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Human Capital Portfolios

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Abstract: This paper assesses the trade-off between acquiring specialized skills targeted for a particular occupation and acquiring a package of skills that diversifies risk across occupations. Individual-level data on college credits across subjects and labor-market dynamics reveal that diversification generates higher income growth for individuals who switch occupations whereas specialization benefits those who stick with one type of job. A human capital portfolio choice problem featuring skills, abilities, and uncertain labor outcomes replicates this general pattern and generate a sizable amount of inequality. Policy experiments illustrate that forced specialization generates lower average income growth and lower turnover, but also lower inequality.

JEL classification: J24, E24

Key words: Human capital, occupational choice, income inequality

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1 Introduction

Every profession requires a different set of skills. Conversely, many skills are useful, to different degrees, in a wide variety of occupations. A literary editor, a corporate lawyer and a marine biologist apply similar skills involving reading, writing and arithmetic but in different amounts. Moreover, some occupations appear to more heavily emphasize a small subset of particular skills whereas other professions more or less weigh skills evenly. Engineers, for instance, are likely to be more specialized than sales reps.

Individuals acquire many of these different skills before entering the workforce at which point they face the uncertainty of settling on a trade or profession. A college graduate may, for example, study music but not make it as a musician. Knowing these risks, students will want to balance their efforts in case their initial target does not work out. They will want to choose the composition of their courses to acquire a set of skills based on inherent abilities and on their expected payoffs in prospective professions.

To help assess the impact of uncertainty in labor market matching on the range of acquired skills and earning dynamics, this paper first establishes panel data evidence linking diversity of individual skill sets with labor market outcomes. The paper then constructs, estimates and assesses a human capital portfolio choice problem for individuals facing an uncertain labor market.

Skill portfolios and natural aptitudes interact with uncertain labor market outcomes to affect earnings and occupational mobility. Students vary in their range of abilities and in their professional callings. As a result, students targeting the same first occupation are likely to acquire different portfolios of skills to use in both the intend job as well as their back-up plan.[1] Individuality leads to idiosyncratic outcomes and a precise economic framework is required to discern the underlying trade-offs from detailed information on human capital choices and labour market histories.

The framework adopted here assumes that agents know from the outset their abilities to acquire imperfectly substitutable skills. They also receive a signal of their prospects in a number of occupations. Since 'fit' is individual specific, it has several

[1] The set-up adopted here shares several features with Lazear (2009) and Schoellman (2010)

interpretations. The signal may reflect expected productivity hence wages or it may be non-pecuniary. Given this personal information as well as the expected skill payoffs in each profession, agents then choose their human capital portfolio, that is the amount of each skill they acquire.

After investing in training, individuals enter their preferred or primary occupation. Each occupation values all human capital types but to a different degree. Human capital, expected productivity and the fitness signal in that profession determine initial pay. At the end of the first period in an occupation, an agent's true productivity is fully revealed. Those with good realizations stay in that job permanently and earn their true productivity. Those with poor draws, try their second best option again without knowing their true quality in the new job until after completing a period of work. Imposing the restriction that workers cannot return to a previous occupation, the process repeats until the individual settles in an occupation.

This framework reveals a tension between specialization and diversity.[2] Innate talents and idiosyncratic signals of fit provide an incentive for individuals to specialize by acquiring skills that reflect their personal characteristics. Students rationally pursue those subjects in which they show promise and talent. In contrast, the risk of low productivity draws in each occupation despite good signals provides an incentive to diversify the portfolio of human capital skills.

Using the 1980 High School and Beyond (HS&B) survey which has detailed information from post-secondary transcripts, we quantitatively assesses this trade-off between specialization and diversity. For the most part, students in the US begin to branch off into specialist areas after high school as they choose post-secondary institutions and then majors. Minors and elective courses further allow students to tailor a portfolio of skills based on their innate abilities and their career aspirations. Transcripts in HS&B thus give empirical measures of human capital portfolios that are used to find the underlying parameters of the skill distribution, the signals of occupational fit and

[2]This familiar tension has long been acknowledged and dates back to Adam Smith (1776)

the technological skill use by occupations.

The HS&B survey also contains labor market histories for individuals early careers - up to around the age of thirty - that link human capital portfolios to individual earnings and labor market dynamics. The estimates, based primarily in human capital portfolios and the pattern of occupational switching, perform well when looking at the implied pattern of earnings. Simulated data found using the human capital estimates mirror the actual data in the relationship between portfolio concentration, career switches and earnings growth.

The portfolio concentration affects earnings growth through both specialization and diversity in similar ways in both the simulated and actual data. The model implies that the realized fit in a profession translates into productivity and hence pay. Agents with more specialized portfolios who remain in an early career choice experience higher earnings growth. Workers with more diverse portfolios who switch earn more than switchers with specialized portfolios. Those who settle early, that is those who realize better draws, receive high and rapid growth in earnings. Those who switch encounter an immediate earnings decline. Similarly, those who settle early tend to earn more than those who try several professions. Occupational mobility also declines and the earnings distribution fans out over time.

Given that the model and data are close along several dimensions of interest, it is natural to consider policy changes. We find that a European-style education system characterized by forcing specialization in an occupation generates a lower degree of turnover, lower earnings growth, and lower variance of (log) earnings. An alternative system that allows for more breadth (the US higher education system) trades off higher growth rates in earnings for a more unequal income distribution.

These results fit with and extend the human capital literature with uncertainty. The early human capital literature developed to understand earnings over the life-cycle (Becker, 1964; Ben Porath, 1967) focusing on investments in homogeneous human capital. Subsequent contributions took in account uncertainty about future rewards. Levhari and Weiss (1974) and Altonji (1993) are two prominent examples. More recently, Wasmer (2006) as well as Gervais, Livshits and Meh (2008) study the trade-off between (more risky) specific and general human capital.

A parallel literature considers multi-dimensional endowments of skills which determine self-selection of individuals into different sectors, as in Heckman and Sedlacek (1985, 1990), or occupations, as in Willis (1986). These studies formalize the static original Roy (1951) model of comparative advantage and occupation selection.[3] Keane and Wolpin (1997) use a dynamic Roy model to estimate a structural model of a joint schooling and occupational choice decisions. In this framework, individuals have an initial endowment of occupation-specific skills (including an ability level to accumulate human capital) and they control their schooling and occupational choice to maximize lifetime earnings. See also Gathmann and Schöberg (2010) and Yamaguchi (2012).

Other papers on occupational and job turnover emphasize the importance of learning through the acquisition of information after individuals enter the labor market. Jovanovic (1979) and Miller (1984) follow up and formalize to some extent the narrative approach of Stigler (1962). Miller's model is close to the one employed here. The distinguishing feature of Miller's framework is the sequential revelation of information as individuals try new occupations or careers that generate a trade-off between exploring new occupations and exploiting the current one.[4]

Finally, a substantial literature studies the nature of shocks individuals obtain over the life-cycle and the cross sectional inequality in earnings that these shocks generate. Huggett, Ventura, and Yaron (forthcoming) investigate whether shocks experienced over the life cycle or differences established early in life determine the bulk of cross-sectional earnings inequality. Kambourov and Manovskii (2010) explore the link be-

[3]Lazear (2002) and Schoellman (2011) are more recent examples of works that share some elements with that earlier literature.

[4]Neal (1995) studies workers' decisions in the early stages of their labor market careers emphasizing the two-stage nature of their search strategy. Individuals first settle on an occupation or career path. After this decision has been made, they start shopping for better jobs. This two-dimensional search leads to a large amount of turnover among the young whose nature is documented in detail in Topel and Ward (1990).

tween the rise in occupational mobility and the rise in earnings inequality. That link is also central to our work here, so much so that restrictions to the choice of human capital in the model generate a lower degree of occupational mobility and a more equal distribution of earnings. When those restrictions are lifted, the opposite results obtain.

This paper contributes directly to these literatures by considering the choice of the optimal mix of skills under occupational uncertainty. It examines the interaction of that choice with the information revealed as labor market histories unravel and their consequent effect on occupational transitions. The framework and empirical evidence presented provide a new way to analyze the dynamics of occupational switching, labor earnings and the accompanying inequality that arise during the early years of individuals' life-cycles.

2 Preliminary Evidence

2.1 Data

This section examines the empirical relationship between portfolios of human capital acquired through formal post-secondary education and the dynamics of labor market earnings observed in the 1980 Sophomore Cohort of the High School and Beyond (HS&B) survey. This panel dataset contains a rare, if not unique, combination of information on post-HS credits obtained in different areas of study as well as information on post-training labor market histories.

The HS&B survey, conducted by the National Center for Education Statistics, interviewed a nationally representative sample of high school students who were sophomores in 1980 once every two years between 1980 and 1986 and once again in 1992. For each student/worker, these interviews recorded labor market outcomes in employment, earnings and occupation that individuals experienced from the first year after graduation until the last year of the panel (1991).

The labor market data from the survey were merged with information about post-secondary credits in different fields found in the Post-Secondary Education Data System (PETS). PETS contains institutional transcripts from all post-secondary institutions attended for a sub-sample of students present in the survey. These high quality, administrative data provide the measures of human capital diversification used here.

The initial HS&B survey contains 14,825 students. A sub-sample of 8,325 students had their transcripts encoded. Most students, however, never earned an advanced degree. To focus on differences in portfolios rather than in the levels of human capital acquisition, the sample is further restricted to those students who earned at least an associates degree, but no more than a one-year masters degree. This restriction yields a sample of about 1,362 students.

As graduation dates (years) differ across students, so do the initial dates and length of observed labor market histories. For histories to be sufficiently long to generate at least two years of labor market data for all individuals, we dropped students who graduated in 1989 or later. In the sample, 79.9% of students graduated in 1988 or before. Further cleaning of the data yields a final sample of 1,106 students. The Appendix provides a step-by-step description of the cleaning process as well as many other data-related issues including details on the construction of human capital portfolios.

Human capital portfolios, calculated from transcript credits, contain four areas or components of study. PETS groups credits into (i) quantitative and scientific courses including engineering and computer science, (ii) humanities including history and foreign languages, (iii) social science, business and communications, and (iv) fine as well as performing arts. Credits in sub-categories (e.g. in fields like biology, literature, sociology and so on) are available but not used. Using this more refined data not only drastically increases computational complexity, but raises the reliability of classification given the widespread existence of overlapping fields.

