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Human capital portfolios ☆

Pedro Silos [a], Eric Smith [a,b,*]

[a] Federal Reserve Bank of Atlanta, 1000 Peachtree St. NE, Atlanta, GA 30309, United States
[b] University of Essex, Department of Economics, Wivenhoe Park, Colchester, Essex CO4 3SQ, United Kingdom

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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 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 generates a sizable amount of inequality. Policy experiments illustrate that mandatory specialization generates lower average income growth, lower turnover and marginally lower inequality.

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1. Introduction

Every occupation requires a different set of skills. Conversely, many skills are useful, to different degrees, in a wide variety of professions. A literary editor, a corporate lawyer and a marine biologist all apply related skills involving reading, writing and arithmetic but in different amounts. Moreover, some occupations appear to more heavily emphasize a 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 occupation 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 occupational matching uncertainty on the range of acquired skills and on earnings dynamics, this paper first establishes panel data evidence linking labor market outcomes with the fit of an individual's acquired skill set in their chosen occupation. The paper then constructs, estimates and assesses a human capital portfolio choice problem for individuals facing an uncertain labor market.

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* Corresponding author.
E-mail addresses: pedro.silos@atl.frb.org (P. Silos), esmith@essex.ac.uk (E. Smith).

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A precise economic framework is spelled out to discern underlying trade-offs. Students who vary in both their innate abilities to learn and in their potential in distinct jobs will choose their set of skills based on these differences. Coupled with labor market uncertainty, these unobservables will also generate idiosyncratic labor market outcomes. As a result, students targeting the same first occupation are likely to acquire different portfolios of skills to use in their intended job as well as in their back-up plan. The skills portfolio decision problem put forward in this paper is used to identify the roles these different unobserved factors play from detailed information on human capital choices and labor market histories.

The framework adopted here assumes that agents know from the outset their abilities to acquire imperfectly substitutable skills. They also receive an initial signal of their potential 'fit' or prospects in a number of occupations. Given this personal information as well as the expected skill payoffs in each profession, agents 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 initial fitness signal in that profession determine initial pay. As employment continues in an occupation, an agent's true productivity is at some point 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 initially knowing their true quality in the new job. The process repeats itself until the individual settles in an occupation.

This framework reveals a tension between specialization and diversity.[1] Innate talents and idiosyncratic signals of potential provide an incentive for individuals to specialize by acquiring skills that reflect their personal circumstances. Students rationally pursue those subjects in which they show promise and talent. In contrast, the risk of low productivity draws in each occupation provides an incentive to acquire a more widely applicable 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 assess this trade-off between specialization and diversity. For the most part, students in the US begin to specialize 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 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. Looking at the pattern of earnings, the estimated model performs well. The estimates of the model are based primarily on matching the observed human capital portfolios and the pattern of occupational switching. None the less, simulated data found using these estimates mirror the observed relationship between portfolio concentration, career switches and earnings.

Targeting and hedging in the portfolios appear to affect earnings 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 targeted portfolios who remain in an early career choice experience higher earnings and earnings growth. Workers with more versatile portfolios who switch earn more than switchers with specialized portfolios. Those who settle early, that is those who realize better first 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.

As the model and data are close along several dimensions of interest, it is natural to consider policies that shape the hedging decision. We find that a European-style education system characterized by mandatory specialization in an occupation generates a lower degree of turnover, lower earnings growth, and lower dispersion of (log) earnings. An alternative system that allows for more breadth and hedging opportunities (the US higher education system) trades off higher growth rates in earnings (and higher education expenditure) for a slightly more unequal income distribution.

These results extend the human capital literature with uncertainty. The early human capital literature developed to understand earnings over the life-cycle, Becker (1994) or Ben-Porath (1967), focused on investments in homogeneous human capital. Subsequent contributions added uncertainty about future rewards. Levhari and Weiss (1974) and Altonji (1993) are two prominent examples. More recently, Wasmer (2006) as well as Gervais et al. (2008) study from a theoretical perspective the trade-off between (more risky) specific and general human capital during periods of aggregate "turbulence".[2]

