ij}, captures idiosyncratic factors that affect the value of the match between sector and individual. For instance, θ_{ij} might represent unique skills that affect the productivity of person i (at all firms) in sector j, or it might represent how person i values the nonwage attributes of employment in sector j. Neither workers nor employers observe θ_{ij} until individual i works in sector j. In the population, I assume that (for $j = A, B$) θ_{ij} is continuously distributed on the interval $[\underline{\theta_j}, \overline{\theta_j}]$ with $\mathrm{E}(\theta_{ij}) = 0$. I also assume that θ_{ij} and θ_{kj} are independent for all $i \neq k$, and that θ_{iA} and θ_{iB} are independent for all i. Given this structure, and a competitive labor market, wages for person i in sector j are given by

$$w_{ij} = Y_j(S) + \theta_{ij}, \;\; j \in \{A, B\}, \; \forall\, i.$$

Individuals seek to maximize the expected present discounted value of lifetime (net) wages. The discount factor is β, and to simplify the analysis I assume that individuals are infinitely lived. I also assume that $\beta(Y_A(S_H) + \underline{\theta_A}) > Y_B(S_H) + \overline{\theta_B}$. This assumption is sufficient to guarantee the following two results. First, if ability were known to be high *ex ante*, obtaining education level S_H and working in the high-education sector would maximize lifetime earnings for *all* realizations of (θ_A, θ_B). Second, once S_H has been earned, there are *no* realizations of (θ_A, θ_B) for which it is worthwhile to move from the high-education sector to the low-education sector.[16]

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[15]One possible justification for this assumption could be that sector A requires labor with specialized skills that can be acquired only through higher education. Alternatively, one could turn the story around and suppose that sector A requires high ability workers and as a result only hires workers with high education. This scenario would rely on production in sector A being highly sensitive to the ability of the labor input, with education serving as the screening device for identifying high ability workers.

[16]Actually, the first result requires that $\beta(Y_A(S_H) + \underline{\theta_A}) > Y_B(S_L) + \overline{\theta_B}$, while the second result

With this background, the school enrollment decision simply becomes a two period decision problem where, in each period, the individual chooses between school or work as lifetime earnings maximization requires. In the first period, individuals decide between work in the low-education sector or school, given their prior beliefs about ability. Individuals who choose school learn their ability with certainty; those who discover they are of high ability succeed in school and go on to work in the high-education sector, while those who are not successful in school are of low ability and are relegated to the low-education sector. Individuals who choose to work in the low-education sector in the first period learn the quality of the match between their skills and tastes, on the one hand, and the characteristics of jobs in the sector on the other. These individuals now face the enrollment decision again, this time with information about their "fit" in the low-education sector in addition to their (unchanged) prior beliefs about their ability to successfully complete additional education. Thus, it is new information about the quality of the match with the low-education sector that might generate re-enrollment. Those who choose school proceed exactly as those who chose school in the first period, while those who again choose employment in the low-education sector remain there permanently.

I am now ready to derive optimal school enrollment behavior. To reduce the notational burden, I drop the individual (i) subscripts on the θ and p terms, but it should be understood that these terms take on different values for different individuals.[17] For compactness, I also denote $Y_j(S_k)$ by Y_{jk}. It is easiest to solve for optimal behavior by beginning with the second period problem. In the second period, the only individuals who face a true decision problem are those who worked in the first period. Within this

requires that $Y_A(S_H)+\underline{\theta_A} > Y_B(S_H)+\overline{\theta_B}$. Provided that $Y_B(S_H) \geq Y_B(S_L)$, the single assumption made in the paper ensures that both of these conditions hold. This assumption simplifies the analysis greatly because, as is described below, it reduces the individual's choice problem to a simple two period enrollment decision. Without an assumption that guarantees that highly educated individuals never move to the low education sector, the decision problem becomes much more complex. In particular, individuals who pursue high education and succeed still would be faced with a choice between sectors after learning their sector-specific match qualities. Thus, without the assumption, the model would allow for "back and forth" transitions between sectors (occupations) that do not occur in the simple version of the model analyzed here. However, even in this more complicated setting, the predictions of the learning model that I derive below would still hold.

[17]In principle, the discount factor β can also vary across individuals.

group, an individual who chooses to work in the low-education sector in the second period will stay in that sector permanently because no additional information ever arrives. Since θ_B is known, the value of choosing work in the second period, V_2^W, is

$$V_2^W = \frac{Y_{BL} + \theta_B}{1 - \beta}.$$

Assuming that the incremental schooling is completed in one "period", the *expected* value of choosing school in the second period, V_2^S, is

$$V_2^S = \frac{\beta p(Y_{AH} + \mathrm{E}(\theta_A)) + \beta(1-p)(Y_{BL} + \theta_B)}{1-\beta} = \frac{\beta p Y_{AH} + \beta(1-p)(Y_{BL} + \theta_B)}{1-\beta}.$$

An individual chooses school in the second period if $V_2^S > V_2^W$ (and if work was chosen in the first period). This condition can be rearranged to yield the condition for enrollment in the second period

$$\theta_B < \left(\frac{\beta p}{1 - \beta(1-p)}\right) Y_{AH} - Y_{BL},$$

which can be expressed equivalently as

$$p > \frac{(1-\beta)(Y_{BL} + \theta_B)}{\beta(Y_{AH} - (Y_{BL} + \theta_B))}.$$

For an individual who optimally chooses work in the first period, re-enrollment is more likely as p increases (the individual's likelihood of success in school increases) and as θ_B decreases (the individual's match with sector B worsens). In addition, re-enrollment is more likely as β increases, as Y_{AH} increases, and as Y_{BL} decreases.

Now consider the first period decision problem. The value function for school, V_1^S, is

$$V_1^S = \beta \mathrm{E}_{\theta_A, \theta_B}\left(\frac{p(Y_{AH} + \theta_A) + (1-p)(Y_{BL} + \theta_B)}{1-\beta}\right) = \frac{\beta(p Y_{AH} + (1-p) Y_{BL})}{1-\beta}.$$

The value function for work, V_1^W, is

$$V_1^W = Y_{BL} + \mathrm{E}(\theta_B) + \beta \mathrm{E}_{\theta_B}(\max(V_2^S, V_2^W)) = Y_{BL} + \beta \mathrm{E}_{\theta_B}(\max(V_2^S, V_2^W)).$$

From the analysis of the second period school enrollment decision, $V_2^S > V_2^W$ if

$$\theta_B < \left(\frac{\beta p}{1-\beta(1-p)}\right) Y_{AH} - Y_{BL} \equiv X.$$

Using the definition of X and letting $F_B(\cdot)$ denote the distribution function for θ_B, one can rewrite V_1^W as

$$\begin{aligned} V_1^W \;=\;& Y_{BL} + \left(\frac{\beta}{1-\beta}\right)[F_B(X)(\beta p Y_{AH} + \beta(1-p)(Y_{BL} + \mathrm{E}(\theta_B \mid \theta_B \leq X))) + \\ & (1 - F_B(X))(Y_{BL} + \mathrm{E}(\theta_B \mid \theta_B > X))]. \end{aligned}$$

Now, the individual chooses school in the first period if $V_1^S > V_1^W$. Using the expressions for V_1^S and V_1^W, one finds

$$\begin{aligned} (1-\beta)(V_1^S - V_1^W) \;=\;& (1 - \beta F_B(X))(\beta p Y_{AH} - (1 - \beta(1-p))Y_{BL}) - \\ & \beta \int_X^{\overline{\theta_B}} \theta dF_B(\theta) - \beta^2(1-p) \int_{\underline{\theta_B}}^X \theta dF_B(\theta) \\ \\ =\;& (1 - \beta F_B(X))(\beta p Y_{AH} - (1 - \beta(1-p))Y_{BL}) + \\ & \beta(1 - \beta(1-p)) \int_{\underline{\theta_B}}^X \theta dF_B(\theta). \end{aligned}$$

Using the definition of X and rearranging gives

$$\begin{aligned} \frac{(1-\beta)(V_1^S - V_1^W)}{(1 - \beta(1-p))} \;=\;& (1 - \beta F_B(X))X + \beta \int_{\underline{\theta_B}}^X \theta dF_B(\theta) \\ \\ =\;& X - \beta \int_{\underline{\theta_B}}^X (X - \theta) dF_B(\theta). \end{aligned}$$

Thus, the individual attends school in the first period if and only if

$$X - \beta \int_{\underline{\theta_B}}^{X} (X - \theta) dF_B(\theta) > 0.$$

The inequality is not satisfied for $X \leq \underline{\theta_B}$, but does hold for $X \geq \overline{\theta_B}$. Furthermore, the derivative of the function on the left-hand side of the above inequality with respect to X is unambiguously positive. Thus, this function is monotonically increasing in X. Together, these results imply that there is a unique value of X in the interval $(\underline{\theta_B}, \overline{\theta_B})$, call it X^*, such that

$$X^* - \beta \int_{\underline{\theta_B}}^{X^*} (X^* - \theta) dF_B(\theta) = 0.$$

Clearly, X^* is a constant and its value is determined by the discount factor, β, and the distribution of match qualities in the low education sector, $F_B(\theta)$. Given X^*, the individual enrolls in school in the first period if and only if $X > X^*$. Using the definition of X, and rearranging (noting that X is monotonically increasing in p), one finds that an individual enrolls in school in the first period if and only if

$$p > \frac{(1-\beta)(Y_{BL} + X^*)}{\beta(Y_{AH} - (Y_{BL} + X^*))}.$$

This condition is analogous to the second period enrollment condition, except that X^*, which depends on the *distribution* of θ_B, is substituted for the actual realization of θ_B, which is only learned after the first period (if the individual works in the first period). Comparing the conditions for enrollment in the two periods, it is clear that the probability of success in school required to make enrollment worthwhile is lower in the second period than in the first period if the realization of θ_B is less than X^*. Thus, re-enrollment can occur for any individual who works in the first period and learns that $\theta_B < X^*$. In fact, the three possible enrollment patterns — seek S_H immediately after completing S_L (Pattern 1), seek S_H but only with an interruption after completing S_L (Pattern 2), never seek S_H (Pattern 3) — depend on the parameters in a straightforward manner.

Pattern 1: $$p > \frac{(1-\beta)(Y_{BL}+X^*)}{\beta(Y_{AH}-(Y_{BL}+X^*))}.$$

Pattern 2: $$\frac{(1-\beta)(Y_{BL}+X^*)}{\beta(Y_{AH}-(Y_{BL}+X^*))} > p > \frac{(1-\beta)(Y_{BL}+\theta_B)}{\beta(Y_{AH}-(Y_{BL}+\theta_B))}.$$

Pattern 3: $$p < \frac{(1-\beta)(Y_{BL}+X^*)}{\beta(Y_{AH}-(Y_{BL}+X^*))} \text{ and } p < \frac{(1-\beta)(Y_{BL}+\theta_B)}{\beta(Y_{AH}-(Y_{BL}+\theta_B))}.$$

Before considering the empirical implications of the model, it might be instructive to consider an example. Suppose $\theta_B \sim U[-\frac{1}{2},\frac{1}{2}]$. In this case, $X^* \in (-\frac{1}{2},\frac{1}{2})$, and is defined by the equation

$$X^* - \beta\int_{-\frac{1}{2}}^{X^*}(X^* - \theta)d\theta = 0.$$

Carrying out the integration yields

$$X^* - \beta\left(\frac{X^{*2}}{2} + \frac{X^*}{2} + \frac{1}{8}\right) = 0.$$

Since the equation is quadratic, it has two roots, but only the solution involving the negative root lies in the interval $(-\frac{1}{2},\frac{1}{2})$. This solution is

$$X^* = \frac{1}{2} - \left(\frac{\sqrt{1-\beta}-(1-\beta)}{\beta}\right).$$

Suppose now that $\beta = 0.9$, $Y_{AH} = 6.4$, and $Y_{BL} = 4.8$. Substituting for β gives $X^* \approx 0.26$. Substituting for β, Y_{AH}, Y_{BL}, and X^* in the expression for the "critical value" of p in the first period, one finds that $\frac{(1-\beta)(Y_{BL}+X^*)}{\beta(Y_{AH}-(Y_{BL}+X^*))} \approx 0.419$. Thus, in the first period, only individuals who have a prior probability that they are of high ability of at least 0.419 enroll in school. All others choose to work in the low-education sector, and learn their specific values of θ_B in the process. After learning θ_B, these individuals reconsider the enrollment decision in light of the additional information. The table below gives "critical values" for p in the second period, for various realizations of θ_B.

θ_B	$\frac{(1-\beta)(Y_{BL}+\theta_B)}{\beta(Y_{AH}-(Y_{BL}+\theta_B))}$
0.25	0.415
0.00	0.333
−0.25	0.273
−0.50	0.228

If $\theta_B > 0.26$ the individual does not return to school because, for re-enrollment to be worthwhile in this case, p would have to exceed 0.419 and then the decision to work in the first period would have been inconsistent with maximization of expected lifetime earnings. In constrast, if $\theta_B < 0.26$, then re-enrollment is possible. An individual whose match with the low-education sector is only of average quality ($\theta_B = 0$) re-enrolls if $p > 0.333$, which is lower than the first period cutoff probability of 0.419. Thus, some of these individuals (those with $0.333 < p < 0.419$) choose to re-enroll. As the quality of the match in the low-education sector worsens, the lower the probability that just makes re-enrollment worthwhile becomes. Intuitively, individuals require a higher probability of success in school in the first period because choosing work in the low-education sector has an option value: if the match turns out to be poor, they can return to school, while on the other hand, if the match is good, they reap the benefits of gaining this knowledge early. After working in the first period, though, the quality of the match with the low-education sector is revealed, and those with insufficiently good matches, given their probability of success in further school, choose to re-enroll.

The learning model has two key implications that can be examined with data from the NLSY. First, at any given level of school, the model predicts that those who re-enroll in school after an interruption should have a lower probability of "success" than those who attend school continuously, since interruptions in enrollment depend precisely on this probability. The preliminary data analysis in Table 2.6, though only a simple tabulation, appears consistent with this view. Since the NLSY contains detailed data on time spent in school and at work, one can test this prediction rigorously by examining the independent effect of previous interruptions in attendance on the probability of grade advance in the current year, after controlling for grade level of current enrollment, time spent at work and in school, and other background factors.

The second prediction concerns the determinants of re-enrollment for those who have left school. Conditional on ability (or, more precisely, the probability of being of high ability, p), the model predicts that those who re-enroll are more poorly matched to the low-education sector (have low θ_B) than those who do not return to school. Thus, the model predicts that workers with unexpectedly low wages conditional on measures of ability and individual and job characteristics should be more likely to re-enroll in school. Since the NLSY contains a wealth of job characteristics data, one can test the hypothesis using this data as well.

2.3.2 A Borrowing Constraints Model of Re-enrollment

The learning model considered above delivers several empirical predictions related to school re-enrollment. However, finding support for these predictions in the data would be evidence for the learning model of re-enrollment only if a borrowing constraints model does not share these predictions. Thus, I now develop a borrowing constraints model of school re-enrollment.

I preserve nearly all of the basic setup from the learning model. There remain two ability levels ($\eta \in \{\eta_L, \eta_H\}$), two education levels ($S \in \{S_L, S_H\}$), and two sectors (A and B). As before, only high ability individuals are capable of obtaining high education. Also as before, sector A hires only individuals with high education, while sector B is not selective. Wages for person i in sector j again reflect general and idiosyncratic components

$$w_{ij} = Y_j(S) + \theta_{ij}, \;\; j \in \{A, B\}, \; \forall\, i.$$

The idiosyncratic components (θ) follow the same distribution in the population as before. I also continue to assume that $\beta(Y_A(S_H) + \underline{\theta_A}) > Y_B(S_H) + \overline{\theta_B}$. Finally, individuals pursue the same objective, the maximization of present discounted lifetime (net) wages, as in the learning model.

Now suppose, however, that individuals have no uncertainty about their academic ability or about their match quality in the two sectors; thus, each individual i knows

η_i, θ_{iA}, and θ_{iB} before undertaking the educational program leading to S_H and before working in either sector. Under this assumption, learning is no longer an issue and, in the absence of borrowing constraints, extended interruptions in school enrollment would never be observed. But suppose that only a proportion q of the high ability individuals can finance high education immediately.[18] Thus, a proportion $1 - q$ of high ability individuals face borrowing constraints and must initially work in the low-education sector B (since sector A has a minimum educational requirement). Since the learning model developed above did not focus on time until re-enrollment, I will not pursue this issue in the borrowing constraints model. Instead, I consider this question in an Appendix, where I develop alternative learning and borrowing constraints models and explicitly consider their implications for the time pattern of re-enrollment. Returning to the present model, it is clear that a constrained high ability individual will re-enroll in school as soon as the constraints stop binding. Moreover, those who re-enroll in school are exclusively high ability individuals who were previously constrained. This completely summarizes re-enrollment behavior in the borrowing constraints model.

The empirical implications of the borrowing constraints model are straightforward. First, the borrowing constraints model predicts that past interruptions should have no independent effect on the probability of grade advancement given current enrollment, after controlling for education level and actual time spent at work and in school. This follows because all individuals who re-enroll in school are of high ability. As a practical matter, the controls for time spent at school and at work are important, since an individual facing borrowing constraints is likely to spend more time at work (to finance education) and less at school. But, after conditioning on time use, the constraints model does not predict that past interruptions should be correlated with grade advancement upon re-enrollment. In contrast, if past interruptions indicate lower probability of success conditional on current enrollment, as the learning model predicts, then a negative correlation is expected.

[18] For instance, one might think of S_1 as representing high school education, which can be obtained at no direct monetary expense, and S_2 as representing (costly) college education.

Second, in the borrowing constraints model developed above, *all* high ability individuals who are financially constrained re-enroll at their first opportunity. In particular, unlike in the learning model, those who re-enroll are not those with unexpectedly low wages (poor matches) in the low education sector. Thus, re-enrollment should not be concentrated among those with unexpectedly low wages after controlling for individual and job characteristics. This prediction contrasts with that of the learning model, where re-enrollment occurs among those who learn that the match with the low-education sector is poor.

While the above predictions are clear, it is important to determine whether they are robust to different formulations of the borrowing constraints model. Thus, consider the following alternative model. Suppose that instead of simply having access to credit or not, different individuals are able to borrow at different rates. If an individual is only able to borrow at a very high rate, he might find it worthwhile to interrupt school, go to work, and delay additional education until it can be financed through savings, rather than borrow and attend school continuously. Suppose further that there are a continuum of abilities and that the marginal return to obtaining high education increases with ability,[19] but now assume that there is no sectoral match component to earnings. In this setting, only individuals of sufficiently high ability, and consequently with a high marginal return to education, borrow and attend school continuously. In constrast, borrowing-constrained individuals of lesser ability prefer to follow the interruption and re-enrollment route. Thus, unlike in the borrowing constraints model presented above, in this version re-enrollment after interruption indicates lower ability.

However, despite this difference, the two predictions from the first borrowing constraints model are largely unchanged, and remain distinct from those of the learning model. First, because there is no uncertainty about ability, it is still true that only individuals of high enough ability to succeed in further education re-enroll. Thus, a previous interruption in enrollment should not reduce the probability of grade ad-

[19]Thus, now both education and ability are arguments of the earnings function, and the gain in earnings from obtaining high education increases with ability.

vance upon re-enrollment. Second, among those who have left school with a given level of previously completed education, those who eventually re-enroll after an interruption are of higher ability than those who never return to school, since the optimal amount of education is increasing in ability. If ability has a direct positive effect on earnings, but is unobserved by the econometrician, then unexpectedly low wages given individual and job characteristics — indicative of low unobserved ability — should be associated with a *lower* probability of re-enrollment. In constrast, if the researcher can measure true ability, there should be no relationship between the wage and the probability of re-enrollment, after already conditioning on individual and job characteristics including ability. However, even this prediction differs from that of the learning model, in which wages should be negatively correlated with the re-enrollment probability, even after controlling for personal and job characteristics. Finally, notice that the simple argument that low wage workers, because they have low opportunity costs of attending school, should be more likely to re-enroll is implicitly a learning story; in the absence of learning (and borrowing constraints), no worker, regardless of his wage, ever returns to school because a fully informed worker would never leave school prematurely in the first place. Thus, there appear to be testable differences in the implications of the learning and borrowing constraints models. I examine these predictions empirically in the next section.