Given credits in each area or type of human capital $k = 1, ...K$, the weights in the human capital portfolio of an individual i readily follow as:

$$\omega_{i,k} = \frac{Credits_{i,k}}{\sum_{j=1}^{K} Credits_{i,j}},$$

where $K = 4$. Table 1 displays these portfolio weights by occupation and overall across the population. For each broad occupation category, the table displays the mean and the standard deviation of the distribution, across individuals, of the weights in each of the four human capital types.

Table 1 reveals substantial heterogeneity in human capital investments across occupations. The mean weight on humanities varies from fairly low values in Engineers (0.08) and Computer Related Technicians (0.12), to values of roughly one third for Professional of the Arts. It is not surprising that Engineers have the highest mean weight in quantitative human capital (0.76), whereas this area of knowledge represents barely 15% of the portfolios of Professionals of the Arts. Business owners and sales professionals have the highest shares of business and social science human capital, allocating about half of total credits on average, to this component.

Substantial heterogeneity also appears across portfolios within particular occupations, although the extent of within group variation in portfolios differs considerably. Engineers appear more homogeneous than Computer Related Technicians or Medical professionals. The standard deviation of their quantitative human capital weight is only 0.15 which produces a relatively small coefficient of variation. In contrast, the average weight in the quantitative area for Computer Related Technicians is somewhat smaller but the standard deviation nearly doubles.

Each student i has a vector of human capital weights $\omega_{i,k}$ in the four components $k = 1, ...K$ for $K = 4$ which measure the weight of skill of type k in the overall portfolio. Viewed on its own, a skewed or balanced portfolio does not imply specialization or diversity of human capital investments. Students may opt for a balanced allocation of credits across fields to self-insure against shocks because a particular occupation explicitly rewards balanced skills. To assess the how well tailored an individual's skill

Table 1: Empirical Human Capital Portfolios By Occupation (1991)

Occupation	Share Hum.	Share Quant.	Share Comm./Bus.	Share F. P. Arts
Clerical	0.219	0.272	0.459	0.051
	(0.159)	*(0.213)*	*(0.197)*	*(0.113)*
Manager	0.181	0.302	0.484	0.033
	(0.123)	*(0.219)*	*(0.196)*	*(0.065)*
Skilled Op.	0.142	0.539	0.288	0.031
	(0.091)	*(0.278)*	*(0.240)*	*(0.050)*
Prof. Arts	0.322	0.148	0.326	0.205
	(0.171)	*(0.099)*	*(0.207)*	*(0.255)*
Prof- Medical	0.182	0.461	0.333	0.024
	(0.107)	*(0.209)*	*(0.179)*	*(0.050)*
Prof - Engineer	0.077	0.759	0.136	0.028
	(0.045)	*(0.146)*	*(0.114)*	*(0.062)*
Prof - Other	0.180	0.304	0.477	0.038
	(0.12)	*(0.194)*	*(0.205)*	*(0.102)*
Owner	0.109	0.320	0.520	0.05
	(0.054)	*(0.224)*	*(0.227)*	*(0.119)*
Sales	0.200	0.263	0.509	0.028
	(0.119)	*(0.157)*	*(0.162)*	*(0.034)*
School Teacher	0.247	0.296	0.394	0.063
	(0.147)	*(0.208)*	*(0.211)*	*(0.116)*
Service	0.252	0.338	0.386	0.024
	(0.182)	*(0.224)*	*(0.158)*	*(0.065)*
Tech. Comp.	0.119	0.588	0.274	0.019
	(0.107)	*(0.259)*	*(0.199)*	*(0.065)*
Tech. Non Comp.	0.203	0.475	0.276	0.046
	(0.130)	*(0.273)*	*(0.21)*	*(0.083)*
All Occupations	0.190	0.352	0.415	0.043
	(0.135)	*(0.247)*	*(0.214)*	*(0.100)*

Notes: Each cell displays the average, across all individuals, of the portfolio weight of a given human capital type working in an occupation. In parentheses we report the standard deviation of the distribution of the portfolio weight across individuals.

set is for a particular job, human capital investments must be viewed relative to a benchmark in that occupation.

There are several potential approaches to (as well as difficulties in) measuring diversification and specialization of a given set of skills. This paper adopts a simple if crude measure. Suppose individual i enters the labor market with human capital vector $(\omega_{i,1}, ..., \omega_{i,K})$ and first works in occupation j. Define the degree of diversification, $\delta_{i,j}$, as the standard Euclidean distance in $\mathbb{R}^K$ that $i's$ portfolio lies from the average portfolio observed in occupation, j :

$$\delta_{i,j} = \sqrt{\sum_{k=1}^{K} (\omega_{i,k} - \bar{\omega}_{j,k})^2}$$

where $\bar{\omega}_{j,k}$ denotes the typical (or average) portfolio for occupation j observed in Table 1. A portfolio is tailored to a given occupation if that portfolio is "close" to the average portfolio of that occupation. Diversification is simply the distance between the portfolio weights and the typical portfolio of the first occupation after graduation.

The upper panel of Table 2 displays summary statistics describing the distribution for this diversity measure as well as for three other important measures. Δy_i denotes the average annual growth rate of earnings for individual i as given by

$$\Delta y_i = e^{\log(y_{i,91}/y_{i,1})/(T_i-1)} - 1,$$

where $y_{i,1}$ denotes $i's$ earnings, (deflated for the appropriate year by the CPI) in the first year after graduation, $y_{i,91}$ (deflated) earnings in 1991, and T_i the time in years of i's labor market history.

CRED denotes the total number of credits. *STAY* is an indicator variable that takes the value 1 if an individual never switches occupation and equals 0 otherwise. The figures given in Table 2 correspond to a distribution of individuals truncated to eliminate the top and bottom 2% of average earnings growth. The lower panel of Table 2 provides the raw correlations of these measures.

Table 2: Summary Statistics - Selected Variables

	Mean	Median	Std. Dev.	Min.	Max.
Δy	0.078	0.057	0.126	-0.263	0.720
δ	0.276	0.238	0.164	0.018	0.848
$CRED$	124	122	27	80	362
$STAY$	0.638	1.000	0.483	0.000	1.000

Notes: Before we compute their growth rate, earnings are deflated by the Consumer Price Index for the appropriate year.

Correlation Matrix - Selected Variables

	Δy	δ	$CRED$	$STAY$
Δy	1.000	-0.007	0.025	-0.126^{**}
δ		1.000	0.079^{*}	-0.064^{*}
$CRED$			1.000	0.062^{*}
$STAY$				1.000

Notes: *: Correlation is significant at least at the 0.05 level. **: Correlation is significant at least at the 0.01 level.

For this sample of students, real earnings growth per year averages about 8% with dispersion in line with other studies. Since retrospective surveys frequently suffer from a large degree of measurement error, we compared the earnings distribution for the years in our HS&B sample to a similar sample from the Current Population Survey (CPS). The results are similar and reported in the Appendix.[5]

The measure of diversification, δ, also displays considerable dispersion across individuals. The standard deviation is 0.16 for a variable that has a mean value of about 0.2 and is bounded between zero and one.

[5] It would be useful to control for hours worked and get a measure of earnings per unit of time but this is only partially feasible. Although the survey reports the monthly unemployment history, it does not contain hours worked during the periods of employment or whether employment is part-time or full-time. As a result, some extreme values, for example, the minimum observed of -0.26 could be due to voluntary changes in hours worked, health, family or other reasons. In what follows, it is very difficult to discriminate among possible causes for those fairly extreme earnings changes.

As the majority of individuals in our sample achieve at most a bachelor's degree, it is not surprising that the median of the distribution for college credits ($CRED$) is 122. Some high-achievers take over three hundred credit hours, but these are the exception as the standard deviation for this measure is only 27. Finally, note that a little over 60% percent of individuals never switch occupations during the observed labor market histories.

Most of the correlations in the lower panel of Table 2 are significant as well as plausible. For instance, there is a strong (unconditional) negative relationship between earnings growth and remaining in the same occupation. The positive relationship between diversification and the number of credits taken hints at the possibility of individuals diversifying by adding credits rather than by transferring credits across areas. It seems sensible that the higher the degree of diversification, the higher the probability an individual switches occupations as reflected in the negative correlation between δ and $STAY$. On the other hand, note that the unconditional correlation between income growth and diversification is near zero and insignificant. Further investigation reveals that interesting patterns emerge once one conditions on occupational switches.

2.2 Empirical Regularities

To investigate the empirical regularities beyond raw correlations, Table 3 presents OLS regression estimates linking income growth, Δy, and the portfolio of acquired skills, δ.The division of human capital into four types of skills is obviously not the only one possible.[6]

The first column of results reports regression coefficient estimates of income growth with three further controls - the logarithm of the respondent's initial earnings $log(y_1)$, the logarithm of the total of credits, $log(CRED)$, and the individual's gender, SEX. All

[6]To assess the sensitivity of the empirical results to an alternative division, we considered three types only, with humanities and fine arts representing one category. The results are very similar to those obtained with four types of skills and for that reason not reported here.

Table 3: Results - Dependent Variable is Δy

	Coeff. (*p-val.*) (1)	(2)	(3)	(4)	(5)	(6)
$log(y_1)$	-0.150	-0.148	-0.150	-0.150	-0.132	-0.133
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
$log(CRED)$	0.041	0.042	0.040	0.037	0.017	0.017
	(0.015)	*(0.013)*	*(0.018)*	*(0.028)*	*(0.325)*	*(0.305)*
SEX	-0.037	-0.032	-0.033	-0.033	-0.035	-0.036
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
δ	-0.042	-0.044	-0.036	0.029	0.061	0.038
	(0.041)	*(0.034)*	*(0.083)*	*(0.394)*	*(0.093)*	*(0.322)*
$STAY$		-0.010	0.003	0.033	0.033	0.027
		(0.157)	*(0.751)*	*(0.026)*	*(0.028)*	*(0.089)*
$CAREER$			0.042	0.047	0.042	0.005
			(nil)	(2×10^{-4})	*(0.001)*	*(0.843)*
$\delta \times STAY$				-0.104	-0.112	-0.089
				(0.015)	*(0.012)*	*(0.055)*
$\delta \times CAREER$						0.173
						(0.108)
Intercept	1.141	1.128	1.146	1.140	1.087	1.098
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
N	980	980	980	980	690	690
R^2	0.291	0.291	0.299	0.303	0.265	0.268

Notes: This table shows results of regressing income growth (Δy) on the variables shown in column 1 for our sample of individuals. Besides variables defined previously we include $log(y_1)$ which is the log of initial earnings; $CAREER$ which is a variable that equals one if an individual begins her labor market experience in a non-managerial occupation and ends in a managerial occupation.

four variables' coefficients are significant with the expected sign. On average, male earnings grow faster than women's earnings. Individuals with more credits also experience higher growth rates. The coefficient on initial wages is also negative. This last result may reflect to some extent on-the-job human capital investments. Workers take lower initial pay in return for on-the-job training in transferable skills that pays off later on. Other explanations are possible and discussed in Section 4.