A parallel literature considers multi-dimensional endowments of abilities which determine self-selection of individuals into different sectors, as in Heckman and Sedlacek (1985, 1990), or occupations, as in Willis (1987). These studies formalize the static Roy (1951) model of comparative advantage and occupation selection.[3] Keane and Wolpin (1997) use a dynamic Roy framework to estimate a structural model of a joint schooling and occupational choice decision. In Keane and Wolpin's framework, individuals have an initial endowment of occupation-specific abilities (including an ability level to accumulate human capital) and they control their schooling and occupational choice to maximize lifetime earnings.[4] See also Gathmann and Schönberg (2010) and Yamaguchi (2012) who extend that literature by redefining occupations as bundles of tasks and

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

[2] An empirical literature has developed to evaluate the degree of mismatch between occupations and the choice of major or field. Malamud (2010) and Robst (2007) are two examples in this extensive literature. Malamud examines the relationship between the timing of the choice of field and the likelihood of working in an unrelated occupation. Robst explores the wage effects of the distance between field of study and occupation.

[3] Lazear (2009) and Schoellman (2010) are more recent examples of works that share some elements with that earlier literature.

[4] Other studies in the literature of occupational choice include Sullivan (2010) and James (2012).

exploring the pattern of mobility of individuals across occupations. Employing a similar framework Sanders (2011) analyzes the interaction between learning about one's abilities and occupations transitions. Finally, Arcidiacono (2004), Kinsler and Pavan (2012) study to what degree the different observed rates of return of alternative majors can be explained by selection into majors and jobs. The focus of these studies is not an optimal portfolio choice motivated by uncertainty about occupational fit and its implications for earnings dynamics.[5]

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 of the labor market is close to the one employed here, although he abstracts from human capital investment. The distinguishing feature of Miller's framework is the sequential revelation of information as individuals try new occupations or careers which generates a trade-off between exploring new occupations and exploiting the current one. More recent work includes Antonovics and Golan (2012) who study the tradeoff between information and wages in a model of occupational choice. They use a model of job choice to infer how much information different occupations reveal about workers' productivities.[6]

Finally, a substantial literature studies the nature of shocks that individuals experience over the life-cycle and the cross sectional inequality in earnings that these shocks generate. Huggett et al. (2011) 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 (2009) explore the link between 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. Lifting those restrictions overturns the results.

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 arises during the early years of individuals' life-cycles.

2. Preliminary evidence

2.1. Data

This section examines the observed 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 combination of information on post-HS credits obtained in different areas of study as well as information on post-training labor market histories.[7]

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 annual 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 14 820 students. A sub-sample of about 8000 transcripts was requested by the PETS study, and those received were encoded. Many students, however, did not advance very far in higher education. An initial sample of about 5700 records is therefore further restricted to those students who earned at least 75 credits. This restriction along with requiring sufficiently complete labor market histories yields a sample of 2130 students. The Online Appendix provides a step-by-step description of the selection process as well as other data-related issues including details on the construction of human capital portfolios.

Human capital portfolios, calculated from transcript credits, contain three areas or components of study. Using information from PETS, we group credits into (i) quantitative and scientific courses including engineering and computer science, (ii) humanities including history, foreign languages, fine and performing arts, and (iii) social science, business and communications. Label these three groups Q, H and SS respectively. Credits in sub-categories (e.g. in fields such as biology, literature,

[5] For an overview of studies on human capital with an emphasis on its multi-dimensional nature, the reader is referred to Sanders and Taber (2012).

[6] Neal (1999) 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 explored in detail by Topel and Ward (1992).

[7] The 1993–2003 Baccalaureate and Beyond Longitudinal Study contains similar information on education but among other things has less information on labor market histories. The NLSY has good labor market data but less complete education information. One feature we do not observed in the HS&B is the amount of hours worked. Thus, throughout the study the terms earnings, wage and income are all used to denote the same concept: compensation for labor in a given period.

Table 1
Empirical human capital portfolios by occupation (1991).

