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WP 14-15

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Abstract

Data reveal that individuals experience a high number of occupational switches. Over 40% of high school graduates transition between white and blue collar occupations more than once between the ages of 18 and 28. This paper develops a life cycle model of occupational choices based on workers learning about their type and sorting themselves to the best job match. Documenting life cycle patterns of occupational choices using data from the NLSY79 supports key predictions from the model. Initial characteristics are predictive of future patterns of occupational switching, including the timing and number of switches. In addition, the average time to the first occupational switch is longer than the time to the second switch for individuals with multiple occupational transitions.

Keywords: Learning, Occupational Mobility, Labor Markets, Life Cycle.

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JEL Codes: E24, J24, J31, J62.

1 Introduction

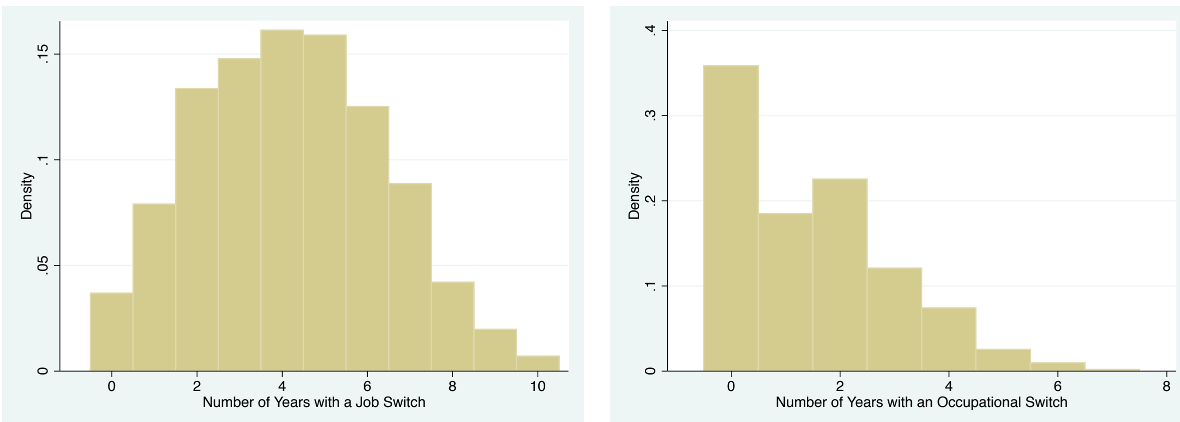
Workers are transitioning across occupations at increasing rates in recent decades.[1] While it has long been known that job mobility plays a crucial role in the wage growth of young workers (see Topel and Ward (1992)), occupational choices are also important for human capital development during a worker's first 10 years in the labor market.[2] Therefore, explaining occupational changes is crucial for understanding human capital accumulation, patterns of job switching, and worker turnover. Leading explanations of why workers switch occupations are based on career ladders as in Jovanovic and Nyarko (1997) and workers learning about their type as in Johnson (1978).

To illustrate the importance of occupational switches, Figure 1 shows histograms for the number of years that individuals with a high school education are observed making job and occupational switches between the ages of 18 and 28. The left panel shows the number of years that each individual has at least one job switch. The right panel shows the number of years where each individual is observed to switch between the broad categories of blue and white collar occupations. The mean for the number of years (out of 10 possible) that include a job switch is 4.2 while the mean number of years with an occupational switch is 1.5. The magnitude of occupational switches implies that they play an important role in job mobility for young workers. While about 36% do not switch occupations, 18% of workers switch occupations exactly one time, and despite only having two broad occupational categories, a large portion of workers switches occupations more than once, with 23% switching exactly twice and another 23% of the population switching more than twice. The rates of transition between finer categories would be even higher. Looking at individual workers' occupational

[1] Kambourov and Manovskii (2008) show that occupational mobility has been increasing in the United States between 1968 and 1997.

[2] Recent research shows that much of the human capital gained through experience occurs at the level of a worker's occupation or industry. Papers by Neal (1995) and Parent (2000) argue that human capital is largely based at the industry level rather than being firm specific, while more recent research by Kambourov and Manovskii (2009b,a) argues that human capital is based at the occupational level and can account for a large amount of observed wage inequality. Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) have shown skills to be task specific. Even under this view skills show strong correlation within occupational categories.

Figure 1: *Histograms of the number of years with job and occupation switches between the age of 18 and 28. Left panel shows the histogram of the number of years that contain at least one job switch. The right panel shows the number of years where workers switch occupations between blue and white collar.*



choices over their life cycle reveals additional information about individual-level occupational patterns beyond the well-known fact that occupational switches decline with age in the cross-section.

In contrast to the main body of literature that uses cross-sectional data to study occupational transitions, this paper uses panel data to study occupational patterns of individuals over their life cycle and understand the role of learning in occupational choices. This new life cycle evidence is consistent with a model where workers learn about their ability and must sort themselves into the occupation where they have a comparative advantage. We construct a simple model where workers choose an initial occupation based on their initial belief about their ability and learn further about their ability while working. Workers learn by observing their output while working in an occupation each period. We follow Pries (2004) in assuming that output noise is uniform so there is a constant probability of a worker receiving a fully revealing signal about her type in each period. However, since the worker receives such a revealing signal at different rates while working in different occupations, she updates her beliefs in each period that her true type is not revealed. This learning process can cause her to switch occupations.