With only these three added controls, the relationship between income growth and diversification is negative. On average, individuals who have portfolios close to the average in their initial occupation (i.e. "concentrated" portfolios) experience higher growth in earnings. From the adjacent column, these results change very little after adding the control $STAY$ which accounts for occupation change. Those whose careers are the same at the beginning and end of the survey tend to earn less (the estimated coefficient equals -0.010) but there is a fairly large amount of uncertainty around that value (the p-value is 15.7%). The negative estimated coefficient implies negative returns to occupational tenure, which would appear to contradict some previous findings in the literature.[7]

Some occupational transitions are primarily lateral moves for people who want to or are induced to do something else. Some job changes are natural progressions up a career ladder. To control for the more vertical (as opposed to horizontal) moves, the third column of results includes a dummy variable, $CAREER$, which equals one for occupational switches (only comparing the first and last period in an individual's labor market) that end in managerial positions either from sales, clerical, or other professional occupations and zero otherwise. Not surprisingly, the estimated coefficient of $CAREER$ is positive and the estimate for $STAY$ becomes small and insignificant.

The last two columns of Table 3 offer interesting evidence on portfolio diversification. These regression results include an interaction term between occupational switchers and the diversification measure, $\delta * STAY$. The effects are intriguing. The coefficient on this interaction term is negative, significant and large (-0.10) implying that individuals who do not switch occupations and who have portfolios close to those found in the first occupation have on average higher earnings growth. Moreover, since

[7]See, for example, Kambourov and Manovskii (2010). However, Groes, Kircher, and Manovskii (2010) note that not all occupational switches are created equal. Movements to occupations higher in the hierarchy (e.g. managerial occupations) should be associated with increases in earnings. Using Danish data they find that the best-performing and the worst-performing workers in an occupation are more likely to switch than those in the middle. Below we show that our data confirms that some occupational switches (e.g. those that end in managerial positions) are associated with increases in earnings.

the coefficient on δ itself switches signs and turns positive (0.029), it appears that if an individual switches occupations ($STAY = 0$), a diverse portfolio pays off. A portfolio further away from the average portfolio of the previous occupation is associated with a higher growth rate in earnings. Although the p-value is fairly large (39.4%) hence the degree of uncertainty in this estimated coefficient is large, these results are informative given the sample size and the relatively higher number of "stayers." Finally, the coefficient on $STAY$ becomes positive (0.033) with a fairly small p-value of 2.5%. On average higher earnings growth occurs for those that remain in an occupation once we take into account their portfolio diversification.

The last two columns explore the robustness of these last results.[8] Column 5 reports the same regression for a subsample of students who earn a bachelors only. The results vary very little. To consider the way in which the diversity of the skill set interacts with promotions to greater wider responsibilities, Column 6 includes an interactive control for $\delta * CAREER$. The estimates confirm the previous outcomes but also point out that these promotions on average reward the more broadly educated.

Finally, Table 4 reports results from a Probit model with $STAY$ as the dependent variable. Recall that variable takes the value one if the individual remains in the first occupational choice and zero otherwise so these estimates relate to occupational mobility. In all four specifications of the controls, the relationship between diversification and the probability of an occupational transition is negative. In other words, the further away an individual's portfolio is from the average portfolio of his first occupational choice, the more likely they are to switch to a different occupation. Women are on average more likely to switch but the relationship between the two variables is weak (the p-value is 0.641). Individuals with a larger number of credits are more likely to stay in their first occupational choice, as are individuals who start with relatively high initial earnings.

[8] Using alternative measures of diversification does not fundamentally alter this picture. For example, using portfolio distance from the average portfolio of the last occupation (instead of the first one) has little effect and not reported here.

Table 4: Probit Regression - Dependent Variable : $STAY$

	Coeff. (*p-val.*) (1)	(2)	(3)	(4)
δ	-0.491	-0.384	-0.421	-0.419
	(0.048)	*(0.128)*	*(0.097)*	*(0.098)*
$log(y_1)$		0.504	0.488	0.483
		(nil)	*(nil)*	*(nil)*
$log(CRED)$			0.301	0.279
			(0.140)	*(0.183)*
SEX				-0.041
				(0.641)
Intercept	0.473	-3.584	-4.891	-4.677
	(nil)	*(nil)*	(2×10^{-5})	(0.002)

3 The Portfolio Problem

The results presented above suggest that specialization as well as risk diversification are important considerations in determining the acquisition of job market skills and the subsequent labor market experience. A more thorough empirical assessment requires a fully specified economic framework. This section therefore presents a decision-theoretic model in which individuals optimally choose a vector of skills, or human capital types, when future occupational fit is uncertain.

3.1 Environment

Suppose individuals with discount factor $\beta \in (0, 1)$ live for an infinite number of discrete periods, $t = 0, 1, 2, ...$ Individuals choose their human capital investments, i.e. their set of individually distinct skills, in the initial period ($t = 0$) to optimize expected discounted lifetime earnings. There are K skills that can be employed in J occupations. All occupations value all skills but to different degrees. Denote an individual portfolio of skills by $\boldsymbol{h} = \{h_1, ..., h_K\}$.

These individuals are well aware of their individually specific ability to accumulate or invest in the different skills that make up their skill portfolio. Before choosing $\boldsymbol{h}$, an individual draws a vector of abilities for each type of human capital, $\boldsymbol{\xi} = (\xi_1, ..., \xi_K)$ from $F(\boldsymbol{\xi})$. The element ξ_k represents an individual's capacity to accumulate skill of type k. The total cost (in utils) of investing in an individual's portfolio is given by $C(\boldsymbol{h}, \boldsymbol{\xi}) : \mathbb{R}^{2K} \to \mathbb{R}$ which is increasing in the size of the human capital stock, decreasing in the level of each ability, convex and twice differentiable.

These individuals also know the payoff structure of each occupation. They are well aware of the technology that maps a human capital portfolio into earnings. They are, however, unsure about an idiosyncratic component of labor market payoffs. Before choosing $\boldsymbol{h}$, individuals receive a noisy signal of their fit in each occupation - they draw a vector $\boldsymbol{\theta} = (\theta_1, ..., \theta_J)$ from the distribution $G(\boldsymbol{\theta})$. Each element θ_j is an uncertain indication about an individual's future productivity in occupation $j \in \{1, ..., J\}$. It is likely that for the individuals in our dataset $\boldsymbol{\xi}$ and $\boldsymbol{\theta}$ are correlated. In other words, agents who get high signals about their productivity in the legal profession, will likely have a higher verbal ability than quantitative ability. To keep the model parsimonious we maintain throughout that those two vectors are uncorrelated .

Once an individual has acquired the skill set $\boldsymbol{h}$, they enter the labor market in the next period $t = 1$. At this point, workers are unable to update or modify their mix of skills. Individuals' only choice in the labor market is to decide in which occupation to work. They can work in only one occupation in a period. Although individuals have a general idea before they invest in their portfolio of skills of how well they are likely to fit into a given occupation, it is only after they complete training and after they try a particular job that their true fit in that profession becomes known. Actual experience in an occupation reveals an individual's true match quality or future productivity in that occupation.[9]

[9]We use the term productivity or match-quality interchangeably. This term corresponds to the com-

Acquired skills, productivity signals and labor market experience determine payoff flows. Assume that the first time an individual tries an occupation, they get paid according to their noisy signal. In particular, if an individual who has skills $\boldsymbol{h}$ along with signals $\boldsymbol{\theta}$ decides to work in occupation j for the first time, the flow payoff or earnings equals $e^{\theta_j} f_j(\boldsymbol{h})$. The function $f_j : \mathbb{R}^K \to \mathbb{R}$ is a constant returns to scale technology that maps a given portfolio of skills into earnings. We allow this technology to differ by occupation, hence the subscript j. At the end of the first period in occupation j an individual's productivity gets updated by adding to the signal an independent random shock ,ϵ_j, drawn from a distribution Γ_j. Should an individual decide to remain in that occupation, earnings grow at a gross rate of $\gamma > 1$, with $\beta\gamma < 1$.[10]

Information revelation is thus sequential. At each point in time, individuals decide whether to remain in their current occupation or to continue exploring new occupations. Exploration enlarges the information set as individuals learn about their match-quality. This setup is a classic multi-armed bandit problem in which the exploration of an arm (an occupation) comes at the expense of obtaining payoffs, that are perhaps larger, in alternative arms.[11].

3.2 The Individual's Problem

Let $V(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_t)$ denote the expected labor market payoff to an individual with skills $\boldsymbol{h}$, productivity signals $\boldsymbol{\theta}$, and labor market history $\boldsymbol{\Phi}_t$ at date t. An individual with

ponent of earnings in an occupation that cannot be accounted for by the individual's portfolio of skills.

[10]In our baseline model we do not allow for the recall of previously sampled occupations. As a result, individuals choose between remaining in a occupation or trying a new one. In the data, recalling previous occupations is rare and in the final remarks we include some empirical values of the fraction of individuals who do. We also solve a version of the model in which individuals are allowed to recall, using as parameter values those we estimate using the baseline model (no recall). The quantitative implications are similar.