2.4 Empirical Analysis

2.4.1 Some Tabulations of Survey Responses

Before attempting the statistical tests outlined in the previous section, I perform some simple tabulations of NLSY survey responses to questions on the reason for school exit and desired educational attainment. Table 2.8 considers self-reported reasons for the most recent exit from school, separately by future re-enrollment behavior. The sample is constructed so that each exit from school is counted exactly once. Thus, for individuals who are never enrolled in school for several years in succession, only the first survey year out of school is included in the sample. Multiple observations on the same individual indicate multiple spells in school separated by interruptions in enrollment. The far left column lists the different reasons for exit from school, while the next three columns break the sample up by re-enrollment behavior. The left-hand column isolates those exits from school that are followed by re-enrollment sometime in the next survey year. The middle column identifies exits from school followed by at least one full survey year out of school before subsequent re-enrollment. The right-hand column represents those exits from school that are not followed by re-enrollment at any time during the remaining sample period. *A priori*, it seems plausible that individuals who re-enroll after leaving school because of "financial difficulties" were borrowing constrained. On the other hand, those who leave school because they "don't like school" or "lack ability" and subsequently re-enroll seem like candidates for the learning model.

Turning to the numbers, the row percentages allow one to see how future re-enrollment behavior varies by reason for school exit, while the column percentages show how the distribution of reason for school exit differs by future re-enrollment class. Looking at the row percentages, one sees that individuals who leave school for "financial difficulties" or "other reasons" are more likely to return to school than those who leave school for different reasons, presumably because a larger fraction of these individuals initially leave school with less than their desired education. Individuals who leave school because they "completed courses", "don't like school", or because of "home responsibilities" are less likely to ever return to school. Looking at the middle column and now focusing on the column percentages, just 11% of those who re-enroll after a lengthy interruption claim to have left school because they "don't like school" or because of a "lack of ability", while only 8% cite "financial difficulties". Thus, even if one views these responses as support for the learning model and the borrowing constraints model, respectively, the great majority of individuals volunteer neither of these answers as the reason for school exit.

More importantly, the other responses do not offer specific support for one model over the other. For instance, roughly 47% of those who leave school and then re-enroll after a long interruption claim to have left school because they "received a degree" or "completed courses". However, an individual could receive a degree and still desire further education but be unable to continue because of borrowing constraints. On the other hand, an individual could begin work after completing a specified program of study only to discover upon working that further education would be desirable. Thus, the "received degree" response is consistent with either model of re-enrollment. The survey responses "offered good job; chose to work" and "other" are similarly unable to discriminate between the theories. Together, these responses account for over 75% of the responses in the middle column. Thus, although Table 2.8 suggests that both the learning and borrowing constraints models are partial explanations for interruption and subsequent re-enrollment, these data do little to clarify the relative importance of the two explanations.

In addition to data on reason for last school exit, the NLSY also gathered data on desired schooling level in the 1979, 1981, and 1982 interviews. In the absence of borrowing constraints, an individual whose actual educational attainment falls below the desired level enrolls in school. In a world of perfect information, an individual who has already attained his desired level of schooling does not enroll in further school. Thus, one might get some idea about the relative importance of borrowing constraints and learning as explanations for re-enrollment by examining how enrollment behavior varies depending on the relationship between actual and desired schooling levels. This comparison is made in Table 2.9.

The three left-hand columns of Table 2.9 consider the enrollment behavior of individuals who claim to have less than their desired level of schooling as of the 1979, 1981, and 1982 interviews. The bottom row shows, not unexpectedly, that the number of people with less schooling than they desire falls as the sample ages. However, the percentage of these individuals who are enrolled in school sometime during the next interview year falls from 75% to 45% between 1979 and 1982. Thus, 25% to 55% of those with less than their "desired education" do not enroll in school in the following year. Whether these numbers imply that borrowing constraints are empirically important depends upon how the sample respondents interpret "desired education".[20] If "desired education" is taken to mean the amount of education that individuals are willing to purchase at market prices, then one is driven to the conclusion that roughly one-quarter to one-half of the sample interrupts or curtails its education prematurely because of borrowing constraints. In contrast, if "desired education" is understood as simply a "desirable" level of schooling, but not necessarily the amount that an individual is willing to pay for, then the percentage of the population inhibited by borrowing constraints is probably much smaller than the above numbers suggest. Nevertheless, for those who actually re-enroll before the end of the sample period, the inference that true financial constraints caused the interruption seems more reasonable. From the second row of the table, between 6% and 10% of those with less schooling than they desire eventually re-enroll in school after a significant interruption.

Moving to the right-hand columns of the table, one sees the future enrollment behavior of those who claim to already have obtained (at least) their desired level of education as of the 1979, 1981, and 1982 interviews. Looking first at the bottom row, one finds that the number of individuals who have reached their desired level of education rises as the sample ages. Moving up one row, one sees that the vast majority of people who have achieved their desired level of education never re-enroll during the remaining sample period. Still, between 12% and 14% of the respondents apparently contradict themselves and eventually re-enroll in school. Most of these individuals, 8% to 11% of the sample, have an interruption in school enrollment of at least one full interview year before returning to school. As before, understanding these numbers depends on how the respondents interpret "desired education". If desired education refers to the amount of education that individuals are willing to pay market prices to acquire, given their budget constraint, then re-enrollment among those who already have at least this much schooling conceivably could be explained by dramatic changes in the budget constraint. On the other hand, if desired education just represents the level of education that the respondent views as ideal abstracting

[20]The question directed to the survey respondent is "What is the highest grade or year of *regular* school, that is elementary school, high school, college, or graduate school that you would *like* to complete?" (emphasis included in the questionnaire).

from budgetary constraints, then a borrowing constraints model cannot explain re-enrollment among those who already have at least this much education. However, the learning model developed earlier can easily explain exactly this type of re-enrollment behavior.

Returning to the bottom row of the table, the sample of individuals with less than their desired level of schooling far outnumbers the sample who have acquired at least as much education as they desire. Taken together, the relative sample sizes and the percentages who re-enroll after an interruption seem to imply that much re-enrollment is driven by borrowing constraints. However, this conclusion relies on the equivalence of "desired education" and the level of education that the respondent is willing to pay for.

I attempt to provide further evidence on the importance of borrowing constraints in Table 2.10, where I examine the relationship between whether an individual with less than his desired level of education does *not* enroll in school in the next sample period and the individual's personal and family background characteristics. Estimations are performed separately for the 1979, 1981, and 1982 survey years. The evidence is consistent with a significant role for borrowing constraints. For instance, growing up in a non-two parent household and having less educated parents, characteristics suggestive of lower wealth, are correlated with a higher probability of not enrolling in school in the next period. In addition, older and married individuals, who are more likely to have assumed head of household responsibilities, are less likely to enroll in school. Individuals who already have a high school degree are, perhaps surprisingly, more likely to enroll in school in the next period.

Thus, borrowing constraints appear to be a significant cause of school interruption and subsequent re-enrollment. But it is not clear whether a pure borrowing constraints model can fully explain the observed data on interruption and re-enrollment. For instance, re-enrollment among those who claim to already have as much schooling as they want seems to lend support to the learning model. To test whether there exists empirical support for learning-induced school re-enrollment, I now examine the contrasting predictions derived from the learning and borrowing constraints models in Section 2.3.

2.4.2 Econometric Tests

The learning model makes several predictions concerning re-enrollment behavior. Recall that the model implies that individuals leave school when the probability of success in further school is not sufficiently high, and subsequently re-enroll if their match with the sector for which they are qualified turns out to be too poor, given their academic success probability. Thus, individuals who re-enroll after an interruption at a particular grade level should have a lower probability of success in school, on average, than those who seek the same grade level with no interruption. Also, those who re-enroll after interruption should be more poorly matched to their sector of employment prior to re-enrollment than observationally equivalent individuals who do not re-enroll. At an empirical level, then, a prior interruption in school enrollment should be associated with a lower probability of a grade advance, after conditioning on previous educational attainment, time spent in school and at work during the current survey year (after re-enrollment), and background factors. In addition, among individuals who have left school at a given grade, those with low wages given their individual and job characteristics and background factors should be the most likely to re-enroll in school.

I address these implications of the learning model beginning with Table 2.11. Table 2.11 presents logit estimates of the probability that an individual makes an advance in grade level since the last interview, given that the individual was enrolled since the time of the last interview. Several explanatory variables are included in the estimation. The first set measures the family background of the respondent: whether or not both of the child's biological parents were living in the household when the respondent was fourteen years old; whether the male and female adults in the household when the respondent was fourteen, if present, were employed; whether the household received a newspaper when the respondent was fourteen; and a set of variables measuring the educational attainment of the child's parents. Since family background is likely to be correlated with wealth, the coefficients on these variables partly reflect the effects of financial constraints, and partly reflect the direct effect of household environment on academic aptitude. The second set of variables consists of individual characteristics: marital status, race, age, education at the time of the last interview, whether the individual lives in the South, and whether the individual lives in an urban area. The third set of variables controls for an individual's time use since the last interview: total weeks elapsed since the last interview, weeks worked since the last interview, hours per week worked since the last interview, and a set of dummy variables for different numbers of months enrolled in school since the last interview.[21] Finally, there is the main variable of interest — an indicator for whether the individual has ever had a long interruption in schooling.[22]

The signs of most of the coefficients are as one would expect. Coming from a less privileged background lowers the probability of making progress in school, given enrollment (and time devoted to school and work). Conditional on measured family background and time use, it appears that nonwhites, older individuals, and those with a higher level of education already completed are less likely to advance in school. The time use variables are all significant and have the expected signs. If more time passes between interviews, the probability that a grade advance occurs is higher. Given the amount of time since the last interview, working more (both weeks and hours per week) is associated with a lower probability of grade advancement, while spending more time enrolled in school strongly increases the probability of grade advancement. However, even after controlling for time spent working and time spent at school, an individual who has had a previous long interruption in schooling has a significantly lower probability of advancing a grade. For a representative individual enrolled during the current interview year,[23] having had a prior interruption reduces the probability

[21] Dummy variables were created for the following enrollment categories: 1–3 months enrolled, 4–6 months enrolled, 7–9 months enrolled, and 13 or more months enrolled. The excluded category is 10–12 months enrolled.

[22] As before, a long interruption is defined as never having been in school for at least one full period between interviews.

[23] My "representative" individual has the following characteristics: both parents live in the household and work; the household receives a newspaper; the highest educated parent has a high school education; the individual is white, unmarried, resides in an urban area outside of the South, has previously completed a high school education, and has the mean values in the sample for the other continuous explanatory variables.

of grade advance from .85 to .68, other things equal. This finding is consistent with the prediction of the learning model.

The coefficient estimates of interest are essentially unchanged if one limits the sample to full-time (by their own definition) college students, or even if one restricts the sample to full-time college students who are enrolled in school during at least nine months since the previous interview. This provides stronger evidence in favor of the learning model, since limiting the sample in this way leaves a subsample of only those students who had very strong attachment to school during the survey year. Because past interruption has a very strong negative effect on grade advancement even for this group of students, it seems highly doubtful that the measured effect of interruption simply represents omitted variable bias in which the dummy for past interruption acts as a proxy for unmeasured strength of attachment to school in the current survey year.

I also consider whether including a measure of a respondent's intellectual ability as an explanatory variable has any effect on the results. The ability measure that I employ is the residual from a regression of the respondent's Armed Forces Qualifications Test (AFQT) score on the respondent's age at the time the test was taken, the respondent's highest grade completed at the time the test was taken, and a constant.[24] Thus, an individual's intellectual ability is measured relative to the ability of others in the same narrow birth cohort and education (at the time of the test) category. Including the AFQT residual has no qualitative effect on any of the coefficient estimates of interest in any of the specifications in Table 2.11; as a result, I do not report most of these estimates. In particular, the effect of past interruption on grade advancement is essentially unchanged after the ability measure is included. This is not to say, however, that ability has no effect on the probability of grade advance, all else equal. The coefficient on the AFQT residual in Column 2, which is representa-

[24]The AFQT score is constructed using the results from the Armed Services Vocational Aptitude Battery (ASVAB), a sequence of ten aptitude tests, administered to nearly everyone in the NLSY in 1980. Specifically, the AFQT score is a weighted sum of the scores on four of the ASVAB tests: word knowledge, aritmetic reasoning, paragraph comprehension, and numerical operations. The weights are 1, 1, 1, and 0.5, respectively.

tive of the other estimates, shows that higher test scores are strongly associated with a higher probability of grade advancement, other things the same. Taken together, the results suggest that the individual characteristics that lead to interruption and a lower probability of grade advancement upon re-enrollment are not highly correlated with the part of ability which the AFQT score measures. This is not too surprising given that the AFQT score is only a crude, and presumably incomplete, measure of general ability.

Finally, the results are qualitatively the same if one allows the effect of previous interruptions in enrollment on the probability of grade advancement to vary depending on how long the individual has been away from school. For instance, if scholastic ability atrophies with time away from the classroom, then one would expect that the probability of grade advance for those with past interruptions in schooling to fall as the time since last enrollment increases. When one restricts the sample to only full-time students, this effect is indeed present. However, the coefficient on the dummy variable for ever having an interruption is hardly affected by including the variable for length of interruption. Moreover, the reduction in the probability of grade advance associated with ever having an interruption in school far outweighs the reduction from an increase in the time since last enrollment for an individual who re-enrolls after an interruption. Since the learning model predicts that individuals who enroll in a given grade after an interruption are of lower ability than those who reach the same grade with no prior breaks, regardless of the duration of the interruption, this finding is consistent with the model.

Tables 2.12 and 2.13 turn to the determinants of re-enrollment for all individuals who have never been enrolled in school since the previous interview. Table 2.12 considers the probability of re-enrollment before the next interview, while Table 2.13 focuses on the probability of re-enrollment during the individual's remaining time in the sample.[25] Recall that the learning model predicts that individuals with unexpectedly low wages, given their individual and job characteristics, should be most

[25]Individuals remain in the sample through the 1988 interview unless they miss an interview, in which case they are dropped from the sample in all years after the first noninterview year.

likely to re-enroll. The main variable of interest in both tables is the real wage. Since job characteristics and individual human capital characteristics are included as explanatory variables, the coefficient on the real wage variable measures the effect on re-enrollment probability of deviations between the actual real wage and the conditional expectation of the real wage given those characteristics.

In both tables, the estimated coefficient on the real wage variable is negative and, except in one case, is at least marginally statistically significant. In the majority of cases, the coefficient is strongly significant. Thus, individuals earning unexpectedly high wages are less likely to to re-enroll in school, as the learning model predicts.[26] Furthermore, this appears to be true even when one does not attempt to control for unobserved ability by including the AFQT residual as an explanatory variable. In a pure borrowing constraints model of re-enrollment, with no sectoral matching and hence no learning about match quality, one would expect that those with the highest ability, given their education level, would be the most likely to re-enroll. Thus, especially if no effort is made to control for ability, one would anticipate that those with unexpectedly high real wages, resulting from high unmeasured ability, would have the highest probability of re-enrollment. However, in the data, the reverse finding seems to be true. This argues against a pure borrowing constraints model of re-enrollment. The results also show that high job satisfaction[27] and low measured ability, all else equal, are associated with a lower probability of re-enrollment. These last findings can be explained by both a learning model and a borrowing constraints model.

2.4.3 Discussion of Results

The estimation results presented in Tables 2.11 through 2.13 yield two main findings. First, past interruptions in school enrollment are associated with lower probability of grade advancement for the currently enrolled, after controlling for background

[26]Marcus (1986) reports the same finding using data from the NLS Young Men survey.

[27]"High" job satisfaction indicates that the respondent assigned his job the highest possible satisfaction rating, while "low" job satisfaction corresponds to the lowest possible rating.

and individual characteristics (including measures of ability), grade level of current enrollment, and time spent in school and at work. Because the estimation controls for the strength of attachment to school and work, one is led to conclude that interruption prior to enrollment at some particular grade level is concentrated among those who are least capable of success at that grade level. This result is consistent with the prediction of the learning model, in which those with sufficiently low probabilities of continued success in school optimally choose to leave school and start work, but reserve the option of re-enrollment if the job match in the low education sector is poor. The other major empirical result is that probability of re-enrollment in school after an extended interruption is higher for individuals earning unexpectedly low wages given their personal and job characteristics. Since a lower than expected wage, conditional on individual and job characteristics, is evidence of a poor match, this finding agrees with the prediction of the learning model as well.

It is worth thinking a bit further about whether these findings also can be reconciled with a pure borrowing constraints model. The first prediction that such a model must have, to be consistent with the evidence, is that a previous interruption in enrollment is associated with a lower probability of grade advancement given current enrollment, other things equal. Interpreted strictly, a borrowing constraints model in which there is no uncertainty about whether an individual can succeed at a given level of school has difficulty explaining this finding; in the absence of uncertainty, individuals only re-enroll if they have at least the minimum ability necessary to successfully complete that level of school. Of course, even in this model, borrowing constraints could generate unplanned interruptions in enrollment and, consequently, unsuccessful spells in school (i.e., enrollment with no grade advancement). But, if this were the sole cause of unsuccessful spells in school, the differences in strength of attachment to school (months enrolled, time spent at work, full-time student status, etc.) should be able to completely account for differences in the probability of grade advancement. In particular, after controlling for strength of attachment to school, there should be no correlation between past interruption and probability of success in school. However, the evidence presented above shows that past interruption in enrollment is strongly correlated with a lower probability of grade advancement, even after controlling for strength of attachment to school.

It is true, however, that some versions of the borrowing constraints model predict that those who return to a given level of school after an interruption should be of lower ability, on average, than those who attend through that level of school continuously. Thus, even though the ability of everyone enrolled in a particular grade exceeds the minimum level needed to complete that level of schooling, those with past interruptions, being of lower ability, might be expected to make slower progress than their more able colleagues who had no interruption. Perhaps this could explain the relationship between past interruption and grade advance in the current survey year. While this is possibly a partial explanation of the data, it is unlikely to be the full story. In the NLSY, a full 48% of those who re-enroll in school after a long interruption never advance a grade in the remaining sample period. However, many in this group spend a large amount of time enrolled in school,[28] and only a small fraction ultimately leave school for reasons clearly suggestive of financial constraints.[29] Given this set of findings — a nontrivial number of individuals who re-enroll in school after a lengthy interruption, remain enrolled in school for a long period of time, never advance in school after re-enrollment, and do not cite financial constraints as the reason for ending the re-enrollment spell — it seems unlikely that the lower frequency of grade advance upon re-enrollment is entirely the result of slower, but still forward, progress in school. Thus, the most reasonable explanation of the lower probability of grade advance, other things equal, for those with prior interruptions in school enrollment, acknowledges that whether one has the ability to complete a particular

[28]Of those who re-enroll but never advance, 24% spend at least 9 months in school after re-enrollment, 14% spend at least 12 months in school, and a few individuals spend 24 or more months in school without advancement. Furthermore, these figures represent a lower bound on the true number of months enrolled in school since monthly enrollment data is only available beginning with the 1981 survey, and, as a result, enrollment prior to the 1981 survey year is not counted.

[29]Of those who re-enroll but never advance, the percentage of individuals who claim to leave school (after re-enrollment) because of "financial difficulties" or "home responsibilities" is only 16.8%. In comparison to the distribution of reasons for school exit for the full sample, a smaller fraction claim to have left school because they "completed courses" or "don't like school", while a larger fraction "chose to work", had "financial difficulties", or gave "other" as their reason for exit. Still, the general magnitudes are the same as in the sample of all school exits, with "completed courses" and "other" being by far the most common reasons.

program of study is uncertain *ex ante*, and those who are least likely to succeed are most likely to delay in trying.

The second implication that must follow from a pure borrowing constraints model, if it is to conform with the evidence, is that individuals who re-enroll in school should earn unexpectedly low wages prior to re-enrollment, given their characteristics. This prediction is not forthcoming from the borrowing constraints models discussed in Section 2.3. In the model that allows for earnings to depend partly upon the match between the individual and the sector of employment, the prediction does not follow because of the assumption that the match with the high education sector can never be so poor that a high ability individual prefers to forego high education and remain in the low education sector. In the model where earnings depend only on schooling and ability, the prediction does not follow because individuals who re-enroll in a given grade of school are of higher ability, on average, than those who choose not to re-enroll, and hence earn more prior to re-enrollment.

For a borrowing constraints model to predict that re-enrollment occurs primarily among those earning unexpectedly low wages, it has to be true that not all high ability individuals who face borrowing constraints choose to re-enroll in school when they finally have the opportunity. To obtain this result, several conditions must hold. First, the return to additional education in the sector that does not require "high" education must be low enough that even individuals who have the ability to complete further education prefer not to if they plan to remain in this sector. Second, the match component of earnings must have enough variation that, for some realizations of (θ_A, θ_B), high ability individuals prefer the low-education sector to the high-education sector. If these conditions hold, and only in this case, the borrowing constraints model implies that those who re-enroll are a selected sample of high ability workers with poor matches in the low-education sector.