Occupation	Share hum.	Share quant.	Share soc. sci.
Clerical	0.253	0.268	0.479
	(0.192)	(0.188)	(0.192)
Manager	0.217	0.311	0.472
	(0.162)	(0.223)	(0.198)
Skilled operative	0.216	0.542	0.242
	(0.196)	(0.287)	(0.203)
Professional – arts	0.532	0.176	0.292
	(0.238)	(0.170)	(0.181)
Professional – medical	0.186	0.519	0.295
	(0.082)	(0.183)	(0.162)
Professional – engineering	0.092	0.798	0.110
	(0.096)	(0.123)	(0.069)
Professional – other	0.225	0.326	0.449
	(0.181)	(0.215)	(0.225)
Sales	0.277	0.322	0.402
	(0.239)	(0.230)	(0.216)
School teacher	0.214	0.280	0.506
	(0.138)	(0.180)	(0.174)
Service	0.332	0.310	0.358
	(0.195)	(0.202)	(0.193)
Owner	0.212	0.409	0.379
	(0.169)	(0.263)	(0.217)
Technician – computer-related	0.119	0.671	0.210
	(0.104)	(0.203)	(0.166)
Technician – non-computer-related	0.200	0.558	0.242
	(0.140)	(0.242)	(0.193)
Laborer/homemaker	0.218	0.446	0.335
	(0.222)	(0.279)	(0.222)
All occupations	0.233	0.372	0.394
	(0.186)	(0.372)	(0.394)

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

sociology and so on) are available but not used. Using these more refined data not only drastically increases computational complexity, but also lowers the reliability of classification given the widespread existence of overlapping fields.

Given credits (weighted by GPA[8]) in each area or type of human capital $k \in \{Q, H, SS\}$ the weights in the human capital portfolio of an individual readily follow as:

$$\omega_k = \frac{Credits_k}{\sum_{j \in \{Q,H,SS\}} Credits_j}.$$

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 three human capital types.

Table 1 reveals substantial variation in the average human capital investments across occupations. The mean weight on humanities varies from fairly low values in Engineers (0.09) and Computer Related Technicians (0.12), to values of a little more than half for Arts Professional. It is not surprising that Engineers have the highest mean weight in quantitative human capital (0.80), whereas this area of study represents barely 18% of the portfolios of Arts Professionals. School Teachers, Clerical, Sales and Other Professionals have the highest shares of business and communications human capital, allocating up to half of total credits on average, to this component.

Substantial variation 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 0.12 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 has a vector of human capital weights ω_k, $k \in \{Q, H, SS\}$. The components measure the proportion of each skill 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 uniform allocation of credits across fields to self-insure against

[8] Using credits unweighted by a students GPA (a standard measure of performance) does not materially affect this analysis. Section 2 in the Online Appendix provides results for that case.

Table 2
Descriptive statistics.

Summary statistics – selected variables

	Mean	Median	Std. dev.	Min.	Max.
δ	0.289	0.246	0.180	0.007	0.994
$\log(Y_{91})$	8.181	8.226	0.520	5.076	10.287
ΔY	0.083	0.058	0.177	−0.417	1.137
CRED	122	120	28	75	363
STAY	0.563	1.000	0.496	0.000	1.000

Notes: The table reports summary statistics for a few variables of interest in the baseline sample of the HSB Study. δ denotes our measure of distance described in the text. $\log(Y_{91})$ is the log of earnings (in 2010 dollars) at the end of our sample (1991), ΔY is growth rate of earnings during a worker's early labor market history, *CRED* is the number of credits taken, and *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise.

Correlation matrix – selected variables

	δ	$\log(Y_{91})$	ΔY	*CRED*	*STAY*
δ	1.000	−0.084**	0.072**	0.027	−0.101**
$\log(Y_{91})$		1.000	0.442**	0.126**	0.12**
ΔY			1.000	0.048*	−0.099**
CRED				1.000	0.032
STAY					1.000

Notes: The table reports unconditional correlations among a few variables of interest in the baseline sample of the HSB Study. δ denotes our measure of distance described in the text. $\log(Y_{91})$ is the log of earnings (in 2010 dollars) at the end of our sample (1991), ΔY is growth rate of earnings during a worker's early labor market history, *CRED* is the number of credits taken, and *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise.
* Correlation is significant at least at the 0.05 level.
** Correlation is significant at least at the 0.01 level.