The model generates a number of testable predictions about how initial information relates to the likelihood and timing of future switches. The model predicts that workers with initial beliefs that their type is more strongly aligned with their initial occupational choice are less likely to ever switch and on average take longer to switch if they do. More surprisingly, we find that for small enough costs of switching occupations that the average time to the second or later switches is shorter than the time to the first switch. This result contrasts with the well-known cross-sectional pattern of decreasing occupational switches with age. The model implies that if workers haven't settled on a final occupational choice, the fact that they just switched means they are less sure about which occupation is better for them and hence are more likely to switch again as long as switching costs are low. Finally, we find that the expected number of total switches for an individual is a function of how close their initial belief aligns with their initial occupation.

We examine data from the the National Longitudinal Survey of Youth, 1979 (NLSY79) to evaluate the life cycle predictions from the model. We test the predictions using broad occupational categories of white and blue collar jobs as in Keane and Wolpin (1997), but the findings are robust to other occupational categorizing schemes such as routine and nonroutine tasks or cognitive and noncognitive tasks. First, we construct initial probabilities of each individual choosing a job in a white collar sector based on observable characteristics before starting work. Using these constructed probabilities as a measure of the worker's initial belief about her type, we test the life cycle predictions of the model. The data support each of the predictions. First, workers who are more likely to be in their initial occupation are less likely to ever switch, and for those who do switch the average time until their first switch is longer. Next, for workers who have more than one switch the average time to their first switch is indeed longer than the average time to the second switch. We view this as the strongest piece of evidence in favor of learning playing an important role in worker occupational choices over the life cycle because it contrasts with cross-sectional evidence of a decreasing hazard of switching as workers age. Finally, the number of observed switches is inversely proportional to the expected probability of choosing the initial occupation.

This paper contributes to an ongoing literature to understand the selection process of workers across occupations. Early studies such as Johnson (1978) and Miller (1984) emphasize uncertainty and imperfect information to explain workers' occupational sequencing decisions. The implication of these models is that young workers would initially choose riskier professions for given expected returns. In models of learning, the higher uncertainty in some occupations allows workers to learn about where they are more productive more rapidly. Jovanovic and Nyarko (1997) question the role of learning about ability in labor markets, presenting evidence that workers are learning skills that allow them to transfer to new jobs, higher in an occupational ladder. This method of learning argues that in observed occupational sequences people learn by completing simple tasks first. Learning should create job ladders instead of transitions from more to less risky tasks. More recent papers in this literature include Papageorgiou (2013) and Groes et al. (2010) who develop equilibrium models consistent with many observed patterns of occupational switches. In both models, worker learning about abilities and sorting to the best occupational fit plays a crucial role. Our model is consistent with the evidence in both of these papers and provides additional life cycle evidence for the importance of learning about abilities as the mechanism that drives observed patterns of occupational choices.[3]

Other related papers on learning and occupational choices include McCall (1990), who demonstrates the presence of occupation-specific learning by showing that job switches within an occupation lead to longer job durations than switches across occupations, Neal (1999), who constructs a model of occupation and job-specific matches, and Antonovics and Golan (2010), who extend the standard learning literature by allowing workers to choose the rate at which they learn.

Section 2 presents the learning model of occupational transitions. Section 3 presents

[3]In particular, our simple model has both high- and low-wage workers in occupations switching as high-ability workers get higher wages in both occupations. This is consistent with the cross sectional patterns of occupational switching with wages documented in Groes et al. (2010).

evidence that the data match the predictions of the model. Section 4 concludes with a discussion of the results.

2 Model

In this section, we develop a learning model to guide the exploration of the data. In particular, we derive the implications of a partial equilibrium model of occupational choice where risk-neutral workers are uncertain about their abilities. A worker learns about her type over time and changes in her belief about her type can motivate occupational switches. In contrast to other papers that examine cross-sectional outcomes of workers as they age, this model will directly focus on understanding life cycle patterns for individual workers.

2.1 The Setup

Time is continuous. Agents are risk neutral and infinitely-lived. They differ in their innate ability a, which can be either be low, represented by $a = 0$, or high, represented by $a = 1$. The ability level is not directly observable to either the agent or the market. Let $p(t) \equiv \Pr_t[a = 1]$ denote the agent's belief of the probability that she is of high ability given all the information available up to time t. We assume that, at the beginnings of time, i.e. at $t = 0$, the worker inherits a signal of her ability p_0, so that $p(0) = p_0$.

In each period, the worker must choose the occupation that she wants to work in. After her initial choice of occupations there is a cost c of switching occupations. Let $s(t) \in \{\ell, h\}$ denote the occupational choice of the agent at time t. An agent can be working in a low-skilled occupation, which is labelled by ℓ, or in a high-skilled occupation, h.

An agent of ability level a in occupation s produces, on average, output y_a^s. We make the following assumptions about y_a^s: (i) $y_1^s > y_0^s$ for all s, (ii) $y_0^\ell > y_0^h$, $y_1^\ell < y_1^h$, (iii) $y_1^h/r - c > y_1^\ell/r$ and $y_0^\ell/r - c > y_0^h/r$, where c denotes the cost of switching occupations and r is the rate of discount. Assumption (i) states that high-ability workers produce more output in either occupation. Assumption (ii) states that low-ability (high-ability) workers have a comparative advantage in low-skilled (high-skilled) occupations. Assumption (iii) states that the cost of switching occupations is small enough so that it is optimal for workers who are certain of their ability to switch to the occupation where they hold a comparative advantage. These assumptions have the further implication that the high-skilled occupation is riskier than the low-skilled occupation as the difference between being a high- and low-skilled worker in the occupation h is larger. However, since the worker is risk neutral, these differences do not play a role in the analysis.