In summary, a pure borrowing constraints model must have the following elements to yield implications consistent with the estimation results. First, individuals must be uncertain about their ability and hence about the level of education that they can complete. Second, the return to education in the sector that does not have minimum education requirements must be low enough that, regardless of ability, no one working in that sector invests in education beyond the minimum. Finally, the match component of earnings must be important enough that a high ability individual, if in a sufficiently good match in the low-education sector, actually prefers remaining in that sector to completing further education and working in the high-education sector. While this set of conditions may not be unreasonable, maintaining these assumptions while simultaneously denying the possibility of learning seems quite arbitrary. Indeed, in a setting where ability is uncertain and the match component of earnings is significant, it seems plausible that learning might be quite important. Moreover, even a pure borrowing constraints model that makes these assumptions, and therefore is capable of explaining the estimation results, cannot easily account for re-enrollment among individuals who claim to have obtained their desired level of schooling already. On the other hand, the learning model offers a simple explanation for this behavior.

2.5 Conclusion

The simplest theories of optimal human capital accumulation predict that schooling should be acquired at the start of the life cycle and that exit from school should not be followed by re-enrollment. While it is well-established that most schooling is acquired when young, there has been little investigation of what the time pattern of school enrollment actually looks like for a typical individual. This essay provides evidence, contrary to the predictions of the basic life cycle model, that a nontrivial fraction of youth return to school after an extended interruption in enrollment. A richer model of the determinants of school enrollment is needed to account for this finding.

I consider two possible extensions of the life cycle model that are consistent with discontinuous school enrollment histories. In the first, interruption and re-enrollment follows from borrowing constraints. In the second, interruption and re-enrollment results from the gradual arrival of new information about the value of further school.

While the two models are complementary, they differ enough in their empirical implications to allow for a test of a pure borrowing constraints model of re-enrollment against an alternative that admits learning-induced re-enrollment as well.

The empirical analysis suggests that both the borrowing constraints model and the learning model offer partial explanations for re-enrollment. Direct survey responses indicate both financial difficulties and lack of ability or interest as reasons for interruption among respondents who leave school but subsequently re-enroll. In addition, some individuals who desire more schooling than they have never acquire further education (consistent with the borrowing constraints model), while others, who claim to have as much education as they want, eventually seek more (consistent with the learning model). The characteristics of those with less than their desired education who delay getting more education also suggest an important role for borrowing constraints.

However, empirical tests of the predictions of the learning model developed in Section 2.3 offer support for learning as a cause of interruption and re-enrollment. Though one possibly can construct versions of the borrowing constraints model that can accomodate the estimation results, the necessary assumptions are themselves suggestive of a role for learning. Moreover, even this model, built to fit the findings, has difficulty explaining re-enrollment among those who claim to have as much education as they desire. Thus, learning, in addition to borrowing constraints, seems to be part of the explanation of the re-enrollment phenomenon. Of course, for policy purposes, the important question concerns the relative importance of the different causes of interruption and re-enrollment. Answering this question will require further work and richer data.

Appendix: More Models of School Re-enrollment

Although only briefly mentioned in the main body of the essay, the numbers presented in Table 2.3 imply that the probability of re-enrollment in school in the next survey year conditional on being out of school currently (the re-enrollment hazard rate) falls as the length of time since the initial exit from school increases. In addition, there is weak evidence in the NLSY data (not presented in the main body of the essay) that the average duration of the spell in school after re-enrollment declines as the length of the interruption prior to re-enrollment increases. However, the models of school re-enrollment developed earlier offer little guidance in interpreting these results since they make no predictions in these dimensions. This appendix develops an alternative learning model that is consistent with both of these findings.

I then show that a borrowing constraints model in which all of the constrained individuals are "equally constrained" generates neither of these predictions. In particular, in this setting the hazard exhibits no duration dependence, and the duration of the re-enrollment spell does not depend on the length of the out of school spell. However, when there exists even a very simple form of heterogeneity across the constrained individuals in their "degree of constraint", the predictions of the borrowing constraints model are identical to those of the learning model. Thus, the learning model developed below does not appear to be empirically distinguishable from a borrowing constraints model. On the other hand, both models at least appear consistent with some basic patterns in the data.

A Second Learning Model of Re-enrollment

Individuals are of one of four ability levels ("types"): $A \in \{A_1, A_2, A_3, A_4\}$, where $A_i > A_j$ if $i > j$. Similarly, there are four possible levels of schooling:[30] $S \in \{S_1, S_2, S_3, S_4\}$, where $S_i > S_j$ if $i > j$. If ability were known to be A_i, an individual

[30]One might think of these educational levels as corresponding to a high school degree, a two-year college degree, a four-year college degree, and a graduate degree.

would choose education S_i, for $i = 1, \ldots, 4$.[31] A person with schooling S_i and ability A_j earns $Y_{ij} \equiv Y(S_i, A_j)$ in the labor market. Individuals have a discount factor of β and seek to maximize the (expected) present discounted value of lifetime earnings. Assuming that it takes one "period" for an individual to advance one grade level, the assumption on optimal schooling levels given ability implies that the following conditions hold for $i \in \{1,2,3,4\}$ and $j \in \{1,2,3,4\}$:

$$\beta^{i-j}Y_{ii} - Y_{ji} > 0, \quad \text{if } i > j,$$

$$\beta^{i-j}Y_{ij} - Y_{jj} < 0, \quad \text{if } i > j.$$

Once individuals have the minimal level of education, S_1, they can choose between investing in further education or going to work. To allow for the possibility of learning, I assume that individuals do not know their ability for certain at the time that they must make this decision. Instead, they have only a (discrete) probability distribution over the four different ability levels. This distribution can vary across individuals to reflect heterogeneity across individuals in terms of prior experiences and information. Given the distribution, each person decides on school or work as demanded by earnings maximization. Regardless of the school/work decision, I assume that the chosen activity generates, as a by-product, further information about an individual's ability. In particular, learning is assumed to take the form of being able to rule out certain "types"; after the first period, an individual learns *either* that $A \in \{A_1, A_2\}$ *or* that $A \in \{A_3, A_4\}$. Intuitively, for an individual from one of the high-ability groups, work (in a low-schooling job) provides evidence of "overqualification" while school similarly provides evidence of the intellectual capacity for a high-schooling job. The signals are analogously informative for individuals from low-ability groups. Given this new information, individuals once again choose between school and work in the second period to maximize lifetime earnings. After the second period, I assume that ability is fully revealed. By the previous assumptions, any individuals who still have less

[31]This assumption simply says that more able people find it optimal to get more education than less able people. Such an assumption is standard in models of educational choice.

education than is optimal given their type will make up the difference immediately.

To formalize the notions in the previous paragraph, I assume that at the time of the initial school/work decision, an individual's prior probability distribution over ability is

$$\begin{aligned} \Pr(A = A_4) &= pq, \\ \Pr(A = A_3) &= p(1-q), \\ \Pr(A = A_2) &= (1-p)r, \\ \Pr(A = A_1) &= (1-p)(1-r). \end{aligned}$$

After the first period, some information about ability is received. With probability p, a high signal is received and the probability distribution over ability is updated to

$$\begin{aligned} \Pr(A = A_4) &= q, \\ \Pr(A = A_3) &= 1-q. \end{aligned}$$

With probability $1-p$, a low signal is received and the probability distribution over ability is updated to

$$\begin{aligned} \Pr(A = A_2) &= r, \\ \Pr(A = A_1) &= 1-r. \end{aligned}$$

After the second period, ability is revealed with certainty.

Given this setup, I want to determine how the decision between school and work in each period depends upon the parameters. Essentially, there are three separate decisions to make: the first period decision, when the individual has only his prior beliefs about ability; the second period decision, when the individual has received some news about ability; and the third period decision, when the individual has full knowledge concerning ability. The simple structure (few periods and few types) of the model allows one to easily solve the individual's decision problem at each stage by backward induction. In principle, one would solve a problem with more ability levels and slower resolution of uncertainty (more "periods"), but with the same general structure, by the same technique. In practice, though, the algebra would be far more involved with little added insight.

I first consider behavior once ability has been fully revealed. By the assumptions made above, it is trivial to determine optimal behavior. Suppose that an individual has obtained schooling S_i at the time that the ability level, A_j, is revealed. Clearly, the individual goes to school for $j - i$ periods (and then works) if $j > i$, and works immediately (and never returns to school) if $j \leq i$.

Next, consider behavior one period earlier, when beliefs have been updated to reflect the ability signal, but when ability still is not known with certainty. At this stage, the agent either has schooling level S_1, if work was chosen in the first period, or schooling level S_2, if school was chosen in the first period. Now, if a high signal was received after the first period, the individual chooses school, regardless of the choice in the previous period, since the optimal level of education is now known to be at least S_3. On the other hand, if a low signal was received and school was chosen last period, then the individual clearly chooses to work since the current level of schooling, S_2, is certainly not less than the optimum. The final case to consider is if a low signal was received and the individual worked last period. In principle, either school or work could be the expected lifetime earnings maximizing strategy for the second period in this case. School maximizes the expected present discounted value of lifetime earnings if

$$\frac{r\beta Y_{22} + (1-r)\beta Y_{21}}{1-\beta} > r(Y_{12} + \frac{\beta^2 Y_{22}}{1-\beta}) + (1-r)(Y_{11} + \frac{\beta Y_{11}}{1-\beta})$$

which reduces to

$$r(\beta Y_{22} - Y_{12}) > \frac{(1-r)(Y_{11} - \beta Y_{21})}{1-\beta}.$$

This condition can hold only if r is very large and β is very small. Agents who work in the first period and receive a low signal choose school in the second period only if they discount the future a lot (so an investment in education which turns out to be a mistake *ex post* is not weighted very heavily) and if additional schooling is very likely to be optimal (the probability that $A = A_1$ is small). For reasonable parameter values, this condition is unlikely to hold. Moreover, if the above inequality does hold, it is in fact optimal for all individuals choose school in the first period, and re-enrollment after an interruption never occurs. Intuitively, an individual who finds it optimal to attend school after receiving bad news about ability must find it optimal to attend school before receiving any news about ability. Thus, I impose the condition that individuals who work in the first period and receive a low-ability signal do not choose school in the second period. Mathematically, the assumption is

$$r(\beta Y_{22} - Y_{12}) < \frac{(1-r)(Y_{11} - \beta Y_{21})}{1-\beta}.$$

One can now examine the decision problem in the first period. At this stage, agents decide whether to go to school or work given their current schooling level (which is S_1 for everyone) and their prior beliefs about their ability (which vary across individuals and are summarized by p, q, and r). Assuming that individuals who receive low signals never choose school in the second period (the assumption made above), the expected payoff from work, V_1^W, is

$$\begin{aligned} V_1^W &= pq(Y_{14} + \frac{\beta^4 Y_{44}}{1-\beta}) + p(1-q)(Y_{13} + \frac{\beta^3 Y_{33}}{1-\beta}) + (1-p)r((1+\beta)Y_{12} + \frac{\beta^3 Y_{22}}{1-\beta}) + \\ &\quad (1-p)(1-r)((1+\beta)Y_{11} + \frac{\beta^2 Y_{11}}{1-\beta}). \end{aligned}$$

The expected payoff from school, V_1^S, is

$$V_1^S = pq(\frac{\beta^3 Y_{44}}{1-\beta}) + p(1-q)(\frac{\beta^2 Y_{33}}{1-\beta}) + (1-p)r(\frac{\beta Y_{22}}{1-\beta}) + (1-p)(1-r)(\frac{\beta Y_{21}}{1-\beta}).$$

The individual chooses school in the first period if $V_1^S > V_1^W$. Rearranging this inequality, one finds that school is selected in the first period if

$$\begin{aligned} V_1^S - V_1^W &= pq(\beta^3 Y_{44} - Y_{14}) + p(1-q)(\beta^2 Y_{33} - Y_{13}) + \\ &\quad (1-p)r(1+\beta)(\beta Y_{22} - Y_{12}) + (1-p)(1-r)(\beta Y_{21} - Y_{11}) > 0. \end{aligned}$$

By the previous assumptions, the first three terms are all positive, while the last term is negative. Thus, for large values of p, the above inequality will probably hold, while for small values of p the inequality need not hold.[32] Intuitively, for individuals who are fairly confident that they are of high ability, the proper choice is school in the first period, while if a reasonably large prior probability is placed on the lowest ability class, then work is the appropriate first period option.

Optimal schooling choices in each informational state now have been derived.[33] In this simple model, optimal behavior is very simple and can be easily summarized as follows.

Period	Condition Required for School Enrollment
1	Have Optimistic Prior Beliefs About Ability ($V_1^s - V_1^w > 0$)
2	Receive Signal that Ability is "High" ($A \in \{A_3, A_4\}$)
3 +	Have Suboptimal Education, Given Ability ($S = S_i$, $A = A_j$, and $i < j$)

It is clear that this model can generate the phenomenon of multiple periods of school enrollment separated by extended breaks in attendance. In particular, agents with sufficiently pessimistic prior beliefs about their ability (low values of p) will choose to work in period 1. However, these individuals will re-enroll in school if subsequent information arrives that indicates that further schooling would be beneficial.

A simple example might be instructive. Suppose that q and r are identical throughout the population, and that there are only two possible values for p, so that $p \in \{\underline{p}, \overline{p}\}$. Thus, there are only two prior distributions over ability. (Recall that p is an agent's prior belief that they belong to one of the higher ability groups.) Suppose that $\overline{p} > \underline{p}$, that $\Pr(p = \underline{p}) = s$, and that an individual finds it optimal to attend school in the first period if $p = \overline{p}$, but not if $p = \underline{p}$. Given this simple structure, enu-

[32] In particular, if p and r are both small, then the inequality probably will not be satisfied.

[33] To be precise, the problem has been fully analyzed in the case where certain restrictions (explained in the text) on the parameters are assumed to hold. These restrictions simplify the problem and are very reasonable. In words, the assumptions on the parameters reduce to the following two propositions. First, in the presence of full information about ability, more able individuals optimally obtain more education than less able individuals. Second, if an individual optimally chooses to work (and therefore not attend school) in the first period, then he will not choose to attend school in the second period if a negative signal about ability (i.e., the person belongs to one of the lower ability groups) is received after the first period.

merating the different possible enrollment histories and their associated probabilities of occurrence is straightforward. I present this table below.[34]

Prior	Signal	True Ability		Enrollment Sequence	Probability
$\overline{p}$	High	A_4	$\Longrightarrow$	11110	$\overline{p}q(1-s)$
$\overline{p}$	High	A_3	$\Longrightarrow$	11100	$\overline{p}(1-q)(1-s)$
$\overline{p}$	Low	A_2	$\Longrightarrow$	11000	$(1-\overline{p})r(1-s)$
$\overline{p}$	Low	A_1	$\Longrightarrow$	11000	$(1-\overline{p})(1-r)(1-s)$
$\underline{p}$	High	A_4	$\Longrightarrow$	10111	$\underline{p}qs$
$\underline{p}$	High	A_3	$\Longrightarrow$	10110	$\underline{p}(1-q)s$
$\underline{p}$	Low	A_2	$\Longrightarrow$	10010	$(1-\underline{p})rs$
$\underline{p}$	Low	A_1	$\Longrightarrow$	10000	$(1-\underline{p})(1-r)s$

This example highlights two noteworthy predictions of the model. First, the average duration of the second spell in school should be longer for individuals who have briefer interruptions. In the example, those who return to school after a one period gap stay enrolled for two or three periods, while those who re-enroll after a two period gap remain enrolled for only one additional period. Second, the probability of starting a second enrollment spell should (eventually) decline as the time elapsed since the first enrollment spell ended increases; equivalently, the hazard rate from non-enrollment (employment) to re-enrollment should (eventually) decline as the length of the non-enrollment spell increases. In the example, the hazard from employment to enrollment is zero when the number of periods since last enrollment (the length of the break) exceeds two. The hazard rate when the number of periods since last enrollment equals one is $\underline{p}s$. When the number of periods since last enrollment equals two, the hazard rate is $\frac{(1-\underline{p})rs}{1-\underline{p}s}$. Which of these probabilities is larger depends on the parameters, but both are clearly positive. Thus, the hazard is eventually declining, and perhaps monotonically so.

Thus, the model makes two empirically testable predictions, holding other things

[34]Enrollment histories are five periods in length. In the first period, everyone is in school (acquiring education level S_1). By the fifth period, no one is enrolled, nor will anyone ever re-enroll. Thus, there is no loss of information in looking at five period histories.

equal. First, the earlier an individual re-enrolls in school the longer her stay should be, and, second, the longer an individual has been out of school the less likely she should be to re-enroll. One would expect both of these predictions to hold quite generally in learning models, even if the uncertainty and the learning process were modelled somewhat differently than they are here. In general, updated beliefs (about ability, say) are some combination of prior information and newly arrived signals. More dramatic signals, given the prior beliefs, have larger effects on those prior beliefs and therefore are more likely to lead to quick revision in optimal behavior. In addition, given the prior beliefs, more dramatic signals are more likely when prior beliefs, though rationally arrived at, are far from the true parameter value. These two points lead to the conclusion that individuals who return to school sooner should stay longer on average. The prediction that individuals are less likely to re-enroll in school the longer they have been out of school hinges on the assumption that information arrives over time. By the time someone has been out of school a long time, a lot of information has been accumulated and additional information is unlikely to alter prior beliefs much. Thus, anyone who has been out of school a long time has decided that this is the right course based upon a wealth of prior information, and is unlikely to receive new information which will lead to a revision of this opinion.

A Borrowing Constraints Model Re-enrollment

Once again suppose that there are four levels of ability, $A \in \{A_1, A_2, A_3, A_4\}$, and four possible schooling levels, $S \in \{S_1, S_2, S_3, S_4\}$, where $S_i > S_j$ if $i > j$. As before, an individual of ability A_i maximizes lifetime earnings by obtaining schooling S_i, for all i. Unlike in the learning model, however, I now suppose that ability (and therefore the appropriate level of schooling) is known with certainty before any worker confronts a decision between work or further schooling. Let

$$p_i \equiv \Pr(A = A_i), \quad i = 1, \ldots, 4$$

describe the frequency of the different ability types in the population. As the model now stands, it is completely analogous to standard models of educational choice.

Now suppose that all individuals acquire the minimum schooling level, S_1, but thereafter there is some chance, in each period, that an individual will run up against financial constraints that prevent the acquisition of additional schooling in that period.[35] Let q denote the *ex ante* probability that an individual can finance additional schooling in any period, if such schooling is desired. Thus, whether additional schooling can be financed in a given period is simply a Bernoulli random variable with success probability q. For simplicity, I assume that q does not vary across the different schooling increments, and for now I assume that q is identical for all individuals.

I am interested in how the re-enrollment hazard rate and the duration of the re-enrollment school spell depend on the length of the interruption in schooling. Let S denote an individual's current level of schooling and S^* the optimal level of schooling given ability. Let G indicate the length of any ongoing spell out of school since the first exit from school. Then, for $n \geq 1$,

$$\Pr(G = n, S < S^*) = (p_2 + p_3(1+q) + p_4(1+q+q^2))(1-q)^n.$$

Now consider an individual who re-enrolls after an interruption of exactly n periods. Such an individual necessarily had less than the optimal level of education given ability ($S < S^*$) and spent n consecutive periods out of school since the first exit from school. Thus, letting L denote the number of periods out of school before re-enrollment occurs, it follows that, for $n \geq 1$,

$$\Pr(L = n) = \Pr(L = n, G = n, S < S^*) = (p_2 + p_3(1+q) + p_4(1+q+q^2))(1-q)^n q.$$

Therefore, *among the sample of individuals who ever re-enroll in school*, the re-

[35]Thus, it again might be useful to think of S_1 as representing a high school degree, and the other education levels as representing various levels of educational attainment beyond a high school degree.

enrollment (first return to school) hazard rate is a constant:

$$\Pr(L = n \mid G = n, S < S^*) = \frac{\Pr(L = n, G = n, S < S^*)}{\Pr(G = n, S < S^*)} = q.$$

Of course, *among the entire population*, the hazard will be declining, since some individuals will obtain all the education they desire with no interruption in schooling and for this group the re-enrollment hazard is zero. Thus, as time since first exit from school increases, those individuals who already have their desired level of education will become an ever larger proportion of the population who have yet to re-enroll in school, and as a result, the population re-enrollment hazard will decline with time since first exit from school. Nevertheless, the proposition that the re-enrollment hazard is constant even within the subsample that eventually re-enrolls distinguishes the borrowing constraints model from the learning model. In the learning model, the hazard should eventually be decreasing, even when just considering the subsample who return to school, since those who have been out of school for a long while have presumably received much evidence in support of this choice and would require a very dramatic piece of new information to reconsider the enrollment decision.

Next, consider the average duration of the second school spell. It is clear that the spell lasts at least one period, but there are two reasons why it might not last longer. First, the individual might only desire one more "period" of schooling, and second, even if the individual desires more than one additional "period" of schooling, the spell continues for a second period only with probability q. Letting D denote the duration of the second spell in school, one can show that, for any length of the interruption prior to re-enrollment,

$$E(D) = \frac{p_2 + p_3(1 + 2q) + p_4(1 + 2q + 3q^2)}{p_2 + p_3(1 + q) + p_4(1 + q + q^2)}.$$

Thus, the average duration of the second enrollment spell does not vary with the length of the interruption preceding re-enrollment. This contrasts with the prediction in the learning model, where individuals who return sooner are expected to stay in school longer.