shocks or because a particular occupation explicitly rewards balanced skills. To assess how well tailored an individual's acquired skill 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 how well suited a given set of acquired skills is to a particular occupation. This paper adopts a natural if crude measure. Suppose an individual enters the labor market with human capital vector $(\omega_Q, \omega_H, \omega_{SS})$ and first works in some given occupation. The degree of hedging, δ, for this particular individual – occupation pair is defined as the standard Euclidean distance in $\mathbb{R}^3$ that the individual's portfolio lies from the average portfolio observed in the first chosen occupation:

$$\delta = \sqrt{\sum_{k \in \{Q,H,SS\}} (\omega_k - \bar{\omega}_k)^2}$$

where $\bar{\omega}_k$ denotes the typical (or average) portfolio of those students who represent a good match in the chosen occupation. A match in an occupation is considered good if a worker initially chooses that occupation and does not leave. A portfolio is tailored to a given occupation if that portfolio is "close" to the average portfolio of those who started and stayed in that occupation. Hedging 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 measure as well as for four other relevant variables. $\log(Y_{91})$ denotes (logged) earnings level observed in 1991, deflated by the CPI. ΔY denotes the average annual growth rate of earnings for individuals as given by

$$\Delta Y = e^{\log(Y_{91}/Y_{91-T})/(T-1)} - 1,$$

where Y_{91-T} denotes earnings (deflated for the appropriate year) in the first year after graduation and T the time in years of individual labor market history. *CRED* denotes the total number of raw credits. Finally, *STAY* is an indicator variable that takes the value 1 if an individual never switches occupations and equals 0 otherwise.[9]

For this sample of students, the measure of hedging, δ, displays considerable dispersion across individuals. The standard deviation is 0.18 for a variable that ranges between 0.007 and 0.994, has a mean value of about 0.3, and is bounded between zero and one.

Real earnings growth per year in this sample averages about 8.3% 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) and found that the two samples are similar. The Online Appendix reports the results of this comparison.[10]

[9] The figures given in Table 2 correspond to a distribution of individuals truncated to eliminate the top and bottom 0.5% of average earnings growth. See Section 1 of the Online Appendix.

[10] 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 (which we account for in our measures), it does not contain hours worked during the periods of employment or

Table 3
OLS regression results – dependent variable is $\log(Y_{91})$.

	Coeff. (*t-stat.*)			
	(1)	(2)	(3)	(4)
$\log(Y_{91-T})$	0.286***	0.272***	0.270***	0.271***
	(14.98)	(14.00)	(13.88)	(13.95)
$\log(CRED)$	−0.117***	−0.116*	−0.131**	−0.138**
	(−1.82)	(−1.81)	(−2.05)	(−2.15)
SEX	−0.095***	−0.093***	−0.097***	−0.097***
	(−4.30)	(−4.21)	(−4.42)	(−4.39)
δ	0.053	0.070	0.096	0.235***
	(0.90)	(1.20)	(1.63)	(2.81)
STAY		0.072***	0.100***	0.185***
		(3.36)	(4.40)	(4.34)
CAREER			0.148***	0.159***
			(3.42)	(3.66)
$\delta \times STAY$				−0.265**
				(−2.34)
Intercept	5.521***	5.561***	5.638***	5.632***
	(14.35)	(14.48)	(14.70)	(14.70)
N	1940	1940	1940	1940
R^2	0.269	0.273	0.278	0.280

Notes: The table reports coefficient estimates (and estimated t-statistics in parentheses) from regressing final earnings ($\log(Y_{91})$) on the variables displayed on the first column. $\log(Y_{91-T})$ denotes initial earnings (post-graduation), *SEX* is defined as 1 if the worker is a female and 0 otherwise, $\log(CRED)$ is the log of credits, δ denotes our measure of distance described in the text, *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise, and *CAREER* is defined as 1 if a worker begins her labor market experience in a non-managerial occupation and ends in a managerial one. Additional regressors (coefficients not shown) are GPA and dummies for occupations, type of degree, and major.

* Coefficient significantly different from zero at least at the 0.1 level.
** Coefficient significantly different from zero at least at the 0.05 level.
*** Coefficient significantly different from zero at least at the 0.01 level.

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 120. Some high-achievers take over three hundred credit hours, but these are the exception as the standard deviation for this measure is only 28. Finally, note that a little over half the individuals never switch their occupations during the observed labor market histories.

The lower panel of Table 2 provides the raw correlations between these measures. Most of these correlations are significant. 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*. The positive albeit insignificant relationship between hedging and the number of credits taken hints at the possibility of individuals diversifying by adding credits rather than by transferring credits across areas. On the other hand, note that there is an intriguing negative relationship between earnings growth and remaining in the same occupation. Note as well that the unconditional correlation between income growth and hedging is positive and significant.