Each period, the worker can observe her output from work, which is given by: $y_a^s + \varepsilon$. As in Pries (2004), workers have noise about their output drawn from a uniform distribution. ε is a random variable that is distributed uniformly with mean zero and parameters that depend on the worker's type and occupation, $\mathcal{U}(\alpha_a^s, \alpha_a^s)$. Under this assumption, the worker will either receive a fully revealing signal about her ability if the draw is inconsistent with one of the two productivity levels or update her belief about her type based on the likelihood of not receiving a fully revealing signal. Uniform noise implies that workers will receive a fully revealing signal about the quality of the match if $\alpha_a^s < \frac{1}{2}(y_h^s - y_\ell^s)$. Hence, to have a nontrivial learning problem, we assume that $\alpha_a^s > \frac{1}{2}(y_h^s - y_\ell^s)$.

Finally, we assume that the labor market is perfectly competitive so that a worker is paid her expected output in each period:

$$w(p, s) = py_1^s + (1 - p)y_0^s \ .$$

Time subscripts are suppressed for convenience.

2.2 Learning

Let λ_a^s denote the Poisson rate at which a worker of ability a receives a fully revealing signal in occupation s. The value of λ_a^s is uniquely determined by a choice of the parameter value α_a^s. In particular, λ_a^s is given by:

$$\lambda_a^s = \frac{y_1^s - y_0^s}{2\alpha_a^s} \ .$$

This holds if the individual is either type 1 or 0. However, this extends the learning framework beyond that found in Pries (2004), since α_0^s can differ across the two types and the individual does not know the speed that they learn in a given occupation. We assume that $\lambda_1^\ell < \lambda_0^\ell$ and $\lambda_1^h > \lambda_0^h$, which implies that the worker learns faster about her ability in the occupation where she holds a comparative advantage. Because of this differential learning, any time the agent does not receive a fully revealing signal she updates her belief that it is more likely that she is not in the correct occupation. The evolution of the belief $p(t)$ is:

$$\frac{dp}{dt} = -(\lambda_1^s - \lambda_0^s)p(1-p) \ .$$

It is immediate to see that dp/dt is positive in low-skilled occupations and negative in the high-skilled one.

2.3 Value Functions

Let $V^s(p)$ denote the value for a worker with current belief p working in occupation s. For a worker currently working in low-skilled occupations their value function in its Hamilton-Jacobi-Bellman representation is given by:

$$rV^\ell(p) = w(p,\ell) - (\lambda_1^\ell - \lambda_0^\ell)p(1-p)V_p^\ell(p) + p\lambda_1^\ell(V^h(1) - c - V^\ell(p)) + (1-p)\lambda_0^\ell(V^\ell(0) - V^\ell(p)) \ .$$

The left-hand side of the equation is the worker's annualized value. The first term in the right-hand side of the equation, $w(p,\ell)$, is the flow payoff for the worker, which is given by the wage. Next, the worker's belief is updated over time if no signal is received. The third term on the right-hand side is the probability that the worker is high skilled and receives the fully revealing signal. Notice that in this case the worker will switch to occupation h paying flow cost c. The final term on the right-hand side is analogous to the third term, but for low skill, so the worker does not need to switch occupations. The value function for a worker in the high-skilled occupation is given by:

$$rV^h(p) = w(p,h) - (\lambda_1^h - \lambda_0^h)p(1-p)V_p^h(p) + p\lambda_1^h(V^h(1) - V^h(p)) + (1-p)\lambda_0^h(V^\ell(0) - c - V^h(p)) \ .$$

The terms in this equation are similar to that of low-skilled workers except the costs of switching show up in different locations.

The value functions can be solved by a guess and verify method. We conjecture that the solution is linear, i.e. $V^s(p) = \alpha^s + \beta^s p$, and then solve for α^s and β^s. The value functions are linear in p as the only unpredictable change in value occurs when the worker learns their type, but that yields a fixed value that goes into the constant term. Using this method, the value functions are given by:

$$\begin{aligned} V^\ell(p) &= \frac{y_0^\ell}{r} + \left[\frac{y_1^\ell - y_0^\ell}{r + \lambda_1^\ell} + \frac{\lambda_1^\ell}{r + \lambda_1^\ell}\left(\frac{y_1^h - y_1^\ell}{r} - c\right)\right] p \ , \\ V^h(p) &= \frac{y_0^h + \lambda_0^h(y_0^\ell/r - c)}{r + \lambda_0^h} + \left[\frac{y_1^h - y_0^h}{r} + \frac{\lambda_0^h}{r + \lambda_0^h}\left(\frac{y_0^h - y_0^\ell}{r} + c\right)\right] p \ . \end{aligned}$$