In deriving the predictions of the borrowing constraints model, I have so far assumed that q is the same for all individuals for whom $q < 1$ (i.e., all individuals in the potentially constrained population). It seems quite plausible, though, that there might be (unobservable) heterogeneity across individuals in the probability of facing borrowing constraints. Thus, it is important to determine whether the predictions of the borrowing constraints model depend on the homogeneity assumption.

Consider a simple form of heterogeneity. The population contains individuals with two different "susceptibilities" to borrowing constraints, summarized by q_1 and q_2 where $q_1 \neq q_2$. The proportion with susceptibility q_1 is θ, and the proportion with susceptibility q_2 is $1 - \theta$. Let

$$\begin{aligned} A &\equiv (p_2 + p_3(1+q_1) + p_4(1+q_1+q_1^2))(1-q_1)^n\theta, \\ B &\equiv (p_2 + p_3(1+q_2) + p_4(1+q_2+q_2^2))(1-q_2)^n(1-\theta). \end{aligned}$$

Then

$$\lambda \equiv \Pr(L = n \mid G = n, S = S^*) = \frac{Aq_1 + Bq_2}{A+B}$$

and

$$\frac{\partial \lambda}{\partial n} = \frac{AB}{(A+B)^2}(q_1 - q_2)\ln(\frac{1-q_1}{1-q_2}) < 0.$$

Thus, if one allows for heterogeneity in the probability of being constrained, then the borrowing constraints model also predicts that the re-enrollment hazard exhibits negative duration dependence. This occurs because individuals with the highest probability of facing constraints in any period (and hence the lowest per-period probability of re-enrollment) are exactly those who are most likely to experience a long period of uninterrupted constraint.

Turning to the average duration of the re-enrollment spell, define the following notation:

$$\begin{aligned} Y_i &\equiv p_2 + p_3(1+2q_i) + p_4(1+2q_i+3q_i^2), \quad i = 1,2, \\ Z_i &\equiv p_2 + p_3(1+q_i) + p_4(1+q_i+q_i^2), \quad i = 1,2, \end{aligned}$$

$$a \equiv \theta(1-q_1)^n q_1,$$
$$b \equiv (1-\theta)(1-q_2)^n q_2.$$

Then

$$E(D) = \frac{aY_1 + bY_2}{aZ_1 + bZ_2}$$

and

$$\frac{\partial E(D)}{\partial n} = \frac{ab}{(aZ_1 + bZ_2)^2}(Y_1 Z_2 - Y_2 Z_1)\ln(\frac{1-q_1}{1-q_2}).$$

One can show that $Y_1 Z_2 - Y_2 Z_1 > 0$ (< 0) if $q_1 > q_2$ ($< q_2$), and from this it follows that $\frac{\partial E(D)}{\partial n} < 0$. Thus, the average duration of the re-enrollment spell falls as the length of time until re-enrollment rises, when one allows for heterogeneity. The intuition for this result is that individuals with a high likelihood of being constrained are more likely both to have a long out of school spell before having an opportunity to re-enroll *and* to have the re-enrollment spell interrupted by renewed constraints. In summary, then, when one allows for heterogeneity in the degree of borrowing constraint, the learning and borrowing constraints models developed in this appendix become empirically indistinguishable.

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Table 2.1: Percent of young men in school, by sequence and group, in each October from 1972 to 1976 (from Manski and Wise (1983), Table 3.6, p. 50)

Sequence	Percent of Total	Group Percent	Group
00000	32.2	32.2	Never in school
10000	6.5	43.8	Continuous attendance
11000	6.5		
11100	3.7		
11110	11.4		
11111	15.7		
01000	2.3	6.2	Delayed entry of 1 year, continuous attendance
01100	1.3		
01110	0.9		
01111	1.6		
00100	1.7	7.7	Delayed entry of 2 or more years, continuous attendance
00110	0.8		
00111	0.8		
00010	1.3		
00011	1.2		
00001	1.8		
10100	1.0	6.3	Single year interruption
10110	0.7		
10111	1.0		
11010	1.0		
11101	1.2		
00101	0.2	3.9	Multiple year interruptions
01001	0.2		
01010	0.2		
01011	0.2		
01101	0.3		
10001	0.6		
10010	0.5		
10011	0.7		
10101	0.1		
11001	0.8		

Note to Table 2.1

Data comes from the National Longitudinal Survey of the High School Class of 1972, a survey of 1972 U.S. high school seniors. The five digits in each sequence number correspond respectively, left to right, to October 1972, October 1973, October 1974, October 1975, and October 1976. A one in any column indicates "in school full time" in the first week of that particular month. Percents have been rounded to the nearest tenth. The total sample is 9,087.

Table 2.2a: Schooling histories for young men, after and including their first long-term interruption in schooling, observed for 3, 4, or 5 years

Years Observed	Sequence	Percent of Total	Group Percent	Group
3	000	83.7	83.7	Never return to school
	010	4.2	10.4	Return after 1 year
	011	6.2		
	001	5.9	5.9	Return after 2 years
4	0000	77.1	77.1	Never return to school
	0100	5.5	12.3	Return after 1 year
	0101	1.1		
	0110	2.2		
	0111	3.5		
	0010	2.2	4.2	Return after 2 years
	0011	2.0		
	0001	6.4	6.4	Return after 3 years
5	00000	79.1	79.1	Never return to school
	01000	4.3	9.0	Return after 1 year
	01011	0.2		
	01100	1.1		
	01101	0.6		
	01110	1.1		
	01111	1.7		
	00100	2.1	4.5	Return after 2 years
	00101	0.4		
	00110	0.7		
	00111	1.3		
	00010	1.7	3.9	Return after 3 years
	00011	2.2		
	00001	3.5	3.5	Return after 4 years

Data comes from the National Longitudinal Survey of Youth, 1979-1988. Each binary sequence represents a possible schooling history starting from the first year in which the individual reports that he was never in school since the previous interview. Thus, the first digit in the sequence is always a zero, and marks the first between interview period in which the respondent attended no school. A one in any column indicates that the respondent attended some school in that interview year. Percents have been rounded to the nearest tenth. There are 306 3-year histories, 454 4-year histories, and 537 5-year histories.

Table 2.2b: Schooling histories (first 6 years only) for young men, after and including their first long-term interruption in schooling, observed for 6 or more years

Sequence	Percent of Total	Group Percent	Group
000000	77.9	77.9	Never return to school
010000	2.8	7.5	Return after 1 year
010001	0.3		
010010	0.1		
010011	0.2		
010100	0.2		
010101	0.1		
010110	0.1		
010111	0.1		
011000	1.1		
011001	0.1		
011010	0.1		
011011	0.2		
011100	0.6		
011101	0.1		
011110	0.5		
011111	1.0		
001000	2.4	5.5	Return after 2 years
001001	0.3		
001010	0.2		
001011	0.1		
001100	1.0		
001101	0.1		
001110	0.4		
001111	0.9		
000100	2.1	3.7	Return after 3 years
000101	0.2		
000110	0.6		
000111	0.8		
000010	1.6	3.1	Return after 4 years
000011	1.5		
000001	2.3	2.3	Return after 5 years

The table is derived from the 3,106 histories at least 6 years in length. See the note to Table 2.2a for further details.

Table 2.3: Percentage who re-enroll in school after interruption, by years until re-enrollment and remaining time in sample

Years Until	Years Observed After and Including First Year Not in School										
Re-enrollment	0	1	2	3	4	5	6	7	8	9	10
Don't Re-enroll	100.0	100.0	85.3	83.4	77.1	79.1	77.0	71.8	72.2	69.8	77.4
1			14.7	10.5	12.3	8.9	9.4	9.4	8.4	8.5	4.1
2				5.9	4.2	4.5	4.0	8.1	5.6	5.4	4.4
3					6.4	3.9	3.4	2.8	4.4	4.1	3.7
4						3.5	4.3	2.1	3.5	3.3	2.5
5							1.9	2.8	1.8	3.5	1.8
6								3.2	2.0	1.2	1.8
7									2.1	2.7	1.5
8										1.6	1.0
9											1.8
N	570	293	313	306	454	537	583	533	659	516	815

Data is from the NLSY, 1979-1988. Each column isolates individuals who are observed for the same number of years beginning with (and including) the first survey year in which the individual receives no schooling since the previous interview. Reading down each column gives the percentage who eventually re-enroll in school (or not) during the remaining sample period, and the number of years until re-enrollment. N gives the number of individuals in each column.

Table 2.4: Percentage who re-enroll in school after interruption, by years until re-enrollment and race

Years Until Re-enrollment	Race Hispanic	Black	Other	All Groups
Don't Re-enroll	80.2	80.4	79.7	79.9
1	7.3	8.4	7.2	7.5
2	3.8	4.0	4.2	4.1
3	3.0	2.8	3.1	3.0
4	2.9	1.7	2.0	2.1
5	1.2	1.6	1.2	1.3
6	0.7	0.6	1.1	0.9
7	0.7	0.3	0.9	0.7
8	0.1	0.1	0.4	0.3
9	0.2	0.1	0.4	0.3
N	947	1451	3181	5579

Data is from the NLSY, 1979-1988. Reading down each column gives the percentage who eventually re-enroll in school (or not) during the remaining sample period, and the number of years until re-enrollment, by racial group. Included in the "Don't Re-enroll" category are those individuals who are in school continuously throughout the sample, and those who leave school for the first time only in their last year in the sample. N gives the number of individuals in each column.

Table 2.5: Distribution of highest grade completed (in percentages) and mean of highest grade completed for school leavers who never re-enroll, and for school leavers who eventually re-enroll (at time of initial exit and at end of sample period)

Grade Level	Non-returners	Returners	
		At Initial Exit	At End of Sample
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.1	0.1	0.0
4	0.3	0.0	0.0
5	0.3	0.1	0.0
6	0.6	0.7	0.4
7	1.4	0.9	0.2
8	4.7	3.6	1.3
9	7.1	5.0	2.4
10	9.4	7.5	4.0
11	10.7	13.0	7.3
12	39.9	36.6	31.0
13	5.3	9.8	16.1
14	4.4	7.6	14.5
15	2.2	3.4	5.9
16	10.5	9.9	10.3
17	1.2	1.0	3.8
18	0.9	0.4	1.5
19	0.4	0.3	0.8
20	0.6	0.3	0.6
Mean	12.0	12.2	13.1
N	3878	1119	1120

Data is from the NLSY, 1979-1988. N gives the number of individuals in each column. Data on educational attainment is missing for one sample member at the time of initial exit from school.

Table 2.6: Percentage of observations (person-years) with an advance in school grade, given enrollment in school since the previous interview, by previous educational attainment and whether an extended interruption in schooling had occurred previously

Prior Interruption		No	Yes
Previous Highest Grade			
Less than high school	% Advance	89.9	55.9
	N	7239	472
Exactly high school	% Advance	71.0	30.2
	N	1487	702
Less than 4 years of college	% Advance	69.3	33.1
	N	3803	744
Exactly 4 years of college	% Advance	45.2	26.4
	N	471	197
More than 4 years of college	% Advance	71.2	37.7
	N	313	69
All levels of education	% Advance	79.9	36.6
	N	13313	2184

Data is from the NLSY, 1979-1988. N gives the number of observations (person-years) in each cell. The results are qualitatively unchanged if the sample is restricted to just those who were enrolled in 9 or more months since the last interview, although the probability of grade advance is somewhat higher in this restricted sample.

Table 2.7: Weeks worked and hours worked per week since the last interview, by educational attainment prior to interview year and current and past school enrollment status

Enrolled		Yes		Yes		No	
Prior Interruption		No		Yes		—	
Previous Highest Grade		Weeks	Hours	Weeks	Hours	Weeks	Hours
Less than high school	Mean	23.4	22.0	24.6	27.0	35.1	36.1
	S.D.	19.4	16.5	23.2	20.7	22.0	18.0
	N	6742	6645	472	466	10557	10426
Exactly high school	Mean	29.2	29.2	33.3	31.6	42.4	38.6
	S.D.	18.8	16.4	23.1	19.7	20.4	16.5
	N	1487	1475	702	696	11959	11863
Less than 4 years college	Mean	32.9	30.0	39.1	31.7	46.5	40.8
	S.D.	19.2	15.4	22.7	18.3	19.0	15.8
	N	3803	3761	744	732	3425	3397
Exactly 4 years college	Mean	39.5	34.2	49.2	40.5	51.9	43.7
	S.D.	20.0	15.6	17.7	15.2	15.4	14.0
	N	471	466	197	196	1875	1857
More than 4 years college	Mean	34.5	30.0	51.3	38.6	54.0	44.3
	S.D.	22.9	20.8	16.6	12.1	14.1	12.4
	N	337	336	73	69	394	386

Data is from the NLSY, 1979-1988. The table presents summary statistics (means, standard deviations, and number of observations) on weeks worked and hours per week for each of the different education-enrollment status cells. The average for weeks worked can exceed 52 since it is weeks worked since the previous year's interview, rather than weeks worked in the last calendar year.

Table 2.8: Reason left school (most recent exit) for individuals not enrolled at the time of the interview, by future re-enrollment behavior

Reason left school		Re-enrollment occurs: Next Period	With Delay	Never	N_r
Received degree; completed courses	Row %	14.5	22.7	62.8	3196
	(Col %)	(40.2)	(46.6)	(52.5)	
Home responsibilities; marriage; pregnancy	Row %	14.3	21.8	63.9	147
	(Col %)	(1.8)	(2.1)	(2.5)	
Don't like school; lack ability	Row %	15.8	21.9	62.3	777
	(Col %)	(10.6)	(10.9)	(12.7)	
Offered good job; chose to work	Row %	15.4	24.2	60.4	565
	(Col %)	(7.5)	(8.8)	(8.9)	
Financial difficulties	Row %	25.8	26.9	47.3	465
	(Col %)	(10.4)	(8.0)	(5.8)	
Other	Row %	24.7	26.5	48.8	1319
	(Col %)	(28.2)	(22.5)	(16.9)	
Missing	Row %	22.6	29.0	48.4	62
	(Col %)	(1.2)	(1.2)	(0.8)	
N_c		1156	1555	3820	6531

Data is from the NLSY, 1979-1988. The numbers are percentages and may not add to 100.0 because of rounding. The category "Other" represents an aggregation of the following possible responses: "Entered military", "Expelled or suspended", "School too dangerous", "Moved away from school", and "Other". Approximately 70% of the responses in the "Other" category had "Other" as their listed reason for leaving school in the raw NLSY data. Thus, the remaining responses that I grouped with "Other" (i.e., "Entered military", etc.) were quite rare. The column titled "Re-enrollment occurs next period" identifies individuals who enrolled in school sometime during the following interview year. The column titled "Re-enrollment occurs with delay" identifies individuals who enrolled in school sometime during the remaining sample period, but not until after the following interview year. The column titled "Re-enrollment occurs never" identifies individuals who never re-enrolled in school in the remaining sample period. N_c gives the number of individuals in each column and N_r gives the number in each row.

Table 2.9: Future re-enrollment behavior, by relationship between actual and desired educational attainment and by interview year

	Desire further schooling			Have desired schooling		
Re-enrollment occurs	1979	1981	1982	1979	1981	1982
Next period	75.5	54.4	44.5	3.0	3.6	4.8
With delay	6.0	9.6	10.2	11.2	10.5	7.7
Never	18.5	36.0	45.3	85.8	85.9	87.5
N	4857	4393	4158	438	702	880

Data is from the NLSY, 1979-1988. The numbers in the cells are percentages. The row titled "Re-enrollment occurs next period" identifies individuals who enrolled in school sometime during the following interview year. The row titled "Re-enrollment occurs with delay" identifies individuals who enrolled in school sometime during the remaining sample period, but not until after the following interview year. The row titled "Re-enrollment occurs never" identifies individuals who never re-enrolled in school in the remaining sample period. N gives the number of individuals in each column.

Table 2.10: Logit estimates of the probability *not* being enrolled in school at any time in the next interview year, conditional on having less education than self-reported desired education

Interview year is:	1979	1981	1982
Not both parents in household at age 14	.3645 (.1125)	.4208 (.1019)	.3671 (.1041)
Newspaper received in household at age 14	-.3404 (.1045)	-.2543 (.0936)	-.1041 (.0970)
Parent with more education has less than high school	.6274 (.1022)	.5402 (.0931)	.4427 (.0964)
Parent with more education has some college	-.4233 (.1487)	-.2341 (.1243)	-.2807 (.1248)
Parent with more education has college degree or more	-1.339 (.1561)	-1.205 (.1260)	-1.080 (.1206)
Married	1.853 (.2609)	.9923 (.1610)	.9375 (.1460)
Nonwhite	-.2711 (.0971)	-.0116 (.0847)	.1005 (.0861)
Age	.8052 (.0311)	.6185 (.0254)	.5206 (.0236)
Has completed high school	-1.002 (.1251)	-1.134 (.1071)	-1.252 (.0995)
Constant	-15.721 (.5835)	-12.133 (.4957)	-10.360 (.4811)
log L	-1789.8	-2132.5	-2041.7
N	4736	4142	3822

Data is from the NLSY waves of 1979, 1981, and 1982. The sample is restricted to those who have completed less education than their self-reported desired educational attainment. The dependent variable takes the value 1 if the respondent is never enrolled in school during the interview year immediately following the current survey year (1979, 1981, and 1982, respectively). Additional explanatory variables, included but not reported, are dummy variables for: working female in household at age 14, working male in household at age 14, residence in the South, and residence in an urban area. Standard errors are in parentheses.

Table 2.11: Logit estimates of the probability of grade advance since the previous interview, given enrolled in school since the previous interview

Sample is students enrolled in:	Any Grade	Any Grade	College	Full-Time College	Full-Time College
Parent with more education has less than high school	-.2638 (.0774)	-.2220 (.0777)	-.2700 (.1143)	-.2461 (.1343)	-.1719 (.1679)
Parent with more education has some college	.0341 (.0831)	-.0242 (.0845)	.0082 (.1086)	.0974 (.1301)	.1811 (.1586)
Parent with more education has college degree or more	.1692 (.0701)	.0943 (.0719)	.0861 (.0904)	.1078 (.1062)	.2550 (.1256)
Married	.1178 (.0837)	.1167 (.0848)	.3046 (.1210)	.4804 (.1602)	.8987 (.2169)
Nonwhite	-.2847 (.0621)	-.0848 (.0665)	-.3673 (.0847)	-.4142 (.1006)	-.5804 (.1229)
Age	-.1312 (.0190)	-.1288 (.0193)	-.1181 (.0308)	-.0991 (.0398)	-.0738 (.0530)
Education at last interview	-.1810 (.0221)	-.1859 (.0225)	-.2215 (.0379)	-.2533 (.0472)	-.4952 (.0625)
AFQT residual		.0154 (.0018)			
Weeks elasped since last interview	.0245 (.0050)	.0206 (.0051)	.0149 (.0085)	.0253 (.0100)	.0609 (.0125)
Weeks worked since last interview	-.0095 (.0017)	-.0100 (.0017)	-.0111 (.0024)	-.0095 (.0026)	-.0094 (.0032)
Hours per week worked since last interview	-.0143 (.0021)	-.0138 (.0022)	-.0125 (.0029)	-.0111 (.0033)	-.0146 (.0038)
Enrolled in school 1–3 months since last interview	-1.090 (.0837)	-1.047 (.0845)	-1.213 (.1294)	-1.306 (.1629)	
Enrolled in school 4–6 months since last interview	-.6981 (.0746)	-.6435 (.0754)	-.8411 (.1048)	-.9682 (.1268)	
Enrolled in school 7–9 months since last interview	-.6195 (.0764)	-.6173 (.0774)	-.6577 (.0941)	-.7773 (.1087)	
Enrolled in school > 12 months since last interview	-.0255 (.1066)	-.0228 (.1077)	.0459 (.1375)	-.1793 (.1536)	
Attended last college full-time			1.029 (.0886)		
Had previous long interruption in enrollment	-1.030 (.0891)	-1.024 (.0903)	-.9986 (.1250)	-1.336 (.1614)	-1.701 (.2262)
Constant	6.553 (.3388)	6.653 (.3443)	6.452 (.6113)	7.022 (.7125)	7.842 (.8701)
log L	-4418.1	-4329.6	-2422.4	-1776.8	-1280.4
N	9137	9025	4950	3862	3362

Note to Table 2.11

Data is from the NLSY, 1979-1988. The far right hand column restricts the sample to individuals who were most recently college students, who attended their last college full-time (by their own definition), *and* who were enrolled in school for at least nine of the months since the previous interview. Additional explanatory variables, included but not reported, are dummy variables for: working female in household at age 14, working male in household at age 14, newspaper received in household at age 14, residence in the South, and residence in an urban area. The AFQT residual, an ability measure, is the residual from a regression of AFQT score on the individual's age at the time the test was administered, the individual's highest grade completed at the time the test was administered, and a constant. The results are qualitatively identical if year dummies are included in any of the estimations, if the AFQT residual is included in any of the estimations, if months enrolled in school enters the equation linearly instead of as a sequence of dummies, and if a measure of the length of the interruption is included along with the indicator for whether a past interruption has occurred. Standard errors are in parentheses.