2.2. Empirical regularities

Interesting patterns emerge after conditioning on occupational switching. To investigate the empirical regularities beyond raw correlations, Table 3 presents OLS regression estimates linking the observed final earnings, $\log(Y_{91})$, and the portfolio distance measure, δ.[11]

The first column of results reports regression coefficient estimates of (log) earnings on δ and three further controls – the logarithm of the respondent's initial earnings $\log(Y_{91-T})$,[12] the logarithm of the total of credits, $\log(CRED)$, and the individual's gender, *SEX*. The regressions also include GPA and dummies for major, occupation and type of degree but for brevity these coefficients are omitted. As one might expect, the coefficient on initial earnings is positive and significant. Likewise, male earnings are on average higher than women's earnings. The estimated coefficient on credits is negative, which can be attributed to a variety of factors.

whether employment is part-time or full-time. As a result, some extreme values, for example, the minimum observed of −0.417 could be due to voluntary changes in hours worked because of health, family or other reasons. In what follows, it is very difficult to discriminate among possible causes for those fairly extreme earnings changes.

11 The division of human capital into three types of skills is obviously not the only one possible. To assess the sensitivity of the empirical results to an alternative division, we consider four types, with humanities and fine arts representing two different categories as reported in PETS. The results are very similar to those obtained with three types of skills and for that reason reported in Section 2 of the Online Appendix.

12 Initial earnings are denoted by $\log(Y_{91-T})$ since the first year of a labor market history is individual-specific and does not correspond to a unique calendar year.

Table 4
Probit regression-dependent variable: *STAY*.

	Coefficient estimate (*t-stat.*)			
	(1)	(2)	(3)	(4)
δ	-0.803^{***}	-0.669^{***}	-0.669^{***}	-0.677^{***}
	(-4.69)	(-3.84)	(-3.84)	(-3.88)
$\log(Y_{91-T})$		0.524^{***}	0.524^{***}	0.519^{***}
		(8.80)	(8.77)	(8.68)
$\log(CRED)$			-0.012	-0.004
			(-0.02)	(-0.15)
SEX				-0.084
				(-1.29)
Intercept	0.729	-3.109^{***}	-3.090^{***}	-2.920^{**}
	(1.39)	(-4.53)	(-2.67)	(-2.50)

Notes: The table reports coefficient estimates (and estimated t-statistics in parentheses) from a Probit regression of *STAY* on the variables displayed on the first column. *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise. $\log(Y_{91-T})$ denotes initial earnings (post-graduation), *SEX* is defined as 1 if the worker is a female and 0 otherwise, $\log(CRED)$ is the log of credits, δ denotes our measure of distance described in the text. Additional regressors (coefficients not shown) are GPA and dummies for occupations, type of degree, and major.

* Coefficient significantly different from zero at least at the 0.1 level.
** Coefficient significantly different from zero at least at the 0.05 level.
*** Coefficient significantly different from zero at least at the 0.01 level.

With only these three added controls, the relationship between income and hedging is positive. It is, however, associated with a large standard error so the estimate is insignificant. On average, individuals who have portfolios close to the average in their initial occupation (i.e. portfolios with limited hedging) experience lower earnings but there is considerable noise associated with this estimate.

From the adjacent column, these results change very little after adding the control *STAY* which accounts for occupation change. Those who never switch occupations tend to earn more. The estimated coefficient is 0.072 and significant. The positive estimated coefficient implies positive returns to occupational tenure, which is in line with previous findings in the literature.[13]

Some occupational transitions are primarily lateral moves for people who want to or are induced to do something else. Other 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, Professional – Engineering or Other Professional occupations and zero otherwise. Not surprisingly, the estimated coefficient of *CAREER* is positive and significant. Adding this control variable has little effect on the other estimates including δ which continues to be insignificant.

The last column of Table 3 offers interesting evidence on portfolio hedging. This regression specification includes an interaction term between occupational switchers and the diversification measure, $\delta \times STAY$. The effects are intriguing. It appears that if an individual switches occupations ($STAY = 0$), a flexible portfolio pays off. For those who change jobs, a portfolio further away from the average portfolio of the previous occupation is associated with a higher and now significant increase in earnings. Note as well that the coefficient on *STAY* becomes substantially higher: 0.19 up from 0.07 and 0.10. The coefficient on the interaction term $\delta \times STAY$ is negative, significant and substantial. On average higher earnings occur for those who remain in an occupation and this effect increases once we take into account their portfolio diversification.[14]

Finally, Table 4 reports results from a Probit model with *STAY* as the dependent variable. Recall that this variable takes the value one if the individual never switches occupations and zero otherwise so these estimates relate to occupational mobility. In all four specifications of the controls, which again include GPA and major, occupation, and type of degree dummies, the relationship between hedging and the probability of an occupational transition is negative, significant and similar across specifications. 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 less likely to stay but the relationship between the two variables is fairly weak (the t-statistic is only -1.29). Individuals who start with relatively high initial earnings are more likely to stay in their first occupation, whereas those with a larger number of credits are more likely to move. Initial earnings are significant but the estimate for credits is not.