From the value functions, it is clear that $V^\ell(0) > V^h(0)$ and $V^h(1) > V^\ell(1)$. These inequalities along with the monotonicity of the value functions with respect to p imply that there exists a unique p^* at which a worker with initial belief below p^* would join the low-skilled occupation and one with an initial belief above p^* would join the high-skilled occupation. A similar argument provides that there exists a unique value $\underline{p}$, that denotes the threshold value for p at which workers decide to migrate from high-skilled to low-skilled occupations. Likewise, $\bar{p}$ denotes the threshold at which workers decide to migrate from low-skilled to high-skilled occupations. These three thresholds solve the following Value Matching conditions:

$$V^h(p^*) = V^\ell(p^*) \ ,$$

$$V^h(\underline{p}) = V^\ell(\underline{p}) - c \ ,$$

$$V^\ell(\bar{p}) = V^h(\bar{p}) - c \ .$$

It is immediate to see that $\underline{p} < p^* < \bar{p}$. Notice that assumption (iii) guarantees the existence of $\underline{p}$ and $\bar{p}$, while the monotonicity of the value functions provides uniqueness of the thresholds.

2.4 Model predictions

The model provides us with several predictions about transitional behavior that we will test empirically. We group the predictions in a sequence of propositions. The first proposition relates initial beliefs to the probability of switching occupations as follows:

Proposition 1 *Let p_0 denote the initial belief of a worker. For those workers initially joining low-skilled occupations, i.e. $p_0 < p^*$, the probability of switching to high-skilled occupations is increasing in p_0. Likewise, for those workers initially joining high-skilled occupations, i.e. $p_0 > p^*$, the probability of switching to low-skilled occupations is decreasing in p_0.*

A proof is available in Appendix A.1. Proposition 1 describes the relationship between individuals' initial occupational choices and future switching behavior. It combines workers' initial information with the likelihood of future switches as they learn by stating that workers who have stronger beliefs that they are the type of their initial occupational choice are less likely to gain enough information to ever switch in the future.

The next group of predictions describes the timing of occupational switches. The connection between initial beliefs and the timing of the first occupational switch is described in the following proposition:

Proposition 2 *Let p_0 denote the initial belief of a worker. Conditional on an occupational switch occurring, we have that: (i) for those initially working at low-skilled occupations, i.e. $p_0 < p^*$, the expected time to the occupational switch decreases with p_0, (ii) for those initially working at high-skilled occupations, i.e. $p_0 > p^*$, the expected time to the occupational switch increases with p_0.*

The proof is straightforward and therefore omitted. Notice that the result is immediate given the results of Proposition 1: A higher occupational switch probability necessary implies, conditional on a switch ever occurring, a lower expected time to switch. Furthermore, when switching costs are arbitrarily small, the model also implies a particular pattern for the second occupational switch, conditional on this one occurring. This case is described in the following proposition:

Proposition 3 *Let p_0 denote the initial belief of a worker. Conditional on two occupational switches occurring we have that, for $c \to 0$ and for any p_0, the time elapsed between the first and second switch is lower than the time elapsed prior to the first switch.*

The proof of the proposition is also omitted as it is straightforward. It follows by noting that when c is small, $\underline{p} \uparrow p^*$ and $\bar{p} \downarrow p^*$. That is, for small costs of switching occupations both $\underline{p}$ and $\bar{p}$ converge to p^*. In the model without switching cost the time elapsed to the second switch is arbitrarily low as the worker will quickly switch back and forth between occupations until she learns her ability, and therefore the subsequent switch times will be lower than the time elapsed prior to the first switch. Given this result in the limit, the model will generate shorter switching times for second switches than first switches as long as the cost of switching is small enough.

Finally, the following proposition describes the relationship between initial beliefs and the expected number of switches:

Proposition 4 *Let n denote the number of switches that a worker completes and let $E[n|\, p_0, s]$ denote the expected number of switches for a worker with initial belief p_0 and initial occupational choice s. We have that: (i) $E[n|\, p_0, \ell]$ is increasing in p_0 for $p_0 < p^*$, and (ii) $E[n|\, p_0, h]$ is decreasing in p_0 for $p_0 > p^*$.*

The proof is available in Appendix A.2. The result follows by noting that the expected number of switches is proportional to the probability of having at least one occupational switch which, through Proposition 1, relates directly to the initial belief p_0.

3 Life Cycle Occupational Switches: Evidence

The remainder of the paper will assess the model's predictions using data about workers' occupational choices over the life cycle. To examine these predictions, data about workers' characteristics and their life cycle patterns of occupational choices are analyzed.

3.1 Data

This paper uses data from the National Longitudinal Survey of Youth 1979 (NLSY79) to document the life cycle patterns of occupational choices. The NLSY79 is a nationally representative longitudinal survey conducted by the Bureau of Labor Statistics that samples 12,686 individuals who were between the ages of 14 and 22 years old when first surveyed in 1979. The individuals were surveyed every year until 1994 and every other year since 1994. NLSY79 provides a rich set of panel data for tracking workers' career outcomes.

The primary analysis in this paper focuses on the annually reported CPS job for high school graduates from the ages 18 to 28. The data are restricted to before 1994 so that annual observations of CPS job and wage data are available. Restricting the sample to people who were at most 18 years old when first interviewed in 1979, report at least five years of job activity, and have a high school degree as the highest degree ever received during the entire sample leaves 2,686 individuals in the sample.[4] These restrictions are made to generate a group that is uniformly in the labor force between the ages of 18 and 28.