Table 2.12: Logit estimates of the probability of re-enrollment before the *next* interview for individuals not enrolled since the previous interview

Not both parents in household at age 14	.1719 (.1009)	.1447 (.1063)	.1323 (.1034)	.1133 (.1087)
Parent with more education has less than high school	-.1525 (.0949)	-.0988 (.0995)	-.0624 (.0970)	.0037 (.1015)
Parent with more education has some college	.1229 (.1163)	.1257 (.1207)	.0791 (.1182)	.0794 (.1228)
Parent with more education has college degree or more	.4798 (.1047)	.4823 (.1074)	.4075 (.1068)	.4115 (.1096)
Married	-.1089 (.0868)	-.0792 (.0885)	-.1469 (.0889)	-.1134 (.0907)
Nonwhite	-.0676 (.0845)	-.1468 (.0887)	.1709 (.0903)	.0873 (.0948)
Age	-.0885 (.0218)	-.0818 (.0225)	-.0808 (.0218)	-.0732 (.0225)
Education	.1887 (.0230)	.1912 (.0237)	.2159 (.0231)	.2172 (.0238)
AFQT residual			.0204 (.0024)	.0202 (.0025)
Employed at interview date	-.4067 (.0995)	-.2956 (.1224)	-.4390 (.1011)	-.3324 (.1244)
Real wage	-.0124 (.0118)	-.0237 (.0128)	-.0199 (.0124)	-.0328 (.0134)
Part-time	.1705 (.1088)	.1807 (.1149)	.1874 (.1105)	.1977 (.1163)
Wages set by collective bargaining	.1373 (.0895)	.1815 (.0927)	.1607 (.0912)	.2040 (.0945)
Experience (months)	.0017 (.0018)	.0019 (.0018)	.0016 (.0019)	.0019 (.0019)
Tenure (months)	-.0037 (.0019)	-.0039 (.0019)	-.0038 (.0020)	-.0040 (.0020)
Job satisfaction low		.2020 (.1957)		.1883 (.1998)
Job satisfaction high		-.2955 (.0806)		-.2869 (.0823)
Constant	-3.431 (.5487)	-3.535 (.5721)	-3.989 (.5589)	-4.106 (.5832)
log L	-3282.7	-3050.7	-3154.5	-2934.2
N	19212	18189	18621	17638

Note to Table 2.12

Data is from the NLSY, 1979-1988. Included observations are all person-years with complete data in which the respondent was not enrolled in school since the previous interview. All of the job characteristics variables refer to the most recent job as of the interview date. Additional explanatory variables, included but not reported, are the unemployment rate in the respondent's local labor market and the following dummy variables: working female in household at age 14, working male in household at age 14, newspaper received in household at age 14, residence in the South, residence in an urban area, dummies for one-digit occupation (most recent job), and year dummies. The AFQT residual, an ability measure, is the residual from a regression of AFQT score on the individual's age at the time the test was administered, the individual's highest grade completed at the time the test was administered, and a constant. Standard errors are in parentheses.

Table 2.13: Logit estimates of the probability of re-enrollment before the *final* interview, conditional on job and individual characteristics as of the first interview year never enrolled in school

Not both parents in household at age 14	-.0064 (.1235)	.0159 (.1331)	-.0201 (.1262)	-.0045 (.1363)
Parent with more education has less than high school	-.2611 (.1132)	-.1921 (.1230)	-.1740 (.1165)	-.0961 (.1265)
Parent with more education has some college	.2122 (.1374)	.2904 (.1449)	.1503 (.1408)	.2224 (.1487)
Parent with more education has college degree or more	.4540 (.1302)	.5324 (.1366)	.3699 (.1333)	.4350 (.1399)
Married	.0367 (.1200)	.1078 (.1246)	-.0069 (.1226)	.0629 (.1275)
Nonwhite	.0421 (.1007)	-.0044 (.1090)	.2867 (.1093)	.2719 (.1186)
Age	.0462 (.0384)	.0512 (.0407)	.0480 (.0392)	.0526 (.0414)
Education	.0002 (.0374)	.0063 (.0403)	.0387 (.0386)	.0497 (.0412)
AFQT residual			.0223 (.0030)	.0240 (.0032)
Employed at interview date	-.1573 (.1190)	.1039 (.1818)	-.1628 (.1220)	.0902 (.1850)
Real wage	-.0363 (.0173)	-.0528 (.0189)	-.0453 (.0178)	-.0649 (.0196)
Part-time	-.0061 (.1256)	.0481 (.1348)	.0171 (.1281)	.0676 (.1376)
Wages set by collective bargaining	.1257 (.1122)	.1181 (.1205)	.1308 (.1151)	.1502 (.1232)
Experience (months)	.0036 (.0026)	.0037 (.0027)	.0030 (.0026)	.0030 (.0027)
Tenure (months)	-.0052 (.0033)	-.0051 (.0034)	-.0055 (.0034)	-.0054 (.0035)
Job satisfaction low		-.1993 (.2782)		-.1835 (.2825)
Job satisfaction high		-.3309 (.1004)		-.3065 (.1028)
Constant	-3.420 (.7380)	-3.636 (.7879)	-4.119 (.7564)	-4.433 (.8114)
log L	-1717.2	-1515.8	-1642.7	-1449.1
N	3429	3078	3322	2983

Note to Table 2.13

Data is from the NLSY, 1979-1988. Only the first year in which a respondent was never enrolled since the previous interview is included in the sample, provided that complete data is available. Thus, there is at most one observation per person. All of the job characteristics variables refer to the most recent job as of the interview date. Additional explanatory variables, included but not reported, are the unemployment rate in the local labor market and the following dummy variables: working female in household at age 14, working male in household at age 14, newspaper received in household at age 14, residence in the South, residence in an urban area, one-digit occupation dummies (for most recent job), and year dummies. The AFQT residual, an ability measure, is the residual from a regression of AFQT score on the individual's age at the time the test was administered, the individual's highest grade completed at the time the test was administered, and a constant. Standard errors are in parentheses.

Chapter 3

Uncertain Returns to Education and Transitions from Part-Time to Full-Time College Enrollment

3.1 Introduction

Human capital models of life cycle earnings and educational investment often do not recognize the possibility that the strength of attachment to school might vary across students. Rather, these models commonly posit individuals as simply in school or not, and the cost of schooling is taken to be the wage foregone by choosing enrollment over employment. The familiarity of this framework makes it easy to imagine that the choice between school and work truly is a dichotomous choice between full-time enrollment (and nonemployment) and full-time participation in the labor market (and nonenrollment).

However, this view of the nature of enrollment and employment does not describe the empirical reality accurately. Clotfelter, et. al., (1991) report that 32% of all students enrolled in U.S. colleges and universities in 1988 were part-time students. The percentage of part-time students falls substantially if one restricts attention to students under the age of 25 attending 4-year colleges and universities, but there remains a significant fraction of the college student population that attends only on a part-time basis. In addition, many college students work while they are in school. Ehrenberg and Sherman (1987) find that, in a sample of *full-time* college students, between one-third and one-half of all students at 4-year colleges and over one-half of all students at 2-year colleges are employed. Hours of work average 20 to 25 hours per week among the group of full-time students who work. Presumably part-time students have considerably stronger work attachment. In any event, these findings highlight two points. First, the strength of attachment to school varies widely across the college student population. In particular, it is incorrect to view college as a full-time activity for all students.[1] Second, schooling and work often are undertaken simultaneously.

By themselves, neither part-time school enrollment nor simultaneous enrollment and employment are inconsistent with standard (i.e., full information and no borrowing constraints) life cycle models of earnings and human capital accumulation. In particular, if individuals can continuously vary their allocation of time to different activities, then this behavior is easily explained. However, as Weiss (1986) notes, even in this more general framework, spells of part-time enrollment and simultaneous enrollment and employment only should be observed as an intermediate step in the transition from full-time school to full-time work, since time allocated to school should decline monotonically over the life cycle. Thus, one can perform an informal test of the basic life cycle model simply by examining enrollment status immediately before and after spells of part-time enrollment. In the next section, I consider the nature of the flows into and out of part-time college enrollment, and more generally summarize college enrollment and employment behavior, using data from the National Longitudinal Survey of Youth (NLSY). The key finding is that the pattern of transition into and out of part-time college enrollment cannot be reconciled with the predictions of the standard life cycle model of earnings and human capital.[2]

[1]Unfortunately, in standard data sets, one can do no better than distinguishing three different levels of school attachment: no enrollment, part-time enrollment, and full-time enrollment.

[2]There exists other evidence that suggests that the basic life cycle model cannot fully account for observed enrollment behavior. Oettinger (1992) shows that extended interruptions in school attendance followed by re-enrollment, also inconsistent with the basic model, are not uncommon. Thus, the findings of the present paper reinforce the view that a richer life cycle model is necessary

In light of these results, I develop a modified life cycle model that can generate transitions from part-time enrollment to full-time enrollment as optimal behavior in Section 3.3. The model builds on standard dynamic models of earnings in which individuals optimally allocate their time between human capital accumulation (schooling) and work in each period. The novel feature is that whether the educational investment in any period is successful (augments the human capital stock) is uncertain, and individuals do not know their true probability of success. Instead, the perceived probability of success evolves as the outcomes of enrollment spells are observed. This learning can lead to transitions from part-time enrollment to full-time enrollment as individuals revise their beliefs. Of course, borrowing constraints offer an alternative explanation for part-time to full-time transitions. Thus, I develop a borrowing constraints model as well. Section 3.4 returns to the NLSY data to test the differing implications of the two models. Section 3 5 concludes.

3.2 Evidence on College Enrollment and Employment

I examine the college enrollment and employment behavior of youths using the National Longitudinal Survey of Youth (NLSY). The NLSY is an annual survey of 12,686 youths who were between the ages of 14 and 21 on January 1, 1979. It is composed of three subsamples: a civilian sample representative of the youth population in the United States, a supplemental civilian sample of poor and minority youths, and a sample of youths in the military. I have data for the period 1979-1988. For the analysis in this paper, I limit the sample to males from the civilian samples who were observed to complete high school during the sample period. I follow this sample of individuals from the survey year immediately following the year in which high school is completed until the end of the sample period or until the first noninterview year, if one occurs.

to explain individual school enrollment histories.

I discard the military sample since it is followed only for a shorter period, and since the individuals might be expected to differ substantially from the civilian population. I limit the sample to men for two reasons. First, until very recently, men and women exhibited quite distinct patterns of college-going behavior. Clotfelter, et. al., (1991) present data showing that only twenty years ago the ratio of male to female college students (under the age of 35) was 1.4. Thus, just a generation ago, women were much less likely to attend college than men. Presumably, this difference in the frequency of college enrollment owed to differences in preferences and constraints (private and social) across the two groups. To the extent that differences in these primitive factors underlying the college enrollment decision still exist today, it makes sense to analyze college enrollment separately for men and women. A second, but related, point is that college enrollment among women has grown dramatically over the past several decades. Between 1980 and 1988 alone, total enrollment among women grew by more than 10% while for men enrollment grew by less than 4%. As a result of the very rapid growth in women's college enrollment, today the frequency of college enrollment among women is slightly higher than among men. Because this trend is such a dominant feature of women's college enrollment data over the last several decades (and because it presumably represents a one-time phenomenon), it is probably less than ideal to use a sample of women from this time period to examine transitions from part-time to full-time enrollment. Finally, I limit the sample to observations after the completion of high school for males who finish high school during the sample period to ensure that the entire post-high school history is observed.

I begin by examining the frequency with which individuals have an immediate and uninterrupted spell of college enrollment upon high school graduation. Standard life cycle models of earnings predict that individuals who would benefit from a college education should pursue this course immediately after completing high school and without interruption. However, in earlier work (Oettinger (1992)) using the NLSY, I found that an extended interruption in school followed by eventual re-enrollment occurs for one in four male youths at some point in their school enrollment history.

Table 3.1 shows that this finding persists even when one restricts the analysis to only the post-secondary enrollment behavior of high school graduates. Each of the three middle columns of Table 3.1 represents a different enrollment pattern. The column titled "Never in school" contains all individuals who never spent any time in school after high school graduation. The column titled "Continuous enrollment" contains all individuals who enrolled in college in the survey year following high school graduation, and possibly continued in school until the end of the sample period, but who *never* returned to college after going a full period between interviews with no college enrollment. Finally, the column titled "Delay or interruption" contains all individuals with any other enrollment history. Any enrollment history in this final category is anomalous from the perspective of the basic life cycle model. Nevertheless, such enrollment histories are not rare. If one follows high school graduates for four or more years after high school graduation, at a minimum 15% of the sample has this nontraditional enrollment sequence. If one restricts attention to those observed for seven or more years, the proportion with delay or interruption in college enrollment exceeds 20%. Thus, a nontrivial minority of the sample of high school graduates exhibits college enrollment behavior inconsistent with the simplest life cycle model.

The main focus of this essay, however, is part-time enrollment in college, not interruption in college enrollment. While part-time enrollment, by itself, is not inconsistent with the basic life cycle model, transitions from part-time to full-time enrollment should not occur. Table 3.2 examines the validity of this proposition by presenting the relative frequencies of college enrollment status in year t given college enrollment status in year $t-1$. Each row sums to 100.0 (except for rounding error), reflecting the fact that, for each enrollment status in the previous interview year, *some* enrollment status is observed in the current interview year. Unfortunately, data on "student status" (full-time versus part-time) for enrolled students is missing for a significant number of observations. This missing data is almost entirely attributable to the structure of the survey questionnaire in the first five years of the panel (1979-1983). In these years, individuals were asked only if they had been enrolled since the previous September (the traditional start of the school year) rather than whether they had been enrolled since the previous interview. Thus, "student status" data is unavailable for individuals whose only college enrollment in a given survey year occurs before the previous September but after the date of the previous year's interview. This means that, in the early years of the panel, "student status" data is missing if an individual is enrolled in college only near the beginning of the survey year. In determining the relative frequency of part-time and full-time college enrollment, I ignore the observations with missing data. Implicitly, this assumes that the relative frequency of part-time and full-time enrollment among individuals with missing data is the same as among those with complete data.[3]

In spite of the missing data, several interesting relationships emerge. Only about 5% of those who are not enrolled in college in a given interview year enroll in the next interview year, with about 57% of those who re-enroll doing so on a part-time basis. In contrast, among individuals who are enrolled in college part-time in a given interview year, approximately 60% enroll in college again in the next interview year. Still, this implies that a significant fraction of part-time students do not seek further education in the next interview year. Given the percentages in the first row, one can conclude that a large proportion of the part-time students who leave school entirely will never return. However, among those part-time students who do choose to continue their education, fully 34% of them continue as full-time students. Thus, in contrast to the prediction of the life cycle model, there is a significant amount of transition from part-time to full-time college enrollment.

Over 82% of full-time students in a given interview year continue in college in the subsequent year. Of those who remain in school, only 10% transit to part-time student status. In addition, it appears much more common for individuals to move from full-time enrollment to no enrollment than from full-time enrollment to part-time enrollment. This suggests that a gradual transition from full-time to part-time

[3]An alternative approach would be to try to impute data on full-time versus part-time enrollment status for those for whom this data is missing. The most reasonable imputation rule would be to assign the same "student status" (full-time or part-time) as the individual reported in the previous year, if the student was enrolled in college in the previous year and had valid data on full-time versus part-time status. Unfortunately, this imputation rule allows one to impute less than one-fourth of the missing data, largely because "student status" data is frequently missing for the first and/or only observation for which the individual is enrolled in college.

enrollment status, and finally to no enrollment, while consistent with the life cycle model, is rather uncommon in the data. Finally, comparing the frequencies of full-time and part-time enrollment, it appears that roughly 20% of all person-years in the sample are accounted for by part-time students. This fraction is substantially lower than the fraction of part-time students in the entire college student population cited by Clotfelter, et. al., (1991) but is of roughly the same magnitude as the proportion they report when they limit their sample to just the population under 25 years of age.

Table 3.3 examines the relationship between "student status" (full-time, part-time, unknown) and highest grade completed as of the previous interview for individuals enrolled in college during the current interview year. For an individual who is enrolled during a given survey year, previous highest grade completed is simply one grade below the grade of current enrollment. I group individuals who have completed more than 16 years of education together because there are very few such individuals. If one ignores the observations with missing data on full-time versus part-time enrollment status one can easily compute the relative frequency of part-time enrollment and full-time enrollment at each previous grade level. As before, not including the observations with missing data is entirely benign only if the relative frequency of part-time enrollment is the same for this group as for those with complete data. For the subsample with valid data, the percentages of full-time and part-time students are shown in parentheses in the columns titled "Full-Time" and "Part-Time", respectively. Within this subsample, part-time enrollment accounts for between 10% and 30% of total enrollment, depending on the level of already completed education. The frequency of part-time enrollment declines throughout the undergraduate years and is highest in the first year of college and the first year of post-baccalaureate education. Overall, 20.7% of the total person-years in college (using only the observations with valid data on part-time versus full-time status) are spent in part-time enrollment. This agrees closely with the numbers in Table 3.2.

Table 3.4 presents evidence on how the frequency of grade advancement, given enrollment in college since the previous interview, varies with student status (full-time, part-time, unknown) and the highest previously completed grade. As was noted earlier, observations with missing data on part-time versus full-time status (i.e., observations with "unknown" enrollment status) represent individuals who were enrolled only briefly at the beginning of the interview year over the 1979-1983 years. These students may have been either part-time or full-time students. Looking at the table, at 15 or more years of already completed education, the frequency of grade advance for students with unknown enrollment status looks quite similar to the grade advance frequency of full-time students. This suggests that, at the higher grade levels, most of the students with missing enrollment status data actually were enrolled full-time. At 14 or fewer years of already completed education, the grade advance frequency for those with missing enrollment status data bears much more resemblance to that of part-time students. Given these patterns and the frequency of missing enrollment status data in the full sample, the numbers in Table 3.3 appear to understate both the frequency of part-time enrollment among those with only 12–14 years of already completed education and the rate at which the frequency of part-time enrollment declines over the college years (12–15 years of already completed education).

Restricting attention to those with valid data on enrollment status, it is clear that full-time students are much more likely to make academic progress and/or make progress much more rapidly than part-time students, at every grade level. The obvious explanation for this difference is that a full-time academic program allows for quicker completion of a given set of academic requirements than does a part-time program. However, self-selection in enrollment status may also play a role. Individuals who are most likely to succeed in or benefit from school are probably the most likely to devote large amounts of time and resources to school. Nevertheless, it seems uncontroversial that a given individual would be expected to make faster academic progress if enrolled as a full-time student than if only enrolled on a part-time basis.

Finally, Table 3.5 considers how attachment to the labor force varies by educational attainment and enrollment status in the current interview year. Three different summary measures of the strength of labor force attachment are presented: average weeks worked since the previous interview, average hours per week worked since the previous interview, and the frequency (in percentages) of "full-time" employment since the previous interview. I define "full-time" work as working in at least 75% of the weeks since the previous interview and averaging at least 35 hours per week in those weeks.[4] A comparison across rows within a column illustrates how labor force attachment varies with educational level, keeping enrollment status in the current year constant. Not surprisingly, among workers never enrolled in college since the last interview, labor force attachment, by each measure, becomes stronger as educational attainment increases. For workers with some college enrollment during the year, this pattern is much weaker, and subject to a few qualifications. First, among all workers with some enrollment, labor force attachment is *weaker* for those enrolled in their second (or later) year of post-baccalaureate enrollment than for those enrolled in just their first year of graduate study. It should be noted, however, that at this level of education the sample sizes are quite small. Second, for those enrolled in their first through third years of college (previous highest grade 12 through 14), regardless of full-time or part-time status, the strength of labor force attachment is essentially constant.

For the present purposes, however, it is more interesting to compare different columns within a row. This shows how labor force attachment varies with college enrollment status since the last interview, at a given level of previous education. Unsurprisingly, labor force attachment is always strongest for those who were never in school since the last interview. The employment data for individuals who were enrolled but are missing data on enrollment status (the far right-hand column) look much more like the employment data for part-time students than for full-time students. One is tempted to conclude that most of those with missing enrollment status data must have been part-time students, but such an inference is unwarranted. Instead, the strong labor force participation of these students follows from the fact that, by the construction of the survey questionnaire, enrollment status data is missing only for students who were enrolled very briefly at the beginning of the interview year. Since these students only had brief spells in school at the start of the year,

[4]35 hours of work per week is also the cutoff used by the CPS in defining full-time work.

their strong employment record over the entire year is not surprising. As a result, though, the high level of labor force participation over the full year is uninformative with respect to the question of whether the brief spell in school was one of part-time or full-time enrollment.