[13] See, for example, Kambourov and Manovskii (2009). However, Groes et al. (2009) 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.

[14] The pattern of the regressions in Table 3 is robust to alternative specifications. It remains unchanged if we use other measures of mismatch in the initial occupation. Likewise, the pattern remains the same if income growth rather than income level is the dependent variable. The pattern also does not change if we do not weight credits by GPA, if we include information about a student's performance on high school standardized tests, if we do not control for type of degree or if we measure δ relative to other students in the same major. See Sections 2 and 3 of the Online Appendix for details.

To gauge the magnitude of the regression estimates, suppose an individual with a mean δ has this distance measure reduced by one half, a change of less than one standard deviation. Given the point estimates in Table 3, the change in final income for those who do not switch occupations is small as the δ and the $\delta \times STAY$ terms offset each other. The rise in income is less than one half of one percent. For those who switch occupations, the impact is more substantial as annual income falls by approximately 3.5%. From Table 4, for an individual with $\beta X = 0$, the same change raises the probability of not switching between 3.8% and 4.6%

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 more 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, $t = 0, 1, 2, \ldots$. 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 $\boldsymbol{h} = \{h_1, \ldots, h_K\}$.

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, $\boldsymbol{\xi} = (\xi_1, \ldots, \xi_K)$ 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.

This specification abstracts from uncertainty in students' abilities. In practice, students start out unsure about their talents and inclinations. As they progress through university, students become more aware and update plans. As a result, majors change. After two years of study, approximately 1 in 5 students have switched out of their intended major reported before going to university (see Arcidiacono, 2004).[15]

Occupational uncertainty at least ranks alongside uncertainty about learning abilities. Almost half the people in our sample switch occupations at the one digit level, a figure consistent with other evidence. There may be many reasons, monetary and otherwise, for switching but these switches are likely to be costly. The emphasis on occupational uncertainty is intended to complement the literature studying variation in human capital arising from the uncertainty present in the university experience.

Along with their innate learning abilities, 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 initial signal of their fit in each occupation – they draw a vector $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_J)$ from the distribution $G(\boldsymbol{\theta})$. Each element θ_j is an uncertain indication about an individual's future productivity in occupation $j \in \{1, \ldots, J\}$.

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 work for a while in 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.[16]

Acquired skills, productivity signals and labor market experience determine payoff flows. Assume that the first time individuals try an occupation, they start in a probationary phase during which they get paid according to their noisy initial signal. In particular, if an individual who has skills $\boldsymbol{h}$ along with initial 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.

An individual completes the probationary phase in occupation j with probability π at the end of each period. When this phase stops, the worker's productivity gets updated by adding to the θ_j signal an independent random shock ϵ_j drawn from a distribution Γ_j. Should an individual decide to remain in that occupation after ending probation and learning their true productivity, earnings then begin to grow at a gross rate of $\gamma > 1$, with $\beta\gamma < 1$.

[15] This figure is substantial but its importance is not immediately apparent. For instance, students may switch early on and so obtain a portfolio of skills close to what they would have obtained if they had chosen their final major from the outset. See Stinebrickner and Stinebrickner (2013, 2014), for an analysis of major changes found at one particular US institution.

[16] We use the term productivity or match-quality interchangeably. This term corresponds to the component of earnings in an occupation unaccounted for by the individual's portfolio of skills.

Information revelation is thus Poisson rather than Bayesian – agents learn completely (with some probability each period) rather than continuously through piecemeal, noisy updates. Although Bayesian learning is arguably more appropriate, Poisson learning has the advantage of being memoryless and thereby significantly easier to derive analytical results and empirically implement. Since we find a high learning rate in annual data, the Poisson specification appears to be a reasonable specification.