[11]Early economic applications of the classical multi-armed bandit model include Weitzman (1979) and Miller (1984). More recent examples include Papageorgiou (2010).

known abilities vector $\boldsymbol{\xi}$ therefore chooses a set of skills in period $t = 0$ to solve[12]

$$\max_{\boldsymbol{h}} -C(\boldsymbol{\xi}, \boldsymbol{h}) + \beta V(\boldsymbol{\xi}, \boldsymbol{h}, \emptyset).$$

Given skills, signals and history, $V(.)$ is the maximum discounted expected lifetime income that the individual can attain when the only action available is whether to switch occupations. In period $t = 0$, the worker has not yet entered the market so that Φ_0 is the empty set. In subsequent periods, labor market histories consist of occupations chosen in previous periods along with the realized draws of true productivity or fit in those occupations:

$$\Phi_t = \{(j_t, \epsilon_{j_t})\}_{j=1}^{t-1}.$$

Expected earnings in the labor market, V, can be written recursively given the appropriate choice of occupation:

$$V(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_t) = \max_{j_t \in \{1,\ldots,J\}} w_{j_t}(\theta_{j_t}, \boldsymbol{h}, \boldsymbol{\Phi}_t) + \beta \mathbb{E}_{\epsilon_{j_t}} V(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_{t+1}),$$

where $w_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t)$ is the immediate flow payoff in occupation j given skills and history. Let $\eta_j(\Phi_t)$ denote the number times that occupation j appears in an individual's history. Recalling that earnings grow with experience in an occupation and that the fit in an occupation does not vary over time ($\epsilon_{j_t} = \epsilon_{j_{t'}}$ if $j_t = j_{t'}$), the flow payoff in a period can be written as

$$w_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t) = \begin{cases} e^{\theta_j} f_j(\boldsymbol{h}) & if \;\; \eta_j(\Phi_t) = 0 \\ e^{\theta_j + \epsilon_j} f_j(\boldsymbol{h}) \gamma^{\eta_j(\Phi_t)} & if \;\; \eta_j(\Phi_t) > 0. \end{cases}$$

Repeated sampling of a given occupation provides no new information about alternative occupations. The first time an individual works in occupation j, the employer and employee both know θ_j and $\boldsymbol{h}$, but neither knows ϵ_j. True match quality becomes

[12]For the sake of clarity, we do not subscript every function by an i. It should be understood that except occupation-specific technologies and the cost function, all other objects are specific to an individual

fully revealed at the very end of the first period. As a result, individual pay in the first period reflects only the noisy signal and human capital. After the individual has tried that occupation, the flow payments equal the true productivity - determined by the signal θ_j and updated with ϵ_j - which grows with occupation-specific tenure at rate $\gamma > 1$. This update becomes part of the individual's information set whether or not they decide to remain in occupation j.

3.3 Switching versus Staying

The optimal portfolio choice involves computing the expected discounted value of earnings after entering the labor market, given by $V(\boldsymbol{\theta}, \boldsymbol{h}, \emptyset)$. Policies controlling occupational choice, j_t, determine the realization of potential outcomes over time and reflect a trade-off between exploring new occupations - therefore obtaining information about fit - and exploiting the current occupation where payoffs are known.

This exploration versus exploitation trade-off is characteristic of multi-armed bandit problems. Arms correspond to occupations with individuals sampling at most one arm per period. Gittins and Jones (1974) reduce the dimensionality of bandit problems by demonstrating that the solution to these problems take the form of an index policy. They formulate the so-called Gittins index which assigns a value to each option that depends only potential outcomes in that option. The chosen occupational choice is the option with the highest index.

Whittle (1982) reformulates this approach in such a way that the index reflects a retirement value for each choice. Following Whittle's approach, the Gittins or retirement index for an occupation that has already been sampled, i.e. $\eta_j(\Phi_t) > 0$ so that the ϵ uncertainty is revealed, is simply the lifetime value of income in that occupation:

$$M_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t) = \gamma^{\eta_j(\Phi_t)} w_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t)/(1-\beta\gamma) = e^{\theta_j+\epsilon_j} f_j(\boldsymbol{h}) \gamma^{\eta_j(\Phi_t)}/(1-\beta\gamma) \quad for\, \eta_j(\boldsymbol{\Phi}_t) > 1$$

On the other hand, if occupation j is untried ($\eta_j(\boldsymbol{\Phi}_t) = 0$), the index must account for the unresolved uncertainty. In general, the index is given by

$$M_j = \sup_{\tau}(1-\beta)\left\{\mathbb{E}\left[\sum_{t=0}^{\tau-1}\beta^t w_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t) + \frac{\beta^\tau}{1-\beta}M_j\right]\right\},$$

where τ is a stopping rule that is contingent on the sequence of events or draws in occupation j.

Recall that all information is revealed after the first work period of employment in an occupation. Without future learning, it is straightforward to see that workers will choose to either move to another occupation or remain forever in j, hence $\tau \in \{1, \infty\}$. The Gittins index therefore reduces to

$$M_j = \mathbb{E}_{\epsilon_j}(1-\beta)\max\left\{e^{\theta_j}f_j(\boldsymbol{h}) + \frac{\beta}{1-\beta}M_j, e^{\theta_j}f_j(\boldsymbol{h}) + \frac{\beta}{1-\beta\gamma}e^{\theta_j+\epsilon_j}f_j(\boldsymbol{h})\right\}. \quad (1)$$

Given this simple choice, continuation in occupation j is given by a simple reservation value for revealed productivity. Let ϵ_j^R denote the critical value of ϵ_j that equates the two options. Given an ϵ_j^R draw from the distribution Γ_j, the individual is indifferent between retiring from j and remaining permanently:

$$(1-\beta)e^{\theta_j}f_j(\boldsymbol{h}) + \beta M_j = (1-\beta)e^{\theta_j}f_j(\boldsymbol{h}) + \frac{\beta(1-\beta)}{1-\beta\gamma}e^{\theta_j+\epsilon_j^R}f_j(\boldsymbol{h})$$

which yields

$$\epsilon_j^R = \ln\left(\frac{(1-\beta\gamma)M_j}{(1-\beta)f_j(\boldsymbol{h})}\right) - \theta_j.$$

Plugging ϵ_j^R into (1) and manipulating gives

$$M_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t) = \frac{(1-\beta)e^{\theta_j}f_j(\boldsymbol{h})\left(1-\beta\gamma+\beta\int_{\epsilon_j^R}^{\infty}e^{\epsilon}d\Gamma_j(\epsilon)\right)}{(1-\beta\gamma)[1-\beta\Gamma(\epsilon_j^R)]} \quad for\ \eta_j(\boldsymbol{\Phi}_t) = 0 \quad (2)$$

which can be solved, at least numerically, given a parameterization Γ_j and f_j.

Proposition 1 *Suppose updates to the productivity signals are bounded above and below such* *that* $\epsilon_j \in (\underline{\epsilon}, \bar{\epsilon})\ \forall j \in \{1, ..., J\}$*. For any set of signals, skills and histories* $(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_t)$*, occupational choice* j_t *solves*[13]

$$j_t = \arg\max_j \{M_1(\theta_1, \boldsymbol{h}, \boldsymbol{\Phi}_t), ..., M_J(\theta_J, \boldsymbol{h}, \boldsymbol{\Phi}_t)\}.$$

The occupational choice problem is comparison of reservation values for each occupation. The payoffs are the values that make the worker indifferent between continuing with an occupation or receiving the reservation payoff.

4 Model Estimation

To quantitatively assess the model, assume there are $K = 3$ human capital or skill types, labeled Humanities (H), Quantitative (Q), and Social Science (SS). Assume the number of occupations equals $J = 12$. These skills and occupations correspond to the HS&B variables described in Section 2.[14]

To keep the number of parameters manageable, assume that abilities $\boldsymbol{\xi}_k$, occupational signals $\boldsymbol{\theta}_j$, and the productivity updates ϵ_j are all independent and distributed normally

$$\begin{aligned}
\xi_k &\sim N(0, \sigma_{\xi_k}) \quad k \in \{H, Q, SS\} \\
\theta_j &\sim N(0, \sigma_\theta) \quad j = 1, ..., 12 \\
\epsilon_j &\sim N(0, \sigma_{\epsilon_j}) \quad j = 1, ..., 12.
\end{aligned}$$

Note that the occupational signals θ_j are assumed to have the same variance as well as

[13] This proposition follows directly from applying Theorem 4.1 in Whittle (1982), Ch. 14.

[14] To lower the number of parameters, we merge credits in Fine and Performing Arts with those of Humanities to get three types of skills. We also eliminate individuals who are listed as *Owner*, due to the low number of respondents with *Owner* as their first occupation.

mean. The cost function for acquiring skills is assumed to be quadratic[15]

$$C(\xi, \boldsymbol{h}) = \sum_{k=1}^{3} e^{\xi_k} h_k^2,$$

while the production technology is Cobb-Douglas

$$f_j(\boldsymbol{h}) = \prod_{k=1}^{3} h_k^{\alpha_{j,k}}, \quad \sum_{k=1}^{3} \alpha_{j,k} = 1.$$

The available data does not allow estimation of the elasticity of substitution among different human capital types within an occupation. Although in the estimation we impose Cobb-Douglas payoffs, we also report results assuming they are CES but for all occupations we assume the same elasticity of substitution across human capital types.

Set $\beta\gamma$ equal to 0.96 and fix γ to be consistent with average earnings growth observed in the data, around 8% per year, resulting in values for γ and β equal to 1.095 and 0.877, respectively. As a result of these assumptions and normalizations, the vector of parameters[16] for estimation is given by

$$\Lambda = \left\{ \{\alpha_{j,1}, \alpha_{j,2}\}_{j=1}^{12}, \{\sigma_{\epsilon_j}\}_{j=1}^{12}, \{\sigma_{\xi_k}\}_{k \in \{H,Q,SS\}}, \sigma_\theta \right\}.$$

4.1 Estimation Methodology

We use a Simulated Method of Moments (SMM) approach to estimate the 40 elements of the structural parameter vector. Let $\hat{\Lambda}$ denote the parameter estimates and $\hat{\Omega}$ the associated estimated covariance matrix. The first step is to choose a vector of auxiliary parameters (moments) from the HS&B dataset, denoted by Y, which describe occupational transitions, skills portfolios across occupations, and the variance of (log)

[15]There is little information to guide our choice for a cost function. In results not reported here we assess the robustness of deviating from a quadratic specification by assuming an exponential function. Results are similar.