Comparing just the part-time and full-time students, labor force attachment is much stronger among the part-time students. In particular, weeks of employment for part-time students exceed those of full-time students by between 8 and 21 weeks on average. In addition, part-time students work between 4 and 28 hours per week more than full-time students, although the median difference appears to be about 6 hours per week. However, focusing only on average differences in hours and weeks may be deceiving. If "full-time" and "part-time" job opportunities differ meaningfully in terms of total compensation (as opposed to simply reflecting different labor supply choices in response to the same compensation package), then relatively small differences in hours and weeks of work may indicate much larger differences in job characteristics. If one looks at the percentage of students who are "full-time" workers, under the definition of full-time given earlier, the figure is around 50% or higher for part-time students, but always less than 20% (and usually closer to 10%) for full-time students. Thus, the combination of full-time employment with part-time college enrollment is quite common, while simultaneous full-time employment and full-time college enrollment is very rare. Finally, by each of the measures of strength of labor force attachment, the difference between part-time and full-time students grows larger at higher levels of educational attainment.

In summary, then, the data from the NLSY highlight three basic facts about part-time enrollment. First, part-time enrollment is not uncommon. In a sample restricted to young civilian male college students, 20% are enrolled only as part-time students. This is a significant fraction in itself, although it understates the frequency of part-time college enrollment in the entire population, since older individuals are disproportionately likely to attend college on a part-time basis. Second, part-time enrollment is frequently part of an enrollment pattern that is inconsistent with the basic life cycle model. In a sample of *part-time* college students in year $t-1$ who enroll in some college in year t, one-third of these students switch to *full-time* status in year t. Third, relative to full-time enrollment, part-time enrollment typically involves slower academic progress and greater commitment to the labor force. While part-time students are less likely to advance academically, or advance less rapidly, than full-time students, their labor force attachment is significantly stronger than that of full-time students. Full-time employment is reasonably common for part-time students but quite rare for full-time students. In the next section, I present a stylized life cycle model of earnings and human capital that can explain transitions from part-time to full-time enrollment and is consistent with the other findings presented above as well. I also outline a borrowing constraints model that can explain the existence of part-time to full-time transitions, and highlight the testable differences between the two models.

3.3 Models of Enrollment Transitions

3.3.1 A Learning Model

The model takes place in discrete time. Individuals have infinite horizons and seek to maximize the expected present discounted value of lifetime earnings (the discount factor is β). There are N different levels of schooling, $s \in \{1, 2, \ldots, N\}$. Earnings depend on schooling according to an earnings function, $y(s)$, which gives the per-period earnings associated with each level of schooling for a *full-time* worker. Earnings are an increasing and concave function of schooling. Thus,

$$y(s) - y(s-1) > y(s+1) - y(s) > 0, \quad s \in \{2, 3, \ldots, N-1\}.$$

I also assume that $\beta y(N) > y(N-1)$, which implies that an individual with $N-1$ years of schooling would always attend school for one final year *if* success in school were assured. Together, the assumptions of concavity of $y(s)$ and $\beta y(N) > y(N-1)$ imply that $\beta y(s) > y(s-1)$, for all $s \in \{2, 3, \ldots, N\}$.

At this point, I depart from traditional models of schooling by assuming that success in school, given enrollment, is not a certainty.[5] Specifically, I assume that, conditional on enrollment, each individual has a constant probability of success in school in any period, p, which is drawn from a common underlying population distribution. Thus, p varies across individuals, but is fixed for any given individual. One can think of p, the probability that an educational investment undertaken in any period augments the human capital stock, simply as "ability", and I will often refer to it in this way. If $p = 1$, the individual has the highest possible ability and success in school is certain. Thus the assumption that $\beta y(N) > y(N-1)$ is equivalent to requiring that an individual of the highest ability type obtain the maximum possible education.

I also assume that individuals do not know their ability when they begin their schooling. Instead, they only have noisy prior beliefs about ability that evolve as new information (the outcomes of previous terms of enrollment) arrives. In period t, an individual's estimate of ability is $\hat{p}_t$. A decision to attend school in period t serves two purposes: first, it increases the human capital stock (completed schooling) *if* schooling is successful, and second, it provides further information about ability, leading to the revised ability estimate $\hat{p}_{t+1}$.[6]

At this point, I incorporate into the model some features suggested by the empirical results discussed earlier. In particular, I do not limit the choice between school and work to an all or nothing decision. Instead, I allow for simultaneous enrollment

[5] Altonji (1991) and Manski (1989) also assume that success in school is uncertain at the time that the enrollment decision is made. Altonji develops a model in which educational outcomes are uncertain as motivation for estimating the probability of various post-secondary education outcomes and for estimating the *ex ante* return to starting college. Manski assumes that educational outcomes are uncertain as a starting point for an analysis of college dropout and the likely effects of policies aimed at curbing such attrition. Both authors argue that the high frequency of college dropout strongly suggests that college completion is far from certain at the time of initial college enrollment.

[6] A convenient way to model the evolution of beliefs about ability would be to assume that ability follows a Beta distribution in the population and that enrollment yields only two outcomes, success or failure. If the true value of p is unknown, the prior distribution of p is Beta, and the new information arrives as a sequence of Bernoulli trials each with success probability p, then by well-known results (DeGroot (1970)), the posterior distribution of p will also be Beta (with changed parameter values reflecting the new information). However, nothing in the analysis that follows requires that beliefs evolve according to this specific process. In the presentation of the model, I assume that schooling is either a success (adds to human capital) or not, but the information content of each outcome might be richer than just "success" or "failure". For instance, the individual might be able to make finer distinctions within the class of successful school outcomes.

and employment. Consistent with the data, however, I assume that stronger school attachment comes at the cost of weaker labor force commitment (see Table 3.5) and that stronger school attachment allows for faster academic progress (see Table 3.4). Specifically, I assume that an individual can select one of three combinations of work and school in each period: full-time work and no school enrollment (Option 1), part-time work and part-time school enrollment (Option 2), or no work and full-time school enrollment (Option 3).[7] An individual with schooling s and ability estimate $\hat{p}$ who chooses Option 1 earns $y(s)$ in the current period. If this individual chooses Option 3, current period earnings are zero and completed schooling at the end of the period rises to $s+1$ with unknown probability p (which the individual estimates to be $\hat{p}$).

If Option 2 is chosen, the individual both attends school and works. I assume that time is divided equally between the activities so that per-period earnings when Option 2 is pursued are $\frac{y(s)}{2}$. Because school is attended only on a half-time basis under Option 2, a successful school attempt takes two periods to complete in this case. However, the individual learns in the first period whether the current school effort will be successful. As before, p is the unknown true probability of success in school, and $\hat{p}$ is the individual's estimate of p. An individual who chooses Option 2 and learns that the current school effort will be successful continues to combine work and school for a second period, with the stock of completed schooling increasing only after the second period of school is finished. Thus, switching to full-time enrollment does not occur when an individual is halfway through a successful part-time program.[8] On the other hand, if a part-time schooling attempt is not successful, the enrollment strategy can be revised immediately in the following period.

In each period, then, the individual's choice problem is to select the option that

[7]This structure is reminiscent of Burdett's (1978) model of job search while employed, in which a worker can choose to search but not work, to work but not search, or to work and search simultaneously. It turns out that the solution in the present model also is analogous to the solution of the problem posed by Burdett.

[8]This assumption can be justified by assuming that full-time and part-time educational programs are sufficiently distinct that if a switch from part-time to full-time were undertaken in the "middle" of a part-time program, the individual would have to start the grade over as a full-time student. In these circumstances, a student would never switch from part-time to full-time status after successfully completing the first half of a part-time program.

maximizes the expected present discounted value of lifetime earnings, given the current level of schooling (s) and current beliefs about ability ($\hat{p}$). Given s and $\hat{p}$, one can write the value of each option, and the Bellman equation, as

$$\begin{aligned} V^1(s,\hat{p}) &= \frac{y(s)}{1-\beta}, \\ V^2(s,\hat{p}) &= \frac{(1+\beta\hat{p})y(s)}{2} + \beta^2\hat{p}W + \beta(1-\hat{p})Z, \\ V^3(s,\hat{p}) &= \beta\hat{p}W + \beta(1-\hat{p})Z, \\ V(s,\hat{p}) &= \max\{V^1(s,\hat{p}), V^2(s,\hat{p}), V^3(s,\hat{p})\}, \end{aligned}$$

where

$$W \equiv \mathrm{E}_{\tilde{p}} V(s+1,\tilde{p} \mid \hat{p}, x = \text{success}) \equiv \int_P V(s+1,\tilde{p}) dF(\tilde{p} \mid \hat{p}, x = \text{success}),$$

$$Z \equiv \mathrm{E}_{\tilde{p}} V(s,\tilde{p} \mid \hat{p}, x = \text{failure}) \equiv \int_P V(s,\tilde{p}) dF(\tilde{p} \mid \hat{p}, x = \text{failure}).$$

Thus, W is the expected value of optimal behavior next period if the current period school investment is successful and Z is the expected value of optimal behavior next period if the school investment this period is unsuccessful. In the definitions of W and Z, x indicates the outcome of the current period school investment, and $\tilde{p}$ represents the revised ability estimate after the current period's school outcome is observed. At the time of the current period decision, $\tilde{p}$ is a random variable with cumulative distribution function $F(\tilde{p} \mid \hat{p}, x)$.[9] I make two assumptions on $F(\tilde{p} \mid \hat{p}, x)$. First, I assume that $F(\tilde{p} \mid \overline{p}, x) \leq F(\tilde{p} \mid \underline{p}, x)$ for any $\overline{p} > \underline{p}$ and for $x \in \{\text{success, failure}\}$. Second, I assume that $\mathrm{E}(\tilde{p} \mid \hat{p}, x = \text{success}) \geq \hat{p} \geq \mathrm{E}(\tilde{p} \mid \hat{p}, x = \text{failure})$. Loosely, the first assumption says that a higher estimated probability of success in school this period makes high estimated probabilities of success next period more likely, other things (namely, this period's school outcome) equal. The second condition implies that an individual's beliefs about ability become more optimistic if school is a success

[9]This formulation is quite general in that it allows for a continuum of possible values of $\tilde{p}$. If beliefs evolved according to the "Beta prior-Bernoulli trials" model, then there would be exactly two possible values for $\tilde{p}$, one following a "success" and one following a "failure".

this period, and more pessimistic if school is a failure.

The value of Option 1, $V^1(s,\hat{p})$, is just the present discounted value of earning $y(s)$ in every period. If an individual ever opts for full-time work, no additional information about scholastic ability ever arrives, and consequently full-time work must continue to be the best choice. This underscores the fact that the model does not seek to explain transitions from non-enrollment to enrollment, but rather focuses on flows from part-time enrollment to full-time enrollment. The expression for $V^2(s,\hat{p})$ makes clear that the individual only earns $\frac{y(s)}{2}$ in any period in which part-time employment is undertaken and that a successful round of schooling takes two periods to complete under Option 2. The value of Option 3 is given by $V^3(s,\hat{p})$.

To characterize the solution to this problem, first consider optimal behavior when $\hat{p} = 0$. For $\hat{p}$, the conditional point estimate of ability, to equal zero, schooling must be doomed to fail with certainty. Moreover, as the assumption on the updating of prior probabilities makes precise, beliefs about ability can never become more optimistic in response to an unsuccessful schooling attempt. Therefore, if $\hat{p} = 0$, then $\tilde{p} = 0$ with probability one. In this case, $V^1(s,0) = \frac{y(s)}{1-\beta}$, $V^2(s,0) = \frac{y(s)}{2} + \frac{\beta y(s)}{1-\beta}$, and $V^3(s,0) = \frac{\beta y(s)}{1-\beta}$. Therefore, $V^1(s,0) > V^2(s,0) > V^3(s,0)$. Intuitively, at any level of schooling, full-time work must be optimal if there is no chance of further success in school.

When $\hat{p} = 1$, the inequalities are reversed so that $V^3(s,1) > V^2(s,1) > V^1(s,1)$. The condition $V^3(s,1) > V^2(s,1)$ is equivalent to $\beta(1-\beta)W > (\frac{1+\beta}{2})y(s)$. After noting that $W \geq \frac{y(s+1)}{1-\beta}$, it is clear that this condition must hold, given the assumptions on the shape of the earnings function and $\beta < 1$. The condition $V^2(s,1) > V^1(s,1)$ is the same as $\frac{(1+\beta)y(s)}{2} + \beta^2 W > \frac{y(s)}{1-\beta}$. Again using the concavity of $y(s)$ and the fact that $W \geq \frac{y(s+1)}{1-\beta}$, it follows that this inequality holds as well. Thus, it has been established that

$$V^1(s,0) > V^2(s,0) > V^3(s,0), \quad s \in \{1,2,\ldots,N-1\}$$

and

$$V^1(s,1) < V^2(s,1) < V^3(s,1), \quad s \in \{1,2,\ldots,N-1\}.$$

Next, consider how $V^1(s,\hat{p})$, $V^2(s,\hat{p})$, and $V^3(s,\hat{p})$ vary with $\hat{p}$.[10] The relevant partial derivatives are

$$\begin{aligned}
\frac{\partial V^1(s,\hat{p})}{\partial \hat{p}} &= 0, \\
\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}} &= \beta(\frac{y(s)}{2} + \beta W - Z) + \beta^2 \hat{p}\frac{\partial W}{\partial \hat{p}} + \beta(1-\hat{p})\frac{\partial Z}{\partial \hat{p}}, \\
\frac{\partial V^3(s,\hat{p})}{\partial \hat{p}} &= \beta(W - Z) + \beta \hat{p}\frac{\partial W}{\partial \hat{p}} + \beta(1-\hat{p})\frac{\partial Z}{\partial \hat{p}}.
\end{aligned}$$

To sign $\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}}$ and $\frac{\partial V^3(s,\hat{p})}{\partial \hat{p}}$, first notice that $\frac{\partial W}{\partial \hat{p}} > 0$ and $\frac{\partial Z}{\partial \hat{p}} > 0$. These inequalities follow from the assumption that $F(\tilde{p} \mid \overline{p},\ x) \leq F(\tilde{p} \mid \underline{p},\ x)$ for any $\overline{p} > \underline{p}$ and for all values of $\tilde{p}$, and from the fact that $V(s,\tilde{p})$ is increasing in $\tilde{p}$. Intuitively, higher current estimates of ability make higher estimates of ability next period more likely. Since, for a given level of schooling, the value of optimal behavior next period must be (at least weakly) increasing in next period's estimate of ability, increases in the current estimate of ability ($\hat{p}$) must raise the value of optimal behavior next period (W and Z). Also, $\frac{y(s)}{2} + \beta W - Z$, which appears in the expression for $\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}}$, must be positive; this term is just the difference between the value of optimal behavior for an individual with schooling s who began a successful part-time enrollment spell last period and the value of optimal behavior for someone with the same schooling who started an unsuccessful part-time enrollment spell last period. Putting these elements together implies $\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}} > 0$. Finally, by the definitions for W and Z, it is obvious that $W > Z$. This ensures that $\frac{\partial V^3(s,\hat{p})}{\partial \hat{p}} > 0$ also.

To see the relationship between $\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}}$ and $\frac{\partial V^3(s,\hat{p})}{\partial \hat{p}}$, note that $W \geq \frac{y(s+1)}{1-\beta}$ implies

$$\frac{\partial V^2(s,\hat{p})}{\partial \hat{p}} = \frac{\partial V^3(s,\hat{p})}{\partial \hat{p}} - \beta(1-\beta)W - \beta(1-\beta)\hat{p}\frac{\partial W}{\partial \hat{p}} + \frac{\beta y(s)}{2}$$

[10]The conditions derived below hold for each $s \in \{1,2,\ldots,N-1\}$. At $s = N$, the value of each option is unaffected by changes in p, since no further education can be acquired.

$$\leq \frac{\partial V^3(s,\hat{p})}{\partial \hat{p}} - \beta(y(s+1) - \frac{y(s)}{2}) - \beta(1-\beta)\hat{p}\frac{\partial W}{\partial \hat{p}}$$
$$< \frac{\partial V^3(s,\hat{p})}{\partial \hat{p}}.$$

Thus, it has been shown that

$$V^1(s,0) > V^2(s,0) > V^3(s,0), \;\; s \in \{1,2,\ldots,N-1\},$$

$$V^1(s,1) < V^2(s,1) < V^3(s,1), \;\; s \in \{1,2,\ldots,N-1\},$$

$$\frac{\partial V^3(s,\hat{p})}{\partial \hat{p}} > \frac{\partial V^2(s,\hat{p})}{\partial \hat{p}} > \frac{\partial V^1(s,\hat{p})}{\partial \hat{p}} = 0, \;\; \hat{p} \in (0,1), \;\; s \in \{1,2,\ldots,N-1\}.$$

An individual always chooses the option that yields the highest payoff. The above results indicate that, for $\hat{p}$ near zero, the highest valued option is full-time work while, for $\hat{p}$ near one, the highest valued option is full-time school. What happens for intermediate values of $\hat{p}$? There are two possible scenarios, which I call Case 1 and Case 2. For a given s, let $\hat{p}_{12}$ denote the value of $\hat{p}$ where $V^1(s,\hat{p}) = V^2(s,\hat{p})$, let $\hat{p}_{13}$ denote the value of $\hat{p}$ where $V^1(s,\hat{p}) = V^3(s,\hat{p})$, and let $\hat{p}_{23}$ denote the value of $\hat{p}$ where $V^2(s,\hat{p}) = V^3(s,\hat{p})$. In Case 1, $\hat{p}_{23} < \hat{p}_{13} < \hat{p}_{12}$. In this situation, the optimal decision rule is to choose Option 1 (full-time work) if $\hat{p} < \hat{p}_{13}$ and to choose Option 3 (full-time school) otherwise. Thus, if the learning model were the "true" model and the conditions of Case 1 prevailed, then part-time enrollment would never be observed. However, behavior is different in Case 2, when $\hat{p}_{12} < \hat{p}_{13} < \hat{p}_{23}$. In this setting, the optimal decision rule is to choose Option 1 if $\hat{p} < \hat{p}_{12}$, to choose Option 2 if $\hat{p}_{12} < \hat{p} < \hat{p}_{23}$, and to choose Option 3 if $\hat{p} > \hat{p}_{23}$. Thus, in Case 2, each of the different enrollment-employment combinations are observed, with the level of commitment to school declining as the estimate of ability falls. Finally, the concavity of $y(s)$ implies that $V(s,\hat{p})$ is concave in s and therefore that $\hat{p}_{12}$, $\hat{p}_{13}$, and $\hat{p}_{23}$ increase with s.[11] In

[11]See Stokey and Lucas (1989) for details of the argument for why concavity of the one-period return function implies concavity of the value function. An informal argument for why $\hat{p}_{12}$, $\hat{p}_{13}$, and $\hat{p}_{23}$ increase with s runs as follows. Consider, for example, $\hat{p}_{13}(s)$, the $\hat{p}_{13}$ corresponding to education level s. At $\hat{p}_{13}(s)$, $V^1(s,\hat{p}_{13}(s)) = V^3(s,\hat{p}_{13}(s))$. Loosely, $V^1(s,\hat{p}_{13}(s))$ is just the present discounted sum of $y(s)$, while $V^3(s,\hat{p}_{13}(s))$ is a weighted average of the present discounted sums of $y(s), y(s+1), \ldots, y(N)$. Therefore, since $y(s)$ is concave, it must be that $V^1(s+1,\hat{p}_{13}(s)) >$

other words, the higher the level of already completed education, the more optimistic an individual has to be about ability to maintain a given level of school attachment. This result is intuitive since the opportunity cost of education rises with completed schooling (since $y(s)$ increases with s), while the returns from further schooling, if successful, decline with already completed schooling (since $y(s)$ is concave in s).

Part-time to full-time enrollment transitions can occur in this model if the conditions of Case 2 hold and if, in response to the previous period's enrollment outcome, an individual's estimate of ability increases sufficiently between periods. Analogously, full-time to part-time enrollment transitions can result from a downward revision of beliefs following a negative school outcome. Of course, full-time to part-time transitions also can result simply from academic progress. Nevertheless, early in the college career, one would expect transitions from full-time to part-time enrollment to be indicative of substandard, rather than superior, academic performance. This is so because learning about ability is likely to be most pronounced early in the college career, and the returns from staying in college until degree completion are likely to be substantial. This suggests a testable implication of the learning model. Conditional on enrollment in year $t-1$, the frequency of grade advance in year $t-1$ should be higher for full-time students in year t than for part-time students in year t, even after controlling for background characteristics, the level of previous educational attainment, and time devoted to school and work in year $t-1$. This prediction should hold separately for a sample of just part-time students in year $t-1$ and a sample of just full-time students in year $t-1$.