To analyze individual occupational choices, the annual CPS job for each worker is used to construct the worker's choice of occupation as either blue collar or white collar.[5] By

[4]The sample is also restricted to individuals who receive their high school degree by age 19. Thus, we exclude individuals who drop out of high school and return for their degree later

[5]We follow Keane and Wolpin (1997) in defining blue and white collar occupations using one digit occupational codes. Blue collar occupations include: craftsmen, foremen, and kindred; operatives and kindred; laborers, except farm; farm laborers and foremen; and service workers. White collar occupations include: professional, technical, and kindred; managers, officials, and proprietors; sales workers; farmers and farm managers; and clerical and kindred. Results are robust for other classifications of workers across occupations. For example, similar results hold if we define occupations along routine and nonroutine or cognitive and noncognitive occupations as in Jaimovich and Siu (2013).

focusing on broad occupation categories the analysis avoids problems in the NLSY79 with coding errors of occupations at finer levels of detail that are discussed in Keane and Wolpin (1997). Using the CPS occupation for each year, individuals' occupational transitions can be tracked at an annual frequency.[6]

To understand workers' initial occupational choice, Table 1 presents summary statistics for the variables used in the analysis broken out by workers' initial occupational category. The variables for mother's and father's education record the number of years of education earned by the mother and father respectively. The variables for mother's and father's main occupation are classified into blue and white collar taking the value of 1 if white collar. There are also categorical variables for male (1 for male, 0 for female), urban (1 if geography at age 14 was urban, 0 otherwise), race (1 for white and 0 for non-white), and age 18 poverty (1 if the family was in poverty when the individual was age 18, 0 otherwise). Class percentile gives respondents' percentile rank in the last year they attended school that is available in the 1981 survey, and AFQT Percentile gives respondents' percentile scores on the Armed Forces Qualification Test. About 36% of the sample's first occupation is white collar, which is not surprising given the restriction to high school graduates. Individuals who choose an initial occupation in the white collar sector tend to have parents with more education and who are more likely to work in white collar occupations. They are also more likely to be female, grow up in an urban environment, less likely to live in poverty at age 18, and have a higher class rank and AFQT score. The number of observations drops substantially for the parental occupation variables and class percentile. To deal with these issues the parental occupation variables are dropped in some specifications and the missing values of class percentile are imputed using the other characteristics in the table.

[6]This method ignores the possibility of multiple switches within the year. This is unlikely to be a major issue as broad occupational categories are used.

Table 1: *Summary statistics for initial occupational choice for the sample with a high school degree for highest education received. Results are broken down by initial occupational choice. The table shows the mean of each variable with standard deviation in parentheses. Number of observations for each variable shown in final column.*

Variable	Blue Collar	White Collar	All	Observations
First Occupation White Collar	0	1	0.362	2686
	(0)	(0)	(0.481)	
Mother's Years of Schooling	10.82	10.98	10.88	2686
	(2.715)	(2.773)	(2.737)	
Father's Years of Schooling	10.55	11.08	10.74	2686
	(3.406)	(3.405)	(3.414)	
Mother's Main Occupation WC	0.403	0.504	0.441	1536
	(0.491)	(0.500)	(0.497)	
Father's Main Occupation WC	0.281	0.347	0.305	2089
	(0.450)	(0.476)	(0.460)	
Male	0.645	0.257	0.505	2686
	(0.479)	(0.437)	(0.500)	
White	0.607	0.587	0.600	2686
	(0.489)	(0.493)	(0.490)	
Urban	0.738	0.824	0.769	2686
	(0.440)	(0.381)	(0.421)	
Age 18 Poverty	0.236	0.198	0.222	2686
	(0.425)	(0.398)	(0.416)	
Class Percentile	0.388	0.496	0.428	1658
	(0.256)	(0.264)	(0.265)	
AFQT Percentile	0.357	0.409	0.375	2686
	(0.235)	(0.230)	(0.234)	

3.2 Initial Occupational Choice

We begin the empirical investigation with a discrete choice model to predict workers' initial beliefs of being high ability, p_0, before making their initial occupational choice. As in Trachter (2014), let $p_0 = f(X'\beta + \varepsilon)$, $\varepsilon \sim N(0, 1)$, where $f(\cdot)$ denotes the function mapping observable (i.e. X) and unobservable (i.e. ε) characteristics of the worker to the space of beliefs. These characteristics of the individual are known at the time of first occupational choice and include parental education, parental occupation, gender, ethnicity, urbanicity, poverty, as well as class rank and AFQT performance. $f(\cdot)$ is assumed to be strictly increasing and continuously differentiable, so that workers with higher characteristics have higher beliefs. The worker starts in a white collar occupation if $p_0 = f(X'\beta + \varepsilon) \geq p^*$. It follows that the probability of starting in a white collar occupation can be expressed as

$$\Pr[\text{start at white collar occupation}] = \Phi(X'\beta - f^{-1}(p^*)) \ ,$$

where $f^{-1}(p^*)$ is a constant. Notice that this motivates a Probit model of an individual's decision to start in a white collar occupation. The predicted values from these regressions are used to estimate a measure correlated with the individual's prior, $\hat{p}_0 = X'\hat{\beta}$.