[16]By the constant-returns assumption, the weight of the third skill type is given once we know the other two.

earnings. Given a value of the structural vector Λ, the model can be solved and simulated. This simulation yields a model-analog for the vector Y, denoted by $\hat{Y}$. The estimate $\hat{\Lambda}$ is then the value of Λ that solves the following criterion: [17]

$$\hat{\Lambda} = \underset{\Lambda}{\operatorname{argmin}}(Y - \hat{Y})'(Y - \hat{Y})'.$$

Standard numerical routines solve this minimization problem. To provide a sense of the amount of uncertainty surrounding our estimates, numerical standard errors are computed following Gourinchas and Parker (2002):

$$\hat{\Omega} = (\hat{H}'_{\Lambda}\hat{H}_{\Lambda})^{-1}\hat{H}'_{\Lambda}\Omega_{\hat{Y}}\hat{H}'_{\Lambda}(\hat{H}'_{\Lambda}\hat{H}_{\Lambda})^{-1}, \tag{3}$$

where $\hat{H}'_{\Lambda}$ is the Jacobian matrix of the vector-valued function $H(\Lambda) = \hat{Y} - Y_{\Lambda}$ evaluated at $\Lambda = \hat{\Lambda}$. In other words, the ij^{th} element of $\hat{H}_{\Lambda}$ is $\hat{h_{ij}} = \partial(Y_j - \hat{Y}_j)/\partial\Lambda_i$. $\Omega_{\hat{Y}}$ is the variance matrix of the set of moments in $\hat{Y}$.

Table 5 displays the statistics found for Y. The columns labeled ω_H and ω_Q report average shares of a skill type - humanities and quantitative - in an individual's portfolio, averaged across individuals in a given occupational group. The ω_H column corresponds approximately to the "Share of Humanities" moment reported in Table 1 but now it also includes credits in Fine and Performing Arts. The column ω_Q corresponds to "Share of Math" in Table 1.[18] The last column of Table 5 reports the share of individuals that begin their labor market career in a given occupation but switch in the second year. These shares range from a high of about one half in *Service* to a low of 4.7% for *Engineers*.

[17]In general, the criterion contains a weighing matrix W:

$$\hat{\Lambda} = \underset{\Lambda}{\operatorname{argmin}}(Y - \hat{Y})'W(Y - \hat{Y})'$$

As the model is exactly-identified the choice of the weighting matrix is not relevant and hence set equal to the identity matrix.

[18]For some occupations the values are not exactly the same across the two tables. The difference is a consequence of having eliminated individuals who reported having ever being occupied as *Owners*.

Table 5: Elements of the Vector $\hat{Y}$

Occupation	Sample Size	ω_H	ω_M	% Switch
Clerical	150	0.266 (*0.016*)	0.277 (*0.018*)	0.225 (*0.014*)
Manager	280	0.214 (*0.009*)	0.304 (*0.013*)	0.155 (*0.008*)
Skilled Op.	10	0.184 (*0.029*)	0.493 (*0.080*)	0.286 (*0.059*)
Prof. Arts	40	0.518 (*0.041*)	0.152 (*0.017*)	0.195 (*0.026*)
Prof- Medical	60	0.208 (*0.015*)	0.464 (*0.027*)	0.054 (*0.007*)
Prof - Engineer	40	0.094 (*0.010*)	0.766 (*0.020*)	0.047 (*0.007*)
Prof - Other	110	0.222 (*0.015*)	0.301 (*0.018*)	0.094 (*0.008*)
Sales	100	0.231 (*0.014*)	0.270 (*0.017*)	0.200 (*0.017*)
School Teacher	40	0.328 (*0.030*)	0.298 (*0.030*)	0.184 (*0.023*)
Service	10	0.329 (*0.049*)	0.260 (*0.046*)	0.521 (*0.075*)
Tech. Comp.	80	0.147 (*0.017*)	0.578 (*0.030*)	0.178 (*0.016*)
Tech. Non Comp.	20	0.266 (*0.042*)	0.431 (*0.058*)	0.286 (*0.052*)
	Sample Size	Statistic		
Standard Deviation (Log) Earnings				
First Period	950	0.454 (*0.010*)		
Standard Deviation ω_H	950	0.178 (*0.004*)		
Standard Deviation ω_Q	950	0.248 (*0.006*)		
Standard Deviation ω_{CB}	950	0.216 (*0.005*)		

The average shares of the two human capital types, ω_H and ω_Q, identify the 24 technological parameters $\alpha_{j,1}$ and $\alpha_{j,2}$, $j = 1, ...12$. The fractions of individuals who leave an occupation after one year identify the 12 variances, $\sigma^2_{\epsilon_j}$, associated with each occupation $j = 1, \ldots, 12$. Occupations in which updates to the productivity signals have a large variability will experience a larger fraction of transitions. The larger variability is itself a consequence of being more likely that the Gittins index for those volatile occupations, after they are explored, falls below the second-best Gittins index.

Four aggregate moments complete the set of moments that comprise the parameter vector Y. The variance of (log) earnings across all individuals in the first year of labor market experience identifies σ_θ, which is the main driver of income differences (in levels) in the first year. Measures of the dispersion across individuals' portfolio shares of the three different skills helps identify the three σ_{ξ_k}.

Given a vector of structural parameters Λ, we simulate labor market histories for a large number of individuals by taking a (ξ, θ) draw from the abilities and productivity signals distributions. Given these draws and a portfolio of skills, we solve for the expected earnings by finding the optimal sequence of occupational switches for each possible update of the productivity signals. The optimal portfolio is the one which maximizes the difference between the maximum expected earnings in the labor market and the cost of purchasing it. This procedure yields the optimal portfolio of one individual as well as a randomly selected simulated labor market history.[19] Repeating those steps for a large number of individuals provides the model-analog to the moments in the vector $Y(\Lambda)$. The appendix provides further details of this estimation routine.

[19]If we allow recall of previously sampled occupations, the solution is more involved because computing expected earnings in the labor market requires Monte Carlo integration. In the model without occupational recall, integrating over labor market histories can be done without resorting to simulation.

5 Results

Table 6 reports the elements of $\hat{\Lambda}$, along with their estimated numerical standard errors. These parameters tend to be tightly estimated. The dispersion (σ_{ϵ_j}) in the productivity update for Other Professionals (j=Prof.-Other) is one exception. The estimated variance is nearly three times the parameter estimate. A second exception is the estimated humanities component in production function, $\hat{\alpha}_{j,H}$, for Computer Technicians (j=Tech.-Comp). The associated standard error is two and a third times larger than the parameter estimate. Otherwise, the standard errors of the other parameters are generally small relative to the estimates.

Notice as well that the estimated Cobb-Douglas shares roughly follow the pattern found in the average portfolio weights across occupations. See Table 5 to compare $\alpha_{j,H}$ and $\alpha_{j,M}$ with $\omega_{j,H}$ and $\omega_{j,M}$. Production displays substantial dispersion in the use of skills across occupations as does the uncertainty in the fit across occupation which is related to the probability of exiting an occupation.

Consider one of the riskiest occupations, Professionals of the Arts. It not only has a relatively high estimated variance of shocks, $\sigma_{\epsilon_j} = .398$, but the technology is also heavily tilted towards humanities with $\hat{\alpha_H} = 0.64$. However, individuals in this profession have portfolios with a humanities weight of only 52%. A high weight in humanities is risky by itself as humanities is not very portable across occupations. The profession with the second highest $\hat{\alpha}_H$ is Service, with a much smaller value of 33%. Moreover, the high volatility of shocks in this profession amplifies this risk leading to a high switching probability. High turnover makes diversification all the more attractive.

Although this pattern is not as extreme in other occupations, the average portfolios across individuals tends to be more balanced than the Cobb-Douglas technology parameters.

Professional of the Arts, Service, and Skilled Operatives appear to be high risk as measured by σ_{ϵ_j} while Managers, Medical and Other Professionals are safer. Note as

Table 6: Estimation Results

Occupation	$\hat{\alpha}_H$	$\hat{\alpha}_M$	$\hat{\sigma}_j$
Clerical	0.199 (*0.028*)	0.428 (*0.027*)	0.191 (*0.055*)
Manager	0.151 (*0.038*)	0.473 (*0.112*)	0.154 (*0.027*)
Skilled Op.	0.102 (*0.078*)	0.719 (*0.014*)	0.248 (*0.092*)
Prof. Arts	0.641 (*0.018*)	0.110 (*0.021*)	0.398 (*0.016*)
Prof- Medical	0.125 (*0.049*)	0.654 (*0.157*)	0.094 (*0.014*)
Prof - Engineer	0.034 (*0.020*)	0.930 (*0.078*)	0.189 (*0.067*)
Prof - Other	0.161 (*0.007*)	0.476 (*0.024*)	0.101 (*0.291*)
Sales	0.158 (*0.007*)	0.447 (*0.048*)	0.164 (*0.132*)
School Teacher	0.206 (*0.038*)	0.417 (*0.056*)	0.177 (*0.012*)
Service	0.257 (*0.121*)	0.404 (*0.015*)	0.414 (*0.130*)
Tech. Comp.	0.069 (*0.161*)	0.773 (*0.116*)	0.165 (*0.022*)
Tech. Non Comp.	0.150 (*0.058*)	0.632 (*0.029*)	0.208 (*0.144*)
	Estimate (*Std. Error*)		
σ_θ	0.175 (*0.052*)		
$\sigma_{\xi,H}$	0.977 (*0.030*)		
$\sigma_{\xi,Q}$	0.159 (*0.009*)		
$\sigma_{\xi,CB}$	1.795 (*0.042*)		

well that the uncertainty in the occupational fit is highest in those professions that emphasize humanities skills, i.e. those with highest $\alpha'_{j,H}s$.

Finally, the dispersion in the distribution of abilities differs across types of human capital. The ability to acquire quantitative skills is very concentrated (the standard deviation is 0.159) compared to the ability to study communication and business (0.977) and especially humanities (1.795).

Table 7 provides statistics from the distribution of (annual) income growth, both for the HS&B sample of students and for the estimated model. Dispersion in the observed data exceeds dispersion in the model. The standard deviation of the distribution of income growth in the simulated distribution is 45% of that in the data. This difference is not surprising. In reality individual earnings vary after workers settle in an occupation. Shocks to earnings that occur after exploration of occupations in the labor market ends are ruled out by construction in the model.