Academic performance in year $t-1$ is correlated with enrollment status in year t, even after controlling for all of the variables (e.g., time use, previous education, etc.) in year $t-1$ that determine academic performance in year $t-1$, precisely because academic ability is uncertain but learned over time. Academic ability (which is only imperfectly known to the student), in addition to time use and personal characteristics, partially determines academic success in year $t-1$. New information

$V^3(s+1, \hat{p}_{13}(s))$. Finally, using the fact that $\partial V^1(s,\hat{p})/\partial\hat{p} < \partial V^3(s,\hat{p})/\partial\hat{p}$, it follows that $\hat{p}_{13}(s) < \hat{p}_{13}(s+1)$. A similar argument works for $\hat{p}_{12}$ and $\hat{p}_{23}$.

about academic ability, unavailable before year $t-1$ but generated by the academic progress observed in year $t-1$, partially determines enrollment status in year t. Thus, enrollment status in year t contains additional information about ability not captured by the time use and background measures from year $t-1$. Consequently, enrollment status in year t should be correlated with academic performance in year $t-1$, even after controlling for the year $t-1$ explanatory variables. More specifically, individuals with strong school attachment (full-time enrollment) in year t should have greater academic success in year $t-1$ than those with weaker school attachment (part-time enrollment) in year t.

3.3.2 A Borrowing Constraints Model

With the exception of two small but important changes, the borrowing constraints model that I develop preserves the assumptions of the learning model in their entirety. First, I assume that each individual knows his ability, p, with certainty. This contrasts with the learning model's assumption that ability is unknown initially but gradually revealed over time. If this were the only change in the assumptions, one still would never observe transitions from part-time to full-time enrollment. Thus, the second new assumption is that individuals may face borrowing constraints. A binding borrowing constraint rules out full-time enrollment as an option, but not part-time enrollment financed through current earnings. As in the learning model, the individual chooses an enrollment path to maximize the expected present discounted value of lifetime earnings, although now borrowing constraints may limit the available schooling options. In all other dimensions, the model is identical to the learning model presented earlier. In particular, the assumptions about the shape of the earnings function and the possible enrollment and employment combinations are unchanged.

For the time being, assume that p is known but that there are no borrowing constraints. As before, one can write down expressions for the value of each option as a function of schooling, s, and ability (now known), p. Also as before, if full-time employment is ever selected, it is always chosen in every future period, since in this case the individual's decision problem is stationary. In addition, though, the absence of learning has important consequences for behavior in the event that either schooling option is chosen. Specifically, given s and p, if an individual ever chooses Option 2 (part-time enrollment and part-time employment), this option is continued without interruption at least until schooling level $s+1$ is achieved. Similarly, if Option 3 (full-time enrollment) is selected, this option is pursued unbroken at least until schooling level $s+1$ is obtained. Individuals behave in this fashion because, if school investment is unsuccessful in some period, the new decision problem is exactly the same as the one faced in the previous period. As a result, if individuals were optimizing in the previous period, the same decision must be optimal in the current period.

Using these results, the value of each of the three options and the Bellman equation can be written as follows.

$$\begin{aligned}
V^1(s,p) &= \frac{y(s)}{1-\beta}, \\
V^2(s,p) &= \frac{(1+\beta p)y(s)}{2} + \beta^2 pV(s+1,p) + \beta(1-p)V(s,p) \\
&= \frac{(1+\beta p)}{1-\beta(1-p)}\frac{y(s)}{2} + \frac{\beta^2 pV(s+1,p)}{1-\beta(1-p)}, \\
V^3(s,p) &= \beta pV(s+1,p) + \beta(1-p)V(s,p) \\
&= \frac{\beta pV(s+1,p)}{1-\beta(1-p)}, \\
V(s,p) &= \max\{V^1(s,p), V^2(s,p), V^3(s,p)\}.
\end{aligned}$$

Not surprisingly, these expressions are very similar to those in the learning model. The only difference is that, in the current model, each individual knows the true value of p for certain. In the learning model, individuals only have an ability estimate, $\hat{p}$, and, as a result, one must take account of the fact that school outcomes in the current period will affect the estimate of ability in the next period.

By substitution, $V^1(s,0) > V^2(s,0) > V^3(s,0)$, for all $s \in \{1,2,\ldots,N-1\}$. In addition, the assumption that $\beta y(s+1) > y(s)$ for all $s \in \{1,2,\ldots,N-1\}$, guarantees that $V^3(s,1) > V^2(s,1) > V^1(s,1)$ for all $s \in \{1,2,\ldots,N-1\}$. These results are identical to those found for the learning model.

The partial derivatives of $V^1(s,p)$, $V^2(s,p)$, and $V^3(s,p)$ with respect to p are

$$\begin{aligned}
\frac{\partial V^1(s,p)}{\partial p} &= 0, \\
\frac{\partial V^2(s,p)}{\partial p} &= \frac{\beta^2 p}{1-\beta(1-p)}\frac{\partial V(s+1,p)}{\partial p} + \frac{\beta^2(1-\beta)V(s+1,p)}{(1-\beta(1-p))^2} - \\
&\quad \frac{\beta^2}{(1-\beta(1-p))^2}\frac{y(s)}{2}, \\
\frac{\partial V^3(s,p)}{\partial p} &= \frac{\beta p}{1-\beta(1-p)}\frac{\partial V(s+1,p)}{\partial p} + \frac{\beta(1-\beta)V(s+1,p)}{(1-\beta(1-p))^2}.
\end{aligned}$$

Now, $\frac{\partial V(s+1,p)}{\partial p} \geq 0$ because, at any given level of education, an increase in ability could never reduce the present value of optimal behavior. This fact alone ensures that $\frac{\partial V^3(s,p)}{\partial p}$ is positive. Combined with the result that $V(s+1,p) \geq \frac{y(s+1)}{1-\beta}$, it also follows that $\frac{\partial V^2(s,p)}{\partial p}$ is positive. Finally, $\frac{\partial V^3(s,p)}{\partial p} > \frac{\partial V^2(s,p)}{\partial p}$, because

$$\frac{\partial V^2(s,p)}{\partial p} = \beta\frac{\partial V^3(s,p)}{\partial p} - \frac{\beta^2}{(1-\beta(1-p))^2}\frac{y(s)}{2}.$$

Thus, the results when p is known and there are no borrowing constraints are completely analogous to those when p is unknown but revealed through experience (the learning model). First,

$$V^1(s,0) > V^2(s,0) > V^3(s,0), \quad s \in \{1,2,\ldots,N-1\},$$

$$V^1(s,1) < V^2(s,1) < V^3(s,1), \quad s \in \{1,2,\ldots,N-1\},$$

$$\frac{\partial V^3(s,p)}{\partial p} > \frac{\partial V^2(s,p)}{\partial p} > \frac{\partial V^1(s,p)}{\partial p} = 0, \quad p \in (0,1), \quad s \in \{1,2,\ldots,N-1\}.$$

Second, and as a consequence, there exists a p_{12} where $V^1(s,p) = V^2(s,p)$, a p_{13} where $V^1(s,p) = V^3(s,p)$, and a p_{23} where $V^2(s,p) = V^3(s,p)$. Third, in analyzing enrollment behavior, there are again two distinct cases to consider and the decision rule is analogous to that of the learning model. In Case 1, $p_{23} < p_{13} < p_{12}$, and the individual works full-time and doesn't enroll if $p < p_{13}$ and enrolls full-time and doesn't work otherwise. In Case 2, $p_{12} < p_{13} < p_{23}$, and the individual enrolls on a full-time basis if $p > p_{23}$, on a part-time basis if $p_{12} < p < p_{23}$, and not at all if $p < p_{12}$. Finally, as in the learning model, concavity of $y(s)$ ensures that p_{12}, p_{13}, and p_{23} increase with s.

Thus, in the absence of borrowing constraints, part-time enrollment only occurs if the conditions of Case 2 hold. However, even in Case 2, this model cannot generate part-time to full-time enrollment transitions if no one faces borrowing constraints. With no borrowing constraints, changes in enrollment status only occur as an individual completes more schooling and moves onto a flatter portion of the human capital production function. Therefore changes in enrollment status are always from stronger to weaker school attachment.[12] To explain part-time to full-time transitions, borrowing constraints must be added to the story.

To this end, suppose that an individual faced with borrowing constraints loses full-time enrollment as an option. On the other hand, part-time enrollment, financed by current period earnings from part-time employment, remains a viable option for this individual. In this setting, individuals are "constrained" only if their choice set is limited by borrowing constraints *and* if, in the absence of borrowing constraints, they would select full-time enrollment. Regardless of whether Case 1 or Case 2 applies, borrowing constraints of this type generate part-time to full-time enrollment transitions. If Case 1 holds, then all unconstrained individuals choose either full-time enrollment (if $p > p_{13}$) or no enrollment. Among the constrained individuals (who, by definition, would choose full-time enrollment if they were not constrained), those of sufficiently high ability (i.e., those with $p > p_{12} > p_{13}$) choose part-time enrollment while those of lower ability ($p_{12} > p > p_{13}$) prefer not to enroll in school. If Case 2 prevails, then unconstrained individuals may choose full-time, part-time, or non-enrollment, while all constrained individuals opt for part-time enrollment. Thus, in either setting, at least some (and perhaps all) constrained individuals choose part-time enrollment. When the constraints cease to bind, some fraction of the part-time students — in particular,

[12]Under Case 1 with no borrowing constraints, only transitions from full-time enrollment to non-enrollment would be observed. Under Case 2 with no borrowing constraints, the set of possible enrollment transitions would be full-time enrollment to part-time enrollment, full-time enrollment to non-enrollment, and part-time enrollment to non-enrollment.

those confronted with borrowing constraints only briefly and/or those who made little academic progress while constrained — will find it worthwhile to return to full-time education. Thus, the existence of borrowing constraints is enough to cause part-time to full-time enrollment transitions.

One concludes, then, that both the learning model and the borrowing constraints model are consistent with transitions from part-time to full-time enrollment. Nevertheless, the models are not identical in their empirical implications. Recall that the learning model predicts a *higher* frequency of grade advance in year $t-1$ for those who enroll as full-time students in year t than for those who enroll on a part-time basis in year t, even after controlling for personal characteristics and time use in year $t-1$. This relationship should hold both for full-time students in year $t-1$ and for part-time students in year $t-1$. In contrast, for a sample of *full-time* students in year $t-1$, the borrowing constraints model predicts a *lower* frequency of grade advance in year $t-1$ for those who enroll as full-time students in year t than for those who enroll as part-time students in year t, after controlling for explanatory variables dated at year $t-1$.

To understand this prediction of the borrowing constraints model, suppose first that the conditions of Case 1 hold and consider a group of students who enroll in school full-time in year $t-1$ and have all completed the same level of education at the start of year $t-1$. Since the students enroll full-time in year $t-1$, it follows that they all must be unconstrained and have $p > p_{13}$. Within this group of students, consider those who choose part-time enrollment in year t. Such individuals must be constrained in year t, since the unconstrained never choose part-time enrollment in Case 1. In addition, they must be from the upper tail of the ability distribution of full-time students in year $t-1$ ($p > p_{12} > p_{13}$), since those in the lower tail ($p_{12} > p > p_{13}$) switch to non-enrollment if they face borrowing constraints. In contrast, those who choose full-time enrollment in year t are not constrained and are drawn from essentially the entire ability distribution of full-time students in year $t-1$ ($p > p_{13}$). Thus, switching from full-time to part-time enrollment status between $t-1$ and t signals not only that the individual is borrowing constrained but also that the individual is of "high" ability.

On the other hand, continuing as a full-time student, while indicating the absence of a borrowing constraint, conveys much less information about ability. One can infer, therefore, that those who switch to part-time enrollment status are of higher average ability than those who continue as full-time students. As a result, prior to becoming constrained, those who switch to part-time enrollment should have made greater academic progress than those who remain full-time students, other things equal.

Next, suppose that the conditions of Case 2 are satisfied, and again limit attention to those with a given level of already completed education who enroll full-time in year $t-1$. These students evidently are unconstrained in year $t-1$ and of ability $p > p_{23}$. Within this group of students, those who choose full-time enrollment again in year t are necessarily unconstrained in year t. On the other hand, those who choose part-time enrollment in year t may be either constrained (those who would prefer full-time enrollment but face borrowing constraints) or unconstrained (those in the "middle" ability group who optimally select part-time enrollment under Case 2). Those who choose part-time enrollment in year t because of borrowing constraints are of the same ability, on average, as those who enroll full-time in year t.[13] Thus, they are as likely to have advanced in year $t-1$ as those who continue as full-time students in year t. In contrast, anyone in the unconstrained group who voluntarily reduces his enrollment status to part-time in year t *must* have advanced a grade in year $t-1$; if the individual did not advance a grade in year $t-1$, then the decision problem in year t is unchanged from the problem in year $t-1$, and the optimal policy from year $t-1$ must continue to be optimal in year t. Taking the constrained and unconstrained part-time students together, then, one concludes that the frequency of grade advance in year $t-1$ should be higher for those who switch from full-time in year $t-1$ to part-time in year t than for those who continue as full-time in year t, other things equal.

Thus, the prediction of the borrowing constraints model that, for *full-time* students

[13]This assumes that an individual's ability is independent of the "susceptibility" to borrowing constraints.

in year $t-1$, weaker school attachment in year t should be correlated with better academic performance in year $t-1$ seems to be quite robust. In contrast, the learning model predicts that stronger school attachment in year t should be indicative of better performance in year $t-1$, for a sample of full-time students in year $t-1$. This prediction of the learning model also holds when the sample is restricted to part-time students in year $t-1$. Unfortunately, the implication of the borrowing constraints model concerning the correlation between grade advance in year $t-1$ and enrollment status in year t for *part-time* students in year $t-1$ is difficult to discern. The reason for the complexity is that (at least under Case 2) part-time enrollment could be, but is not necessarily, indicative of borrowing constraints. For example, an individual who enrolls part-time in consecutive years could be constrained in both years, in just the first year, or in neither year. Fully enumerating the different possible causes of each enrollment history, and determining the probability of each cause, appears quite difficult. Thus, although the learning model predicts that grade advance in year $t-1$ should be less frequent for those who remain enrolled as part-time students in year t than those who switch to full-time status in year t, it is far from clear that this prediction is unique to the learning model.

To summarize, predictions about labor market outcomes have been analyzed in four distinct theoretical settings: the learning model under Case 1 and under Case 2, and the borrowing constraints model under Case 1 and under Case 2. Under Case 1 the learning model does not generate part-time enrollment at all, much less transitions from part-time to full-time enrollment, and thus is inconsistent with the observed data. The learning model under Case 2 allows for part-time to full-time enrollment transitions, and also predicts that individuals who move from full-time enrollment in year $t-1$ to part-time enrollment in year t are *less* likely to have advanced a grade in year $t-1$ than individuals who are full-time students in both years, all else equal. This latter prediction follows because the year t enrollment decision depends partly on new information about ability, conveyed through academic performance in year $t-1$, which is not contained in the explanatory variables from year $t-1$.

The borrowing constraints model offers an alternative explanation for part-time to full-time enrollment transitions; however, in both Case 1 and Case 2, the borrowing constraints model predicts that individuals who switch from full-time enrollment in year $t-1$ to part-time enrollment in year t are *more* likely to have advanced a grade in year $t-1$ than individuals who attend full-time in both years, other things the same. In Case 1 this prediction arises because those who switch to part-time enrollment are constrained individuals selected from the upper tail of the ability distribution, and therefore should have had above average success in school before becoming constrained. In Case 2, the prediction follows because some individuals switch from full-time to part-time enrollment voluntarily, and those who do must have advanced in school in the previous period. Thus, the learning model and the borrowing constraints model are empirically distinguishable.

While a testable difference between the learning and borrowing constraints models has been highlighted, still other models can be contemplated. It is conceivable that these alternative models might yield identical predictions to one or both of the models developed above. In an Appendix, I very briefly discuss two alternative models. The first model replicates the predictions of the borrowing constraints model. The second model appears to be a borrowing constraints model that reproduces the predictions of the learning model. On closer examination, however, this second model implicitly relies on learning itself. Thus, the learning model appears to have an empirical implication distinct from those of models in which no learning occurs. I now return to the NLSY data to test this prediction.

3.4 Empirical Tests

I begin, in Table 3.6, by presenting frequencies of grade advancement in year $t-1$ for each of the four possible across period enrollment combinations (part-time in both years, full-time in both years, part-time followed by full-time, or full-time followed by part-time). While this table does not control for many of the other factors that may influence the probability of grade advancement, it clearly illustrates that there exists a correlation between academic performance in year $t-1$ and enrollment status in year t, even after controlling for enrollment status in year $t-1$. The first row of the table isolates part-time college students in year $t-1$. Within this group, 31.5% of those who enroll as part-time students again in year t advanced a grade in year $t-1$ while the percentage is 40.9% for those who enroll as full-time students in year t. A χ^2 test of the hypothesis that success in year $t-1$ is unrelated to enrollment status in year t has a p-value of .065; thus, the difference in the probability of grade advance is marginally significant at conventional significance levels. The higher probability of grade advance in year $t-1$ for part-time students who switch to full-time in year t in comparison to those who continue as part-time students is consistent with the prediction of the learning model. However, since the borrowing constraints model makes no clear prediction for students who were enrolled part-time in year $t-1$, this finding does not constitute evidence against the borrowing constraints model.

The second row of the table focuses on full-time college students in year $t-1$. Among these students as well, the frequency of grade advance in year $t-1$ is higher for those who enroll on a full-time basis in year t than for those who only enroll on a part-time basis in year t. For the former group, 78.8% of the individuals advanced a grade in year $t-1$, while for the latter group the figure is 60.3%. For this sample, the χ^2 test unequivocally rejects the hypothesis that grade advance in year $t-1$ and enrollment status in year t are unrelated (p-value ≈ 0). This finding goes against the prediction of the borrowing constraints model but is consistent with the learning model. For both part-time and full-time students in year $t-1$, the magnitude of the difference in year $t-1$ grade advance frequencies for full-time and part-time students in year t seems large.

Although the frequencies presented in Table 3.6 agree with the predictions of the learning model, it is possible that the results simply reflect the effects of other omitted determinants of grade advancement. To account for this possibility, I present logit estimates of the determinants of grade advancement in Table 3.7. The dependent variable is whether or not an enrolled college student advances a grade in year $t-1$. The control variables fall into two main classes. First, I include individual characteristics (measured intellectual ability, age, race, amount of previously completed education, etc.) and family background variables (parental education, whether the individual comes from a "broken home", etc.) which are likely to affect academic performance.[14] Second, I include measures of time allocated to work and school in period $t-1$. Clearly, these variables — weeks elapsed since the previous interview, weeks worked and average hours worked per week since the previous interview, and a measure of the number of months enrolled in college since the previous interview — should affect the probability of grade advancement in year $t-1$. In addition to these variables, I include the individual's enrollment status in year t as an explanatory variable. Both the learning model and the borrowing constraints model make predictions about how this variable should be related to the previous period's academic performance. I estimate the equations separately for full-time college students in year $t-1$ and part-time students in year $t-1$. In addition, for both the full-time and the part-time samples, I present the results for two different specifications of the effect of months enrolled on grade advance. In the first, months enrolled enters the equation linearly, while in the second months enrolled enters as a sequence of dummy variables.[15]

The estimates for the sample of full-time students in year $t-1$ are of greater interest, since it is for this group that the learning and borrowing constraints models make different predictions. In addition, these estimates are sharper, probably partly because the sample is much larger than the sample of part-time students. While some of the coefficient estimates are imprecise, certain relationships stand out. Other things equal, students from broken homes, older students, students with greater previous educational attainment, and students of lower measured ability are less likely to

[14]The measure of ability is the residual from a regression of each individual's Armed Forces Qualifications Test (AFQT) score on a constant, the age of the respondent at the time the test was taken, and the highest grade completed by the respondent at the time the test was taken. The AFQT score is a standard aptitude measure which was obtained from a battery of tests which were administered to (nearly) the entire sample in the NLSY in 1980. At the time of the test, the age of sample members ranged between 15 and 22, and the highest grade completed varied accordingly. The residual is a more appropriate measure of "native ability" than the raw AFQT score since it compares individuals within the same age and completed education categories.

[15]Separate dummy variables were created for each of the following months enrolled categories: 1–3 months, 4–6 months, 7–9 months, and 13 or more months. The excluded category, 10–12 months of enrollment, represents about half of the observations.

advance a grade. In addition, regardless of whether months of enrollment enters the equation linearly or as a sequence of categorical variables, more months of enrollment is uniformly associated with a higher probability of grade advance.[16] The estimated effects of weeks and hours at work on the probability of grade advance are negative, as theory predicts, but these estimates are not statistically significant. Time since the last interview has a stronger negative effect on the probability of grade advance, although the theory offers no explanation for this finding. Of course, weeks elapsed since the last interview and weeks worked since the last interview are positively correlated. If the weeks elapsed variable is dropped, the weeks worked and hours per week variables become marginally significant.