Table 2 reports the results from a Probit regression of the initial observable characteristics on the worker initially choosing a white collar occupation. In the first specification the variables for mother's and father's main occupation are dropped. The second specification includes these additional variables. The values in the table are reported as marginal effects at the mean. In the first specification, an additional year of father's schooling generates a 0.012 increase in the probability of choosing white collar. Being male and white reduce the probability of choosing white collar by 0.352 and 0.072 respectively. Living in a city increases the probability of choosing white collar by 0.116 while having experienced poverty decreases the probability by 0.033. Finally, a 10% increase in class and AFQT test percentile increase the probability of choosing a white collar initial occupation by 0.019 and 0.020 respectively. Mother's education is not significant. In the second specification, all variables have the same sign and are similar in magnitude. Additionally, if the respondent's mother works in a white collar occupation they have a 0.097 increased probability of working in a white collar occupation. Father's main occupation is not significant.

3.3 Testing Model Predictions

While the results of workers' characteristics on initial choice are of interest, we want to know if the predicted initial beliefs have the power to explain workers' future occupational transitions as the model in Section 2 predicts. We first examine the result of Proposition 1, which shows that individuals are more likely to switch occupations if their initial beliefs imply that they have a lower probability of being of the type best suited for their current job. Table 3 reports the results from a second probit regression of whether individuals ever switch occupations based on the fitted probability of their initially choosing a white collar occupation. The first two columns show results from the first specification where the fitted probabilities are constructed from column 1 of Table 2, dropping parental occupation variables. The results are broken down by the individual's initial occupational choice. The table shows that workers with a 0.10 higher imputed probability of choosing a white collar initial occupation are 0.098 points less likely to ever switch occupations if they start in white collar ($\frac{\partial P^h(p)}{\partial p} < 0$, see Proposition 1). Similarly, the second column shows that workers who start in blue collar are 0.072 points more likely to switch occupations if their fitted probability of choosing white collar is 0.10 higher ($\frac{\partial P^\ell(p)}{\partial p} > 0$, see Proposition 1). The final two columns replicate the results using fitted probabilities from column 2 of Table 2, which includes parental occupational variables in the specification. The magnitude and significance of the findings are similar.

Next, we test the prediction that individuals who switch sectors will take a shorter time to switch occupations when their beliefs are further from matching their initial job sector, as described in Proposition 2. Table 4 examines whether the fitted probability of initially choosing white collar is informative about the timing of switches for workers that switch occupations. The table shows the results of regressions of the timing of the first occupational

Table 2: *Probit regression of choosing white collar as the initial occupation on observable initial characteristics at time of first occupational choice. Marginal effects are reported with standard errors in parentheses. Specification (1) omits parental occupation variables while specification (2) includes them.*

Variables	(1) First Occupation WC	(2) First Occupation WC
Mother's Years of Schooling	-0.005	-0.011
	(0.004)	(0.007)
Father's Years of Schooling	0.012***	0.014**
	(0.004)	(0.006)
Mother's Main Occupation WC		0.097***
		(0.032)
Father's Main Occupation WC		0.021
		(0.034)
Male	-0.352***	-0.333***
	(0.019)	(0.028)
White	-0.072***	-0.079**
	(0.023)	(0.034)
Urban	0.116***	0.092***
	(0.022)	(0.034)
Family Poverty	-0.033	-0.070*
	(0.024)	(0.038)
Class Percentile	0.186***	0.182**
	(0.054)	(0.080)
AFQT Percentile	0.195***	0.128
	(0.056)	(0.084)
Observations	2686	1245
R^2	0.141	0.128

*** p<0.01, ** p<0.05, * p<0.1

Table 3: *Probit regression of ever switching occupations on the fitted probability of initially choosing a white collar occupation. Results are broken down by initial occupational choice. First two columns present results from the first specification with parental occupation variables dropped. Final two columns show result for specification with probabilities from the probit including parental occupation variables. Marginal effects presented. Standard errors in parentheses.*

Variables	(1) White Collar	(1) Blue Collar	(2) White Collar	(2) Blue Collar
Probability	-0.982***	0.721***	-1.096***	0.899***
	(0.095)	(0.067)	(0.139)	(0.104)
Observations	972	1714	474	771

*** p<0.01, ** p<0.05, * p<0.1

switch on the fitted probability of choosing white collar. Separate regressions are run by observed initial occupational choice. In the first specifications, the fitted probabilities are obtained from column 1 of Table 2. The regressions show that for workers starting in a white collar occupation who are observed switching, a 0.10 increase in their probability of initially choosing white collar increases the time by an average of 0.25 years, consistent with Proposition 2. For workers starting in blue collar, an increase in their probability of choosing white collar decreases the average time to their first switch by a similar amount, also consistent with Proposition 2. In the second specification where the predicted probabilities are constructed from column 2 of Table 2, the point estimates are of the same sign and significance, but slightly larger in magnitude.

To further test the implications of the model beyond workers' initial occupational choices and first switches, the timing of occupational switches is examined for the workers that make more than one occupational switch. For each worker, the number of years between occupational switches is recorded. As described in Proposition 3, the model predicts that the time to one's second switch will be shorter than the time to one's first switch as long as switching costs are small enough. Table 5 reports the average time for workers to make their first and second switches conditional on observing them switch at least twice during

Table 4: *Regression of the timing of the first occupational switch on the probability of initially choosing a white collar occupation. Results broken down by initial occupational choice. The first two columns use the fitted probability from the probit regression with the parental occupation variables omitted. The second two columns include these variables in the construction of the fitted probability. Standard errors in parentheses.*