Table 7: Income Growth Distribution Summary - Model vs. Data

	Min.	1st. Quart.	Median	Mean	3rd Quart.
Data	-0.2634	0.0132	0.0577	0.0787	0.1209
Model	-0.2924	0.0586	0.0742	0.0811	0.1004

	Max.	Std. Dev.	Skew.	Kurt.
Data	0.7204	0.1255	1.3557	6.9617
Model	0.4164	0.0601	0.3509	6.0886

Despite this limitation, the model generates an earnings growth distribution with a substantial amount of inequality that shares important characteristics with earnings growth responses found in the HS&B survey. The minimum growth rate observed in both distributions is similar (-0.26 in the data and -0.29 in the model). Because the model generates a modest right tail of the distribution of earnings growth - some individuals in the data report high positive growth rates compared to the highest values generated by the model[20], the simulated skewness is only a third of the empirical counterpart. On the other hand, the model generates a substantial mass of negative earnings growth rates (these are associated with occupational switchers), so that the simulated kurtosis is in the ballpark to that found in the data, 6.1 versus 7.

To further explore the relationships among income growth, diversification in human capital portfolios and individual occupational transitions, Table 8 replicates the regressions from Table 3 on model-simulated data. Obviously, not all of the control

[20]One respondent in the data reports an average annual growth rate in earnings of 72%.

variables employed in the analysis with actual data in Section 2 are available with our model-generated output. Gender is absent in the simulated model and occupations in the model are exclusively horizontal. There are no vertical career transitions. Hence, SEX and $CAREER$ do not appear in the simulated regressions. The remaining variables - $STAY$, $log(y_1)$, and δ - are constructed the same way as in the actual data.

The structural model, however, has the advantage of an alternative measure of diversification, δ^*. For an individual i with a labor market history beginning in occupation j, define δ^* as

$$\delta^*_{i,j} = \sqrt{\sum_{k=1}^{K} (\omega_{i,k} - \hat{\alpha}_{i,j,k})^2}. \tag{4}$$

As is the case with δ, δ^* measures the distance from an individual's portfolio to a benchmark portfolio. For δ, the benchmark is the average portfolio of individuals working in the occupation chosen first. This benchmark is tainted as the average portfolio in an occupation is likely to reflect diversification to some extent. Workers in any given occupation will have faced uncertainty when choosing their skill portfolio. For δ^*, the benchmark portfolio is conceptually more straightforward. It is the optimal vector of human capital shares or weights an individual would choose if they knew from the outset that they were going to be employed in the same occupation from the first period onwards.

Table 8 displays the results of regressing income growth on portfolio diversification and other variables that summarize labor market histories. To ease the comparison between model and data, the last two columns report the same coefficients found when fitting the regression to actual data. The first four columns display results with model-generated data; the first two do not use the variable $STAY$.

The coefficient estimates from simulated data compare favorably to those estimated from the observed data in Table 8. They are all in line with the HS&B empirical estimates except for the coefficient on the interaction term $\delta \times STAY$, which is discussed

Table 8: Regression Results - Model-Simulated Income Growth (Δy)

Coeff. (*p-val.*)	(1)	(2)	(3)	(4)	(5)	(6)
$log(y_1)$	-0.007	-0.008	-0.014	-0.013	-0.150	-0.150
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
δ	0.082		0.103		-0.042	0.029
	(nil)		*(nil)*		(0.041)	(0.394)
δ^*		0.006		0.050		
		(0.194)		*(nil)*		
$STAY$			0.054	0.059		0.033
			(nil)	*(nil)*		(0.026)
$\delta \times STAY$			0.033			-0.104
			(nil)			(0.015)
$\delta^* \times STAY$				-0.050		
				(nil)		
Intercept	0.086	0.098	0.054	0.068	1.141	1.140
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
N	35,000	35,000	35,000	35,000	980	980
R^2	0.017	0.004	0.2077	0.179	0.291	0.303

below.

The positive coefficient (around $0.05 - 0.06$ when we condition on switching) on $STAY$, which is higher than the empirical counterpart (0.03) shown on Table 3, reflects simple selection. Those who stay in the job receive good ϵ draws and earn more relative to similar workers who try other occupations. The negative coefficient on initial earnings (-0.014) may initially seem peculiar in simulated data but this result too follows from a self-selection mechanism. Entrants with the lowest wages will in general be the least attached and most likely to leave. They are more prone to have signals or human capital profiles that payoff elsewhere. Among those who do leave for another occupation, those with lower initial wages not only do not fall as far but also tend to be better placed to absorb a transition. Among those who do not switch occupations, the initially low wage workers must receive higher draws on average when true productivity is revealed. Everything else constant, these less prepared workers would need a larger permanent shock to productivity to induce them to continue in that occupation. A small ϵ_j will lead to an occupational change. Individuals with low initial earnings who do not switch occupations thus experience higher income growth on average.

Now consider the relationship between diversification, income growth, and occupational exploration. Note first that the coefficient on diversification is positive, either 0.05 or 0.10 depending on the measure of diversification. For an individual who switches occupations ($STAY = 0$), average income growth would rise $5\% - 10\%$ of its mean given a 1% increase in the value of δ. An intriguing result here is the contrast between the regressions for those who stay in an occupation. Using the more natural benchmark of diversification relative to technological parameters, the estimates find that $\delta^* + \delta^* \times STAY$ equals zero. On this evidence, there is no return to a diversified portfolio among those who stay in a profession. Self selection which might bias the estimate appears to balance out in this case.

Table 9: Probit Regression Results - Model-Simulated Occupational Switches ($STAY$)

	Coeff. (*p-val.*) (1)	(2)	(3)	(4)	(5)	(6)
$log(y_1)$		0.325		0.320		0.504
		(nil)		*(nil)*		*(nil)*
δ			-2.085	-2.040	-0.491	-0.384
			(nil)	*(nil)*	(0.048)	(0.128)
δ^*	-0.516	-0.285				
	(nil)	*(nil)*				
Intercept	0.611	-0.107	0.887	0.188	0.473	-3.584
	(nil)	*(nil)*	*(nil)*	*(nil)*	*(nil)*	*(nil)*
N	35,000	35,000	35,000	35,000	980	980

Notes: The first four columns of the table display results of fitting a Probit model to model-simulated $STAY$. The last two columns display the same estimates as the first two columns of Table 4 for ease of comparison.

Using the alternative benchmark based on average skills in an occupation, δ, those stayers who deviate more from their peers have even more earnings growth, $\delta * STAY =$

0.03. This result contrasts sharply with the estimates from the HS&B data estimates in Table 3. The self selection mechanisms outline above plus the arbitrary nature of the benchmark present a number of issues and potential biases interpreting these results. This highlights the need for careful modeling. Taken together, the OLS estimates in Table 8 none the less present a picture consistent with the importance of diversification and with the estimates found in the simulated data.

Replicating Table 4, Table 9 reports Probit estimates from the model generated data in which the probability of switching occupations is a function of the diversification measure and other observables. The first four columns of the table display coefficients when fitted to the occupational transitions found in our model-simulated data. The last two columns of Table 9 display the relevant estimates from the first two columns of Table 4. The first two columns display results when the measure of diversification is δ^*, and the second two when that measure is δ. The model matches well the magnitudes of the coefficients on initial earnings (0.3 in the model vs. 0.5 in the data) and the negative association between the probability of switching and our measure of distance in the portfolios.

Table 10 presents some additional moments from the earnings (growth and levels) distributions, distinguishing also between individuals who switch occupations and those who do not. The first column reports $\mathbb{E}(\Delta y)$, the cross-sectional average of earnings growth. The first number, for "All" corresponds to the number reported in Table 7, 8.11%. The second and third row report the same moment for "Switchers", 4.22%, and for "Non-Switchers", 9.63%. The second column reports the standard deviation of the logarithm of earnings in the 5^{th} period. We label that period 1991 for consistency with the HS&B dataset. We focus on the log of earnings and not on earnings themselves because the distributions have different means.

The model delivers an earnings distribution for "Non-Switchers" with less dispersion than that of the "Switchers". This is a common feature of the simulations: switchers experience lower growth in earnings but their distribution is relatively more disperse. On the other hand, earnings of those who remain in their initial occupation grow faster on average and their earnings distribution is less disperse. The standard deviation of earnings for all individuals is 0.54; for non-switchers is 0.51 and for switchers 0.53.

Non-switchers enjoy higher earnings growth for two reasons. The first channel is the same self-selection mechanism discussed previously that makes switching optimal only in the event of a relatively low productivity shock. The second channel is the earnings growth of γ that accrues for a longer time period if individuals do not switch. As all non-switchers have relatively high productivity updates, dispersion of earnings among non-switchers is lower. If not, the optimal policy would be to switch. As for switchers, they are not all the same. The lucky ones, those who switch only once, end up with relatively high earnings. An unlucky group find it optimal to switch several times. Their earnings growth and their final level of earnings are both low. Both the lucky and the unlucky are labeled "Switchers" and hence their distribution of earnings is quite disperse.

Finally, the table also reports the fraction of people who switch occupations; 28.14% with our estimated parameters.

Table 10: Baseline Earnings Distribution - Summary

	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switchers$
All	0.0811	0.5368	28.14
Switchers	0.0422	0.5285	
Non-Switch.	0.0963	0.5081	

Now relax the assumption of a unit-elasticity of substitution across skills, but otherwise keep the same parameter values as before. In particular assume the payoff function for occupation j (net of an individual's productivity) is given by,

$$f_j(\boldsymbol{h}) = \left(\sum_{k=1}^{3} \alpha_{j,k} h_k^{\rho} \right)^{1/\rho}.$$

This technology implies an elasticity of substitution equal to $1/(1-\rho)$. We report results with $\rho = -0.15$ and $\rho = -1.15$, which imply an elasticity of substitution equal to 0.87 and 0.47. Given these two elasticities, Table 11 report the same statistics as Table 10. Decreasing the elasticity of substitution across human capital types, increases the average growth rates in earnings and the cross-sectional dispersion in earnings levels. Perhaps contrary to one's intuition, it also increases the number of switchers.