The key variable, however, is the dummy for full-time enrollment status in year t. Even after controlling for the other variables, the probability that a full-time student in year $t-1$ advances a grade in year $t-1$ is significantly higher for a student who subsequently enrolls full-time in year t than for one who only enrolls part-time in year t. For a representative full-time student in year $t-1$, the probability that no grade advance occurred in year $t-1$ is about .10 for a student who enrolls full-time in year t but about .15 one who switches to part-time in year t.[17] This finding is consistent with the implication of the learning model but contradicts the prediction of the borrowing constraints model.

From the point of view of testing the theory, the estimates for the sample of part-time students in year $t-1$ are less useful. Moreover, these estimates are less precise. In light of the small sample size, the reduced precision is not surprising. Still, it is worth analyzing the results. The effects of several of the individual and family background variables differ from those for the sample of full-time students. Among part-time students, those with more educated parents and those who are nonwhite

[16]However, the coefficient estimates in the specification in which months enrolled enters categorically suggest that the effect of months enrolled probably is not linear. For instance, the probability of grade advance is much higher for those who are enrolled 10–12 months than those who are enrolled for only 7-9 months, but is virtually identical for those who are enrolled 13 or more months and those who are enrolled 10–12 months.

[17]The "representative" student comes from a two parent home, has parents with a high school education, is unmarried, is white, and has the mean values of all of the continuous explanatory variables.

may be more likely to advance a grade, all else equal.[18] As was the case for full-time students, older and less able part-time students are less likely to advance a grade, other things the same. The effects of time spent at school and time spent at work also seem similar to those found for full-time students. Finally, recall that the learning model predicts that full-time enrollment in year t should be correlated with a greater frequency of grade advance in year $t-1$, while the borrowing constraints model makes no clear prediction. Returning to the table, one sees that the estimated coefficient on full-time enrollment status in year t, though positive, is far from statistically significant.

3.5 Conclusion

Time devoted to school and work varies substantially within the college student population. For instance, while a majority of college students are enrolled in school full-time, a significant fraction attend only on a part-time basis. With respect to labor force behavior, although a majority of college students work while in school, some do not, and the labor force commitment of part-time students is appreciably stronger than that of full-time students. This large variation across students in the allocation of time indicates that a simple choice model of full-time school versus full-time work cannot explain the data. Nevertheless, this behavior does not pose a large problem for life cycle model of earnings and human capital accumulation, since even slight generalizations of the theory can explain this variation in the cross-section data.

More puzzling from the perspective of the life cycle model are the data on individual enrollment histories. In particular, transition from part-time enrollment status to full-time enrollment status is quite common; over one-third of all part-time students in a given year who continue in college in the following year switch to full-time enrollment status. In contrast to the other findings, this last one is difficult to explain within the context of standard life cycle models of earnings and human capital, since

[18]This last finding suggests that nonwhite part-time students might be of higher unmeasured ability than white part-time students. This result would be consistent with the existence of greater borrowing constraints for nonwhites than for whites.

these models predict that, for any given individual, time devoted to school should be nonincreasing over the life cycle.

This essay develops two extensions of the life cycle model that are consistent with part-time enrollment and, more importantly, with transitions from part-time to full-time enrollment. In the first model, the probability of success in school depends on ability, but ability is unknown *ex ante* and only learned by observing the outcomes of previous terms of school enrollment. In this setting, individuals with more optimistic beliefs about ability optimally devote more time to school and less to work. A transition from part-time to full-time enrollment occurs when a successful spell in school leads an individual to revise his beliefs about ability sufficiently upwards so that full-time enrollment becomes optimal. In the second model, the probability of success in school again depends on ability, but each individual knows his ability. In addition, though, there is some probability in each period that an individual will face borrowing constraints that make full-time enrollment impossible. As in the first model, individuals of higher ability optimally devote more time to school. In this model, however, a transition from part-time to full-time enrollment occurs when a borrowing constraint ceases to bind an individual whose most preferred option is full-time enrollment in school.

Thus, both models can explain the existence of part-time to full-time enrollment transitions. At the same time, the models have different implications concerning full-time to part-time enrollment transitions. In particular, the learning model predicts that a full-time to part-time enrollment transition should be indicative of worse academic performance in the first period than a full-time to full-time transition. In constrast, the borrowing constraints model implies that a full-time to part-time enrollment transition should be evidence of greater academic progress in the first period than a full-time to full-time transition.

The evidence from a sample from the NLSY clearly supports the learning model; *ceteris paribus*, full-time students who continue on a full-time basis are more likely to have advanced a grade in the previous period than those who switch to part-time enrollment status. To be sure, some transitions from part-time to full-time enrollment undoubtedly result from borrowing constraints. However, gradual learning about ability, coupled with the sequential nature of the enrollment decision, is the probable explanation for most of these transitions. Thus, the present findings offer support for the idea that individuals learn about their abilities in school.

Appendix: Some Additional Models

This appendix considers very briefly some additional models that are capable of generating part-time to full-time enrollment transitions. Attention is focused on their predictions about the relationship between current enrollment status and previous academic performance.

A "Program Completion Shock" Model

Suppose that programs of study can be undertaken on either a full-time or a part-time basis. Suppose further that large-scale changes in school attachment (switches from part-time to full-time enrollment, or the reverse) are more likely to occur when one program of study ends and another begins. This assumption seems reasonable if some programs can only be pursued only on a part-time basis or only on a full-time basis, or if part-time and full-time versions of the same program are sufficiently different so that switching enrollment status midway through a program is difficult. Finally, as with the models discussed earlier, assume that grade advance in any year, conditional on enrollment, occurs with probability less and one.

Under these conditions, changes in enrollment status between year $t-1$ and year t should indicate greater academic progress in year $t-1$ than continuity in enrollment status across consecutive years. This prediction should hold both for full-time students in year $t-1$ and for part-time students in year $t-1$. Thus, the predictions of the "program completion shock" model run exactly counter to the predictions of the learning model. On the other hand, the prediction of the program completion shock model about the relationship between enrollment status in year t and academic performance in year $t-1$ for full-time students in year $t-1$ agrees with the prediction of the borrowing constraints model. Notice that the evidence in Table 3.7 does not support the predictions of the program completion shock model.

A Scholarship Model

Consider a model of scholarships or financial aid, in which more assistance is given to students with better (previous) academic performance. Thus, better academic performance in year $t-1$ implies that one is less likely to face borrowing constraints in year t. As a result, better academic performance in year $t-1$ might be expected to increase the probability full-time enrollment in year t. Similarly, worse academic performance in year $t-1$, by reducing a student's financial aid, might lead to weaker school attachment, on average, in year t. Thus, it seems plausible that a scholarship model that makes borrowing constraints endogenous can reproduce the prediction of the learning model that, conditional on enrollment status in year $t-1$, strength of enrollment in year t is positively correlated with academic performance in year $t-1$.

In light of this model, can the results from Table 3.7 still be interpreted as evidence for a learning-induced enrollment transitions? I argue that the answer is yes, in the following sense. In this model of endogenous borrowing constraints, the degree of constraint varies with prior academic performance precisely because the granting agency learns about students through their academic performance. Thus, this model still can be viewed as a learning model, albeit a different one than that developed in the main body of this essay. So, while the evidence in Table 3.7 might not distinguish among different learning models, it does offer support for the idea that enrollment transitions are driven partly by learning.

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Table 3.1: Frequency of different college enrollment patterns (in percentages) for males immediately after completing high school, by number of years observed after completing high school

Years Observed	College Enrollment Pattern: Never in School	Continuous Enrollment	Delay or Interruption	*N*
1	66.7	33.3	—	57
2	59.7	35.1	5.3	57
3	53.3	35.9	10.9	92
4	57.6	27.3	15.1	205
5	40.2	46.0	13.8	450
6	40.3	41.9	17.8	477
7	34.6	43.2	22.2	451
8	41.0	37.5	21.5	400
9	32.7	41.2	26.1	245

Data is from the NLSY, 1979-1988. The sample is restricted to a sample of males who obtained their high school degrees during the sample period. The table reflects their enrollment experience for the sample period after completing high school. The column "Never in school" consists of those individuals who attended no further school in the remaining sample period. The column "Continuous enrollment" consists of those individuals who began college in the interview year immediately following the year in which high school was completed, had one or more consecutive interview years of college enrollment, and never returned to college (in the remaining sample period) after the first interview year with no college enrollment. The column "Delay or interruption" consists of individuals with any other college enrollment history. The percentages in each row may not sum to 100.0 because of rounding. *N* gives the number of individuals in each row.

Table 3.2: Frequency (in percentages) of detailed college enrollment status in the current interview year by detailed college enrollment status in the previous interview year, for males with a high school degree

Enrollment/Student Status Last Year	Enrollment Status, Student Status This Year: Not Enrolled	Enrolled, Part-Time	Enrolled, Full-Time	Enrolled, Unknown	N
Not Enrolled	94.7	1.7	1.3	2.2	12704
Enrolled/Part-Time	39.6	28.7	14.7	17.1	897
Enrolled/Full-Time	17.6	6.7	62.4	13.4	3481
Enrolled/Unknown	57.6	4.2	6.8	31.3	1015

Data is from the NLSY, 1979-1988. The sample contains all observations (person-years), except for the last person-year (when it is impossible to determine enrollment status in the next interview year), for a sample of males who already have at least a high school degree. The table can be interpreted as a transition matrix giving the probability of each college enrollment status in the current interview year conditional on a given college enrollment status in the previous interview year (a given row). The percentages in each row may not sum to 100.0 because of rounding. N gives the number of observations in each row (college enrollment status) in the full sample.

Table 3.3: Frequency (in percentages) of full-time and part-time student status by previous highest educational attainment, for males enrolled in college since the previous interview

	Student Status at Most Recent College			
Previous Highest Grade	Part-Time	Full-Time	Unknown	N
12	20.2	56.7	23.2	2442
	(26.2)	(73.8)		
13	17.2	67.5	15.3	1303
	(20.3)	(79.7)		
14	10.7	70.1	19.3	1042
	(13.2)	(86.8)		
15	6.8	57.2	36.0	739
	(10.6)	(89.4)		
16	13.0	30.6	56.5	301
	(29.8)	(70.2)		
> 16	5.0	20.0	75.0	120
	(20.0)	(80.0)		

Data is from the NLSY, 1979-1988. The sample contains all observations (person-years) for a sample of males who already have at least a high school degree. The percentages in each row give the frequencies of different enrollment states (full-time, part-time, or full-time versus part-time unknown) at each previous highest grade level. For example, the row with previous highest grade of 12 represents individuals in their first year of college. The numbers in parentheses are the relative frequencies of part-time versus full-time enrollment at each grade level. Thus, in calculating these percentages, the observations for which part-time versus full-time status is unknown are ignored. The percentages in each row may not sum to 100.0 because of rounding. N gives the number of observations in each row.

Table 3.4: Frequency (in percentages) of grade advancement, by student status (full-time, part-time, or unknown) and previous highest educational attainment, for males enrolled in college since the previous interview

		Student Status at Most Recent College			
Previous Highest Grade		Part-Time	Full-Time	Unknown	All
12	% Advance	24.4	70.9	29.3	51.9
	N	492	1384	566	2442
13	% Advance	33.0	79.6	50.0	67.1
	N	224	882	200	1306
14	% Advance	26.1	72.9	43.8	62.3
	N	111	730	201	1042
15	% Advance	46.0	68.8	68.0	67.0
	N	50	423	266	739
16	% Advance	15.4	52.2	42.9	42.2
	N	39	92	170	301
> 16	% Advance	33.3	83.3	73.9	73.7
	N	6	24	88	118
All	% Advance	27.5	72.8	45.1	58.9
	N	922	3535	1491	5948

Data is from the NLSY, 1979-1988. The sample contains all observations (person-years) for a sample of males who already have at least a high school degree. "% Advance" gives the frequency of grade advance for individuals in a particular cell. *N* gives the number of observations in a particular cell.

Table 3.5: Average weeks worked, average hours per week worked, and frequency of "full-time work" during the interview year, by detailed college enrollment status and previous highest grade completed, for males with a high school degree

Previous Highest Grade		Enrollment Status, Student Status This Year: Not Enrolled	Enrolled, Part-Time	Enrolled, Full-Time	Enrolled, Unknown
12	Weeks	42.7	35.5	27.2	37.7
	Hours	38.7	32.1	27.9	35.2
	% Full-Time	65.3	51.0	10.4	45.1
	N	12315	488	1374	557
13	Weeks	44.3	39.5	29.1	40.5
	Hours	39.0	33.9	27.4	34.0
	% Full-Time	66.0	49.3	11.6	49.0
	N	1106	223	877	194
14	Weeks	48.3	40.1	29.1	42.0
	Hours	40.9	32.4	26.7	32.9
	% Full-Time	71.5	49.5	10.2	43.7
	N	657	109	722	199
15	Weeks	49.8	44.6	32.4	42.9
	Hours	42.2	36.2	30.3	35.4
	% Full-Time	71.2	49.0	17.5	42.1
	N	226	49	417	261
16	Weeks	53.3	52.4	31.5	49.8
	Hours	44.0	42.3	30.6	37.6
	% Full-Time	84.6	84.6	19.8	53.6
	N	772	39	91	166
> 16	Weeks	56.6	44.8	24.3	39.2
	Hours	43.0	42.3	14.1	31.5
	% Full-Time	88.9	66.7	12.5	39.3
	N	81	6	24	89

Data is from the NLSY, 1979-1988. The sample contains all observations (person-years) for a sample of males who already have at least a high school degree. The "Weeks" row gives the average number of weeks worked by individuals in each cell. The "Hours" row gives the average number of hours per week worked by by individuals in each cell. The "% Full-Time" row gives the percentage of individuals in each cell who worked in at least 75% of the works since the last interview, and averaged at least 35 hours per week in those weeks. *N* gives the number of observations in each cell.

Table 3.6: Frequency of grade advance (in percentages) for college students in the *current* interview year conditional on student status (full-time or part-time) in the *current* interview year and in the *next* interview year

Student Status This Year		Student Status Next Year Part-Time	Full-Time	All
Part-Time	% Advance	31.5	40.9	34.7
	N	257	132	389
Full-Time	% Advance	60.3	78.8	77.0
	N	232	2173	2405
All	% Advance	45.2	76.7	71.2
	N	489	2305	2794

Data is from the NLSY, 1979-1988. The sample contains all observations (person-years) for a sample of males who have at least a high school degree, who are enrolled in college in consecutive years, and who have valid data on full-time versus part-time enrollment status for both years.

Table 3.7: Logit estimates of the probability of grade advance since the previous interview, given enrolled in college since the previous interview

Enrollment status this year:	Full-Time		Part-Time	
Not both parents in household at age 14	-.4195	-.4343	-.3866	-.4046
	(.2062)	(.2073)	(.5394)	(.5430)
Parent with more education has less than high school	-.1578	-.1693	-.0717	-.0863
	(.2211)	(.2230)	(.4835)	(.4858)
Parent with more education has some college	.0352	.0501	-.1594	-.1727
	(.2009)	(.2018)	(.4507)	(.4508)
Parent with more education has college degree or more	-.0442	-.0153	.6144	.6228
	(.1554)	(.1566)	(.3556)	(.3569)
Married	-.1242	-.0804	-.6649	-.5544
	(.3151)	(.3129)	(.5084)	(.5090)
Nonwhite	-.0973	-.0731	.6777	.6345
	(.1679)	(.1689)	(.3720)	(.3774)
Age	-.3369	-.3300	-.2054	-.2090
	(.0537)	(.0534)	(.1029)	(.1038)
Education at last interview	-.2442	-.2360	-.0971	-.1078
	(.0748)	(.0742)	(.1716)	(.1724)
AFQT residual	.0274	.0272	.0281	.0270
	(.0049)	(.0050)	(.0118)	(.0119)
Weeks elasped since last interview	-.0497	-.0359	-.0850	-.0814
	(.0159)	(.0159)	(.0370)	(.0379)
Weeks worked since last interview	-.0036	-.0040	-.0046	-.0043
	(.0036)	(.0036)	(.0116)	(.0117)
Hours per week worked since last interview	-.0036	-.0060	-.0162	-.0170
	(.0044)	(.0044)	(.0141)	(.0140)
Months enrolled since last interview	.3247		.2107	
	(.0267)		(.0488)	
Months enrolled dummies	No	Yes	No	Yes
Enrolled full-time next year	.4[illegible]43	.4846	.1360	.1618
	(.1962)	(.1963)	(.3201)	(.3202)
Constant	11.311	14.107	8.585	10.838
	(1.323)	(1.393)	(3.245)	(3.364)
log L	-808.4	-800.7	-150.3	-151.1
N	1956	1956	274	274

Note to Table 3.7

Data is from the NLSY. The sample period covers only the years 1981-1987 because monthly enrollment data is only available beginning with the 1981 interview, and the use of enrollment status in the *next* interview year as an explanatory variable forces one to drop data from the last interview year (1988). The left hand columns restrict the sample to individuals who are full-time students in the current interview ye . The right hand columns limit the sample to individuals who are part-time students in the current interview year. Additional explanatory variables, included but not reported, are dummy variables for: working female in household at age 14, working male in household at age 14, newspaper received in household at age 14, residence in the South, and residence in an urban area. The AFQT residual, an ability measure, is the residual from a regression of AFQT score on the individual's age at the time the test was administered, the individual's highest grade completed at the time the test was administered, and a constant. The months enrolled dummies cover the following categories: 1–3 months enrolled, 4–6 months enrolled, 7–9 months enrolled, and 13 or more months enrolled. The base group is 10–12 months enrolled. The results are qualitatively identical if year dummies are included. Standard errors are in parentheses.

Conclusion

This thesis provides evidence that learning influences labor force behavior and labor market outcomes early in worker careers. Previous theoretical and empirical work has shown that learning models offer an explanation for early career patterns of turnover and wage growth. The present work shows that, in addition, the learning framework can provide a consistent theoretical explanation for the black-white wage differential observed in earnings data and for the volatile longitudinal enrollment behavior exhibited by a significant fraction of youth.

The black-white wage gap observed in earnings data can be explained by a dynamic model of statistical discrimination, in which the productivity of a job match is learned by observing performance on the job and in which individuals engage in job mobility to maximize expected discounted lifetime earnings. The model has a large number of additional testable implications. Evidence on these predictions from the National Longitudinal Survey of Youth (NLSY) is mixed. Certain predictions, not shared by other models of discrimination, receive empirical support. On the other hand, some predictions of the model, on which alternative models are silent, do not receive support. On balance, the evidence suggests that the mechanism underlying the learning model — that the quality of new job matches is more uncertain for blacks than for whites — may be a partial explanation for the different pattern of labor market outcomes for blacks and whites in the early part of careers.

Re-enrollment in school after long interruptions in attendance also can be explained by a learning model, here one in which the quality of an individual's match to a particular employment sector (broad occupational category) is only learned by working in the sector. If different sectors require different levels of education, and if academic ability is uncertain, then individuals who optimally leave school to work in a given sector and discover that the match is poor optimally return to school after this fact is revealed. The model has two key implications. First, individuals who return to school after an interruption are of lower ability, and therefore are less likely to succeed in school, than those who attend through the same level of school uninterrupted. Second, those who re-enroll earn less prior to returning than observationally equivalent individuals who do not re-enroll. These predictions receive strong support in the NLSY data. Under enough assumptions, a borrowing constraints model might mimic these predictions, but more general versions of a borrowing constraints model cannot. Thus, the evidence suggests that the phenomenon of interruption and re-enrollment is partly the result of learning. At the same time, however, the data does not warrant the conclusion that learning is the sole source of this enrollment behavior; borrowing constraints seem to be important as well.

Finally, transitions from part-time to full-time school enrollment can be explained by a simple learning model in which academic ability is unknown but gradually revealed by past performance in school. Commitment to school increases in response to strong academic performance in the previous period, and is reduced when past academic performance is weak. Thus, other things equal, weaker school attachment in the current period should be correlated with worse academic performance in the previous period. In contrast, a borrowing constraints model actually predicts that less attachment to school in the current period should be correlated with stronger academic performance in the previous period. Evidence from the NLSY supports the learning model, suggesting that learning is an important cause of transitions from part-time to full-time enrollment.

On balance, then, the empirical evidence offers support for the idea that individuals learn in labor markets and that learning plays an important role in shaping future labor market behavior. At the same time, however, it is clear that the simple learning models developed here offer only partial explanations for the empirical phenomena which motivated the modelling efforts. Nevertheless, the finding that learning is a significant consideration in labor markets raises a host of questions about the actual learning process. Are there cross-sectional differences in how fast parties learn? Are there cross-sectional differences in how much parties know initially? Do these differences, if they exist, depend on observable characteristics? Answers to these questions must await further research.