Variables	(1) White Collar	(1) Blue Collar	(2) White Collar	(2) Blue Collar
Probability	2.514***	-2.447***	2.722***	-3.258***
	(0.478)	(0.362)	(0.741)	(0.549)
Constant	1.821***	4.204***	1.806***	4.500***
	(0.223)	(0.138)	(0.347)	(0.219)
Observations	604	1119	296	522

*** p<0.01, ** p<0.05, * p<0.1

the time period. Results are reported by their choice of initial occupation. The table also reports the number of observations in each group and the t-statistic from a test of the time to first switch being different than the time to second switch. In contrast with the well-known decline in occupational transitions with age, the life-cycle data show that the average time to second switch is lower than the time to first switch. This result is consistent with the model when switching costs are low. One might worry that measurement issues bias these results, however the findings are robust to alternate measurement schemes. The sample is truncated to an 11-year period. This truncation leads to biases in both directions. First, since the first occupation is recorded at age 18, workers could have started in their initial occupation earlier. This effect will tend to decrease the time to first switch variable and understate the observed differences.[7] Second, since the data is truncated at 11 years, occupational transitions that occur later in life are omitted. If later first or second switches are missed, this will cause the average switch times to increase, but it is unclear if the effect would be larger for the time to first or second switch as it depends on the fraction of people who are

[7] One might also worry that this approach misses occupational switches before the age of 19 and hence biases the results in a more complicated way. These effects however do not change the overall patterns as they show up in the data without selecting the sample to provide uniform observations across individuals.

done switching occupations. The patterns continue to hold even when the sample is further restricted to those who have at least three switches during the first 11 years.

Table 5: *Average time to first and second occupational switch by initial occupational choice. Results are conditional on switching at least twice. Mean of each variable with standard deviation in parentheses. Number of observations and t-statistics for a test that the means are different between the two means are reported in each case.*

	Blue Collar	White Collar	Total
Time to First Switch	3.029	2.452	2.822
	(2.010)	(1.743)	(1.938)
Time to Second Switch	1.779	2.118	1.901
	(1.271)	(1.655)	(1.429)
Observations	787	440	1227
t-statistic	13.323***	2.586***	11.978***

*** p<0.01, ** p<0.05, * p<0.1

Finally, we test the model prediction presented in Proposition 4 that shows the expected number of job switches one makes is related to one's initial beliefs. Table 6 examines whether the fitted probabilities based off initial characteristics are informative about the realized number of switches an individual makes between the ages of 18 and 28. The table shows the results of regressions of the number of occupational switches on the fitted probability of choosing a white collar job. Separate regressions are run by observed initial occupational choice. In the first specification, the fitted probabilities come from column 1 of Table 2 and in the second specification the fitted probabilities come from column 2 of Table 2. The first specification shows that for workers who begin in a white collar occupation, a 0.10 increase in the probability of initially choosing white collar is associated with a decrease in the number of switches by 0.20, which is consistent with the predictions of the Proposition 4. Similarly, for those who begin in a blue collar occupation, a 0.10 increase in the probability of initially choosing white collar is associated with an increase in the number of job switches by 0.12.

Table 6: *Regression of the number of occupational switches on the probability of initially choosing a white collar occupation. Results broken down by initial occupational choice. The first two columns use the fitted probability from the probit regression with the parental occupation variables omitted. The second two columns include these variables in the construction of the fitted probability. Standard errors in parentheses.*

Variables	(1) White Collar	(1) Blue Collar	(2) White Collar	(2) Blue Collar
Probability	-2.036***	1.199***	-2.527***	1.544***
	(0.254)	(0.193)	(0.359)	(0.302)
Constant	2.406***	1.161***	2.633***	1.105***
	(0.129)	(0.068)	(0.184)	(0.110)
Observations	972	1714	474	771

*** p<0.01, ** p<0.05, * p<0.1

Results in the second specifications are similar in sign and significance and even larger in magnitude.

These empirical results provide support for predictions from the simple learning model where workers are initially unsure about which type of occupation they are suited for. We find new evidence that workers' initial information is important not only for the choice of their initial occupation but also their future switching behavior. Therefore, learning about occupational talents begins even before workers enter the labor market.

4 Discussion

Recent papers such as Papageorgiou (2013) and Groes et al. (2010) have constructed models where learning is important to understand workers' occupational transitions. While these models are consistent with a broad range of cross-sectional evidence about life cycle occupational choices, this paper provides additional evidence about the role of learning in such choices by examining life cycle patterns of occupational transitions. We construct a life cycle model with learning that is consistent with the evidence in Groes et al. (2010)

that workers can sort themselves both into higher- and lower-skill occupations as they learn. After generating empirical predictions from the model, we document that these life cycle predictions are present in the data. Workers' initial information is informative both about initial occupational decisions and future decisions to switch occupations, there are a sizable portion of workers who switch occupations frequently, and, most surprisingly, the average time to a worker's first occupational switch is longer than the average time to the second switch. The life cycle evidence presented here provides evidence that workers learning about their ability is important in generating the observed patterns of occupational switches in contrast with job ladder models such as Jovanovic and Nyarko (1997).