Table 11: Earnings Distribution - Relative Complements - Summary

	$\rho = -0.15$		
	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switchers$
All	0.0816	0.5413	28.63
Switchers	0.0436	0.5367	
Non-Switch.	0.0968	0.5118	
	$\rho = -1.15$		
	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switchers$
All	0.0876	0.5811	33.17
Switchers	0.0550	0.5713	
Non-Switch.	0.1036	0.5658	

These effects are attributed to a change in the cross-sectional distribution of individual across occupations. As switching becomes more costly (because earnings drops are larger) individuals try to avoid occupations with portfolios that are on average specialized, i.e., having a very large weight in a given human capital type. For instance, Engineering requires a very high weight in Quantitative human capital and a very low weight in Humanities and considered a very specialized occupation. On the other extreme, Service is a very diversified occupation. The weights in each human capital type are close to each other.

When the elasticity of substitution decreases, a reallocation from specialized occupations to diversified occupations takes place. Engineering becomes the first choice for a smaller of individuals, while the opposite happens to Service. The volatility of the shocks in Engineering is on the low end (0.189), while Service has the highest (0.414) among all occupations. The higher variance increases the possibility of large productivity draws, increasing the average growth rate and the dispersion of earnings for the non-switchers. This higher variance also increases the overall rate of switches, but these are concentrated in early periods, increasing the average growth rate for those who switch.[21]

5.1 Counterfactual Earnings Distributions

To quantify the effects of occupational uncertainty on the distribution of earnings in the estimated model, two thought experiments based of restrictions on portfolio choice emerge. Both experiments capture a feature characteristic of European higher educations systems: their relative inflexibility when diversifying across areas of study. A student wishing to be a biologist is given a curriculum from which there is little freedom to deviate. The baseline model resembles an American system in which students have a relatively large degree of freedom to diversify across areas of study.

The first experiment (labeled "Specialization to First Occupation") posits that students must specialize in the occupation they would pick as their first choice in the baseline model. In doing so, they perceive the vector of signals ` to be perpetual pro-

[21]There is a second effect but one which in principle would lead to a lower fraction of switchers. As skills become more complementary, individuals prefer occupations with a lower volatility of productivity shocks. Because switching is costlier, individuals want to avoid having to switch. This preference towards more stable occupations also changes the distribution of individuals across professions but leads to a lower fraction of switchers (unlike the effect described in the text). Given the pattern estimated empirically between the volatility of shocks and the degree of specialization in average portfolios, it is not certain that decreasing the elasticity of substitution will always result in a higher fraction of switchers.

ductivities across occupations. Denoting the first-chosen occupation in the baseline model by j', he optimal portfolio solves

$$\max_{\boldsymbol{h}} \left\{ -C(\boldsymbol{\xi}, \boldsymbol{h}) + \beta e^{\theta_{j'}} f_{j'}(\boldsymbol{h}) / (1 - \beta\gamma) \right\},$$

Denote this solution portfolio as $\mathbf{h}'$.

In the second experiment (labeled "Optimal Specialization"), agents are forced again to specialize choosing their optimal portfolios as if they were to remain in that occupation indefinitely without updates to their productivity signals. The essential difference with respect to the first experiment is that they can now choose which occupation in which to specialize. Let

$$j'' = \arg \max_{j \in \{1,\ldots,J\}} \left\{ \max_{\boldsymbol{h}} -C(\boldsymbol{\xi}, \boldsymbol{h}) + \beta e^{\theta_j} f_j(\boldsymbol{h}) / (1 - \beta\gamma) \right\},$$

Let the optimal portfolio associated with this optimal occupational choice be $\boldsymbol{h}''$

For each information setup, we give $\mathbf{h}'$ and $\mathbf{h}''$ to individuals in the stochastic world, and construct earnings distributions. Table 12 provides the results from the two experiments with quantities reported relative to the baseline case. When individuals are endowed with portfolios of the first chosen occupation under uncertainty the fraction of switchers falls. This is expected. As most switches occur in the first few periods, having a portfolio of skills precisely tailored to the first occupation reduces the attraction of trying a new one. The growth rate of income is very low for switchers who are ill-prepared for the bad draw. Average income growth of non-switchers also falls albeit much less than the switchers, as now more individuals who experience low shocks are inclined to remain in the first occupation. Taken together, average incomes also fall.

The variability of earnings also falls but it falls more for the non-switchers than for the switchers. Since the reservation productivities for switching occupations fall, the distribution of earnings within the switchers is more compressed; this experiment adds workers located towards the "middle" of the productivity distribution. The fact that few individuals switch several times, because portfolios are more concentrated, contributes to lowering the variance of earnings for switchers. Switching is based upon the expectation associated with drops in income, and hence as concentrated portfolios prevent individuals from switching several times, extreme values in the left tail are not as likely.

In the second experiment these results are somewhat mitigated but qualitatively the message is the same. Inflexible systems that result in concentrated portfolios decrease labor market turnover, average earnings growth, and the cross-sectional variance of (log) earnings.

Table 12: Counterfactual Earnings Distributions
(Percentage Changes Relative to Baseline (Table 10))

	Cobb-Douglas		
	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switchers$
Specialization to First Occ.			
All	-3.79	-2.68	-12.54
Switchers	-22.51	-1.82	
Non-Switch.	-3.63	-3.58	
Optimal Specialization			
All	-0.37	-3.22	-8.28
Switchers	-10.66	-2.54	
Non-Switch.	-0.52	-4.41	

Table 13 displays the outcome of performing the two counterfactuals when we relax the assumption of Cobb-Douglas payoffs and the accompanying unit elasticity of substitution. Although intuitively one would expect the effects to be more pronounced, the tables show this is not the case. The reason is that with "inappropriate" portfolios, individuals self-select into relatively safe occupations. In general switching rates fall less; this is particularly true for the "Optimal Specialization" case. The effect of forced specialization on the drop in average income growth is smaller with the lower elasticities of substitution.

Table 13: Counterfactual Earnings Distributions
(Percentage Change Relative to Table 11)

		$\rho = -0.15$			$\rho = -1.15$	
	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switch.$	$E(\Delta y)$	$\sigma(log(y_{1991}))$	$\%Switch.$
Specialization to First Occ.						
All	-3.06	-2.58	-15.58	-3.16	-0.24	-11.70
Switchers	-22.43	-2.61		-17.33	2.23	
Non-Switch.	-3.34	-3.36		-2.51	-3.06	
Optimal Specialization						
All	-0.12	-3.82	-6.64	-0.06	-3.84	-3.08
Switchers	-4.58	-5.53		-5.89	-5.38	
Non-Switch.	-0.81	-3.48		3.37	-0.33	

6 Concluding Remarks

This paper assesses the way in which the composition of workers' skills interact with labor market uncertainty to determine the evolution of earnings. Human capital consists of a portfolio of imperfectly substitutable skills acquired through formal education. Different potential occupations value these skills differently and uncertainty about one's fit in any particular occupation introduces uncertainty in the investment decision. A trade-off arises between acquiring specialized skills targeted for a particular occupation and acquiring a package of skills that diversifies the risk across occupations.

Individual-level data on the amount of college credits across different subjects and labor market dynamics in early careers reveals that income growth is higher for the more specialized individuals who do not switch occupations whereas income growth is higher for more diversified individuals who switch occupations.

To further evaluate tension between specialization and diversification, we construct and estimate a portfolio choice problem that features an interaction between skills, abilities, and uncertain labor market outcomes. The model replicates the basic patterns observed in the individual data and generates a sizable amount of inequality. Counterfactual earnings distributions found by endowing individuals with portfolios chosen under certainty about occupational fit illustrate that the underlying stochastic structure generates large effects both on the income growth distribution and the variance of earnings.

The baseline model restricts an individual's choice by eliminating the possibility of choosing previously sampled occupations. Although it makes the model tractable and easier to estimate, this restriction seems arbitrary. It could be optimal to recall an occupation that has been tried in the past. Evaluating the model without the restriction is too costly for a simulation-based estimation so the focus here is first on the extent of occupational recall. In the HS&B data, it is extremely rare to observe individuals in the data who work in an occupation, try a new one, and come back to the previous one. Table 11 reports individuals who, among triples of years, report working at an occupation, switching the following year, and returning to the same occupation of two years before. To be specific, the column entitled 1986-1988 reports the number and fraction of individuals who report the same occupational code in 1986 and 1988, but a different one in 1987. Recalling previous occupations is very rare, with about 1% of individuals experiencing it.

Table 14: Evidence of Occupational Recall in the HS&B Sample ($N = 980$)

	1986-1988	1987 − 1989	1988 − 1990	1989 − 1991
Number of Recalls	15	9	8	13
Fraction	1.54%	0.9%	0.8%	1.33%

Even if recall were more pronounced, it would be unlikely to substantially alter the model. Allowing individuals to recall occupations in the simulated model given the no-recall estimates generates relationships between earnings growth, diversification, and occupational switching that are no different than when recalling occupations is not allowed.[22] Although infrequent in the model, recalling previous occupations happens more often there than in the HS&B data. Figure 1 shows the pattern of switches per year in the model without recall *vis-a-vis* the model with recall. The magnitudes of occupational switches are similar and there are no discernible differences in the pattern of switching.

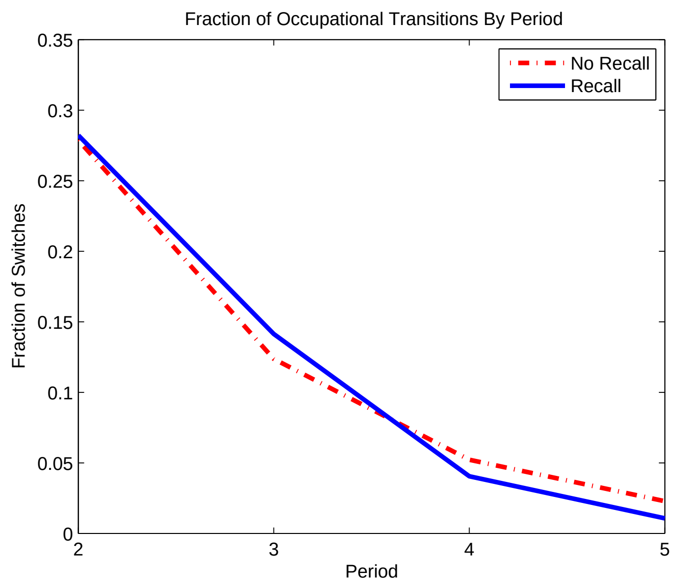

Figure 1: Comparison in the fraction of occupational transitions (vertical axis) in the model with occupational recall relative to the model without recall, from period $t-1$ to t (horizontal axis).

[22]Results for the model with recall analogous to those presented in Tables 8 and 9 for the model without recall, are available upon request.

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7 Appendix:

7.1 Data

Merging the PETS and *Sophomores in 1980* - HS&B datasets yields an initial sample of 8,395 students. Dropping those who do not have an associates degree or who have a doctorate / advanced professional degree (doctors and lawyers, primarily) eliminates 3,637 individuals. Deleting those with missing data on earnings, employment status, or occupation reduces the sample to 2,499 individuals.

To account for possible unemployment spells which may distort measures of annual earnings, dividing annual earnings by number of months employed yields monthly earnings for all years in the sample, 1986-1991. Individuals reporting negative or zero monthly earnings for a given year are dropped as are individuals who report working in one of the following occupations: farmer, laborer, protective services, and the military.

To find portfolios, human capital is partitioned into four broad areas of knowledge: *Quantitative (Q)*, *Social Science (SS)*, *Humanities (H)*, and *Fine and Performing Arts (FPA)*. Each of these areas is the sum of credits taken in areas of study belonging to that area of knowledge.

- Q = Non-Additive Pre-College Level Math+Credits in College-Level Math + Credits in Calculus and Advanced Math+ Other Math Credits from Math Depts.+ Credits in all Statistics Courses + Credits in Science + Credits in Engineering + Credits in Computer Science + Credits in Computer-Related Courses

- H = Total Credits in Humanities Courses.

- SS = Total Credits in Business Courses + Total Social Science Credits + Credits in Basic Communications Courses

- FPA = Total Credits in Arts and Performing Arts.

Students with less than 80 credits or those who report missing values for credits in any of the four categories are dropped.[23]

This procedure reduces the sample to 1,362 students with complete labor market histories - average earnings per month and occupation for given year - plus a description of their human capital investments. The total number of credits in the four areas of knowledge (and consequently the vector of portfolio weights ω) summarize these human capital investments.

The year of graduation further reduces the sample. Students who graduated in either 1989, 1990, or 1991 are dropped because despite reporting labor market histories from the perspective of the model those histories are irrelevant. In the model, we analyze histories *after* investing in human capital and therefore discard labor market histories contemporaneous to those human capital investments. Discarding such histories leaves a total of 1,016 students.

The OLS regressions reported in Table 3 in Section 2 use a sample truncated of 980 students. Students in the bottom and top 2 percentiles are dropped. 686 student in this sample hold bachelor's degree. We also report results for this group separately.

Students who become workers are grouped into broader occupation categories than those defined in the original HS&B dataset. For example, in the original HS&B there are four categories of managers, three categories for owners, and three categories for clerical workers. We group them all into "Managerial", "Owner", and "Clerical" categories. This aggregation reduces the number of occupations (increases the sample size and therefore decrease the degree of sampling error) in the empirical analysis.

Finally, because the Sophomores of 1980 data set is not as widely used in the economics literature as other panels such as the PSID, NLSY, or SIPP, we compare the unconditional distribution of income by year from HS&B with Current Population Survey

[23]The PETS dataset provides no direction on what subjects exactly constitute each of the definitions included in the main four areas of knowledge. They provide a definition for each of the variables used to avoid the double-counting of credits as much as possible. For instance, in the categories of humanities credits, they include Foreign Languages, but they report as a separate category credits in Foreign Languages.

(CPS) data. Figure 2 displays kernel-smoothed estimates of the annual (nominal) earnings distribution from the CPS and the HS&B. Since the objective is to assess the overall quality of the survey, the figure includes all respondents, not just the sub-sample of relatively-higher educated individuals. To get the appropriate population in the CPS we restricted it to those respondents having roughly the same age as the respondents in the HS&B. The figure illustrates that except for the lower levels of earnings in 1986 and 1987, the two distributions are comparable for the remaining years. If anything, it seems as if the CPS shows a large mass of individuals with unreasonably low levels of annual earnings.

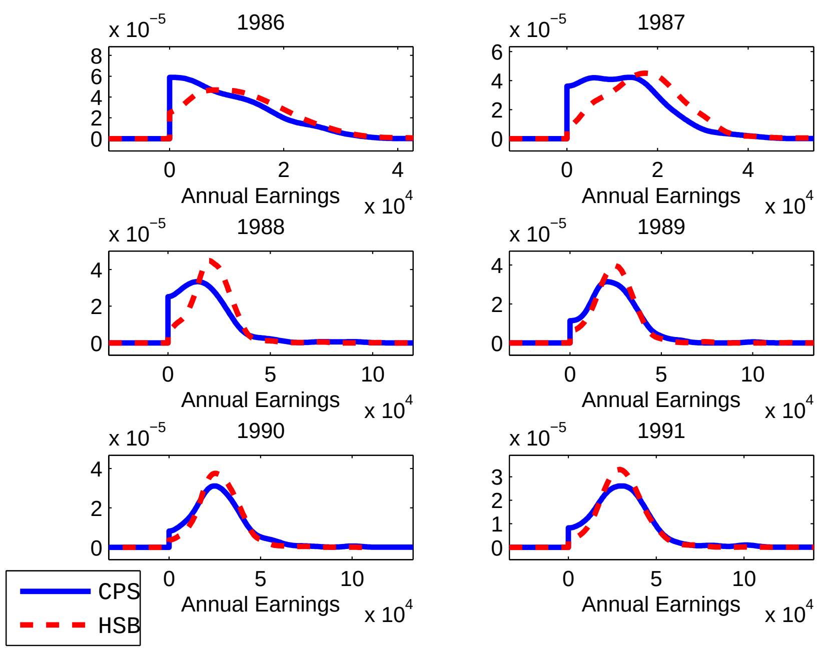

Figure 2: Comparison of unconditional annual earnings distribution in the CPS and the HS&B.

7.2 Appendix: Model Solution and Estimation

Given a value for the structural vector of parameters Λ, the following algorithm describes the solution of the model described in the text. Individuals are not allowed to return to previously sampled occupations:

- For a given individual, draw a vector $\boldsymbol{\theta}$ (productivity signals) and $\boldsymbol{\xi}$ (abilities).

- For a given value of the portfolio $\boldsymbol{h}$, compute the cost function $\mathcal{C}(\boldsymbol{h}, \xi)$.

- Compute the Gittins index for each of the J occupations by finding a zero in equation (2). Standard zero-finding (in particular *dzreal* in IMSL) and numerical integration (*dqdag* in IMSL) routines are used. The computation of the Gittins index gives an initial ranking of occupations $\{n_1, n_2, \ldots, n_J\}$ given by $M_{n_1} > M_{n_2} > \cdots > M_{n_J}$. This ranking provides the individual with his first occupational choice.

- Compute the switching probabilities. Given J occupations there are $J-1$ switching probabilities to compute because without occupational recall there are only J possible paths the individual can take. Denote p_{n_i,n_j} the probability of moving to occupation n_j, having tried occupation n_i and observed its productivity update ϵ_{n_i}. The probability p_{n_i,n_j} is given by

$$p_{n_i,n_j} = Prob\left(M_{n_j} > \frac{e^{\theta_{n_i}} e^{\epsilon_{n_i}} f_{n_i}(\boldsymbol{h})\gamma}{1-\beta\gamma}\right) = Prob\left(\epsilon_{n_i} < log(\frac{1-\beta\gamma}{\gamma}\frac{M_{n_2}}{f_{n_i}(\boldsymbol{h})})\right) =$$

$$Prob(\epsilon_{n_i} < \epsilon^*_{n_i}). \tag{5}$$

  Given normality for the distribution of ϵ_{n_i} that probability is straightforward to calculate. The probability of the j^{th} possible labor market history (path) is given by

$$p_j = \prod_{k=1}^{j} p_{n_{j-1},n_j}(1 - p_{n_j,n_{j+1}})$$

  if $j < J$ and

$$p_j = 1 - \sum_{i=1}^{J-1} p_i$$

if $j = J$.[24]

- Given the probabilities for each of the paths compute the expected value of earnings in the labor market :

$$\beta V(\theta, \boldsymbol{h}) = \sum_{j=1}^{J} p_j \beta \left(\sum_{k=1}^{j} \beta^{k-1} e^{\theta_{n_k}} f_{n_k}(\boldsymbol{h}) + \frac{\beta^j \gamma}{1-\beta\gamma} \mathbb{E}(e^{\theta_{n_j}} e^{\epsilon_{n_j}} f_{n_j}(\boldsymbol{h}) | \epsilon_{n_j} \geq \epsilon^*_{n_j} \right).$$

  Note that the individual always starts from occupation n_1. After that, if they switch, they switch to occupation n_2, then n_3, and continue writing-off occupations as long as they do not settle in a given occupation.

- Maximize the function $-\mathcal{C}(\boldsymbol{h}, \xi) + \beta V(\theta, \boldsymbol{h})$ by choosing an optimal portfolio $\boldsymbol{h}^*$ using a standard optimization routine that assumes differentiability of the objective function.

- Draw $u \sim Unif[0, 1]$ and using the set of probabilities $\{p_j\}_{j=1}^{J}$, randomly generate a sequence of earnings and a sequence of occupational choices.

These steps determine the optimal portfolio and a sequence of earnings and occupational transitions for a given individual i. Repeating the same steps (independently) for a large cross-section of individuals yields a distribution of earnings, growth rates of earnings, occupational choices and optimal portfolios. Although individuals live forever, we truncate the number of periods 5 which roughly corresponds to the number of periods in the data

This distribution provides the elements of the vector $\hat{Y}$. A typical element of that vector is a statistic from that distribution of a panel of individuals. We use a Nelder-Mead algorithm to find the minimizer $\hat{\Lambda}$ of the criterion function (6).

[24] The steps to compute the model with recall are the same, however, the switching probabilities have to be computed by Monte Carlo integration, increasing exponentially the computational intensity of the exercise.

$$\hat{\Lambda} = \underset{\Lambda}{\operatorname{argmin}} (\mathrm{Y} - \hat{\mathrm{Y}})'(\mathrm{Y} - \hat{\mathrm{Y}}) \tag{6}$$

We use forward-difference numerical differentiation to compute the Jacobian matrix of the criterion function. After finding the Jacobian, evaluating (3) is straightforward.