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A Proofs

A.1 Proof of Proposition 1

Let $P^s(p)$ denote the probability of a switch conditional on current belief p, and occupation s. Likewise, let $P^s(p;\mu)$ denote the probability of a switch conditional on current belief p, occupation s, and ability level a. We have that

$$P^s(p) = pP^s(p;1) + (1-p)P^s(p;0) \ .$$

Low-skilled occupations. For low-skilled occupations we have that

$$\begin{aligned} \lambda_0^\ell P^\ell(p;0) &= -(\lambda_1^\ell - \lambda_0^\ell)p(1-p)P_p^\ell(p;0) \ , \\ P^\ell(p;1) &= 1 \ , \end{aligned}$$

with boundary condition $P^\ell(\bar{p};0) = 1$. Then,

$$P^\ell(p;0) = \left(\frac{1-p}{1-\bar{p}}\frac{\bar{p}}{p}\right)^{\frac{\lambda_0^\ell}{\lambda_1^\ell - \lambda_0^\ell}} \ .$$

In the end, for the low-skilled sector we obtain that

$$P^\ell(p) = p + (1-p)\left(\frac{1-p}{1-\bar{p}}\frac{\bar{p}}{p}\right)^{\frac{\lambda_0^\ell}{\lambda_1^\ell - \lambda_0^\ell}} \ . \tag{1}$$

Differentiating with respect to p provides that

$$\frac{\partial P^\ell(p)}{\partial p} = 1 - P^\ell(p;0)\left(1 + \frac{\lambda_0^\ell}{\lambda_1^\ell - \lambda_0^\ell}\frac{1}{p}\right) \ .$$

Notice that, because $\lambda_1^\ell < \lambda_0^\ell$ and $P^\ell(p;0) \in [0,1]$, we have that $\frac{\partial P^\ell(p)}{\partial p} > 0$.

High-skilled occupations. For high-skilled occupations we have that

$$\begin{aligned} P^h(p;0) &= 1 \ , \\ \lambda_0^h P^h(p;1) &= -(\lambda_1^h - \lambda_0^h)p(1-p)P_p^h(p;1) \ , \end{aligned}$$

with boundary condition $P^h(\underline{p};1) = 1$. Then,

$$P^h(p;1) = \left(\frac{1-p}{1-\underline{p}}\frac{\underline{p}}{p}\right)^{\frac{\lambda_0^h}{\lambda_1^h - \lambda_0^h}} \ .$$

In the end, for the high-skilled sector we obtain that

$$P^h(p) = p\left(\frac{1-p}{1-\underline{p}}\frac{\underline{p}}{p}\right)^{\frac{\lambda_0^h}{\lambda_1^h-\lambda_0^h}} + (1-p)\ . \tag{2}$$

Differentiating with respect to p provides that

$$\frac{\partial P^h(p)}{\partial p} = -1 + P^h(p;1)\left(1 - \frac{\lambda_0^h}{\lambda_1^h - \lambda_0^h}\frac{1}{1-p}\right)\ .$$

Notice that, because $\lambda_1^h > \lambda_0^h$ and $P^h(p;1) \in [0,1]$, we have that $\frac{\partial P^\ell(p)}{\partial p} < 0$.

A.2 Proof of Proposition 4

Let $N^s(p;n)$ denote the probability of n occupation switches conditional on the initial occupational choice s and belief p. Notice that,

$$N^\ell(p;n) = \begin{cases} 1 - P^\ell(p) & \text{if } n = 0\ , \\ P^\ell(p)[1 - P^h(\underline{p})] & \text{if } n = 1\ , \\ P^\ell(p)P^h(\underline{p})[1 - P^\ell(\bar{p})] & \text{if } n = 2\ , \\ P^\ell(p)[P^h(\underline{p})]^{\frac{n-1}{2}}[P^\ell(\bar{p})]^{\frac{n-1}{2}}[1 - P^h(\underline{p})] & \text{if } n \geq 3,\ \text{and } n \text{ odd}\ , \\ P^\ell(p)[P^h(\underline{p})]^{\frac{n}{2}}[P^\ell(\bar{p})]^{\frac{n}{2}-1}[1 - P^\ell(\bar{p})] & \text{if } n \geq 3,\ \text{and } n \text{ even}\ , \end{cases}$$

and

$$N^h(p;n) = \begin{cases} 1 - P^h(p) & \text{if } n = 0\ , \\ P^h(p)[1 - P^\ell(\bar{p})] & \text{if } n = 1\ , \\ P^h(p)P^\ell(\bar{p})[1 - P^h(\underline{p})] & \text{if } n = 2\ , \\ P^h(p)[P^\ell(\bar{p})]^{\frac{n-1}{2}}[P^h(\underline{p})]^{\frac{n-1}{2}}[1 - P^\ell(\bar{p})] & \text{if } n \geq 3,\ \text{and } n \text{ odd}\ , \\ P^h(p)[P^\ell(\bar{p})]^{\frac{n}{2}}[P^h(\underline{p})]^{\frac{n}{2}-1}[1 - P^h(\underline{p})] & \text{if } n \geq 3,\ \text{and } n \text{ even}\ . \end{cases}$$

It then follows that

$$E[n|\,p_0, s] \;=\; \sum_{n=0}^{\infty} N^s(p_0;n)n \sum_{n=1}^{\infty} N^s(p_0;n)n = P^s(p_0)A_s$$

where A_s is a constant independent of p_0. Finally, using that $P^\ell(p_0)$ is increasing in p_0 and that $P^h(p_0)$ is decreasing in p_0 (by Lemma 1), we obtain that $E[n|\,p_0,\ell]$ is increasing in p_0 and that $E[n|\,p_0,h]$ is decreasing in p_0.