Learning is also occupation specific. For tractability, information from one occupation does not reveal anything about other occupations. 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.[17]

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 known abilities vector $\boldsymbol{\xi}$ therefore chooses a set of skills in period $t = 0$ to solve[18]

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

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:

$$\Phi_t = \left\{(j_s, \epsilon_{j_s})\right\}_{s=1}^{t-1},$$

where the ϵ_{j_s} appropriately convey if and when the probationary phase in occupation j finished.

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

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

where $w_j(\theta_j, \boldsymbol{h}, \boldsymbol{\Phi}_t)$ is the immediate flow payoff in occupation j given skills and history. The notation makes clear that recalling previous occupations is allowed.[19] Let $\eta_j(\Phi_t)$ denote the number of periods an individual worked in occupation j with knowledge of her true productivity. Recalling that after acquiring that knowledge, earnings grow with experience in an occupation and that the fit in an occupation does not vary over time after learning takes place, ($\epsilon_{j_t} = \epsilon_{j_{t'}}$ if $j_t = j_{t'}$ and $\eta_j > 0$ at t, t') the flow payoff in a period can be written as

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

Repeated sampling of a given occupation provides no new information about alternative occupations. If probation has not ended, i.e. learning has not taken place, the employer and employee both know θ_j and $\boldsymbol{h}$, but neither knows ϵ_j. As a result, individual pay reflects only the noisy signal and human capital. After the individual has completed probation and learned her true fit, 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 (1972) reduce the dimensionality of

[17] Early economic applications of the classical multi-armed bandit model include Weitzman (1979) and Miller (1984). More recent examples include Weitzman (2009, 2011).

[18] 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.

[19] The expression does not include an expectations operator if the probationary phase does not end. In this case, the notation emphasizes and makes clear whether learning occurs in the history Φ_{t+1}.

bandit problems by demonstrating that the solution to these problems takes 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 in which true productivity is known (the individual completed probation) is simply the lifetime value of income in that occupation:

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

On the other hand, if productivity in occupation j is unknown because it has either not been tried or because the true productivity has not yet been revealed, 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 with probability π, all information about true productivity in occupation j is revealed in each period of probationary employment in j. Once the true productivity is revealed, there is no further learning and workers will choose to either move to another occupation or remain forever in j. Hence once productivity is revealed, $\tau \in \{1, \infty\}$. On the other hand, if learning does not occur, workers face the same problem as the previous period. Given that wage growth through γ does not occur until productivity is found out, the decision is stationary. The Gittins index therefore reduces to

$$\begin{aligned} M_j = (1-\beta)\bigg[&(1-\pi)\left\{e^{\theta_j} f_j(\boldsymbol{h}) + M_j\right\} \\ &+ \pi \mathbb{E}_{\epsilon_j} \max\left\{e^{\theta_j} f_j(\boldsymbol{h}) + \frac{\beta}{1-\beta} M_j, e^{\theta_j} f_j(\boldsymbol{h}) + \frac{\beta\gamma}{1-\beta\gamma} e^{\theta_j+\epsilon_j} f_j(\boldsymbol{h})\right\}\bigg]. \end{aligned} \tag{1}$$

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

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

which yields

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

This reservation cutoff does not depend on the probability of learning except through the Gittins index M_j. Plugging ϵ_j^R into (1) and manipulating gives

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

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

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

$$j_t = \arg\max_j \left\{M_1(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_t), \ldots, M_J(\boldsymbol{\theta}, \boldsymbol{h}, \boldsymbol{\Phi}_t)\right\}.$$

The occupational choice problem is a 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. To lower the number of parameters, we eliminate individuals who are listed as Owner, due to the low number of respondents with Owner as their first occupation.[20]

To keep the model parsimonious, we assume that occupational signals θ_j and the productivity updates ϵ_j are all independent and distributed normally

$$\theta_j \sim N\left(-0.5\sigma_\theta^2, \sigma_\theta^2\right) \quad j = 1, \ldots, 12$$
$$\epsilon_j \sim N\left(-0.5\sigma_{\epsilon_j}^2, \sigma_{\epsilon_j}^2\right) \quad j = 1, \ldots, 12.$$

Note that we assume that the occupational signals θ_j all have the same variance as well as mean.

The abilities vector $\boldsymbol{\xi}$ is distributed as,

$$\boldsymbol{\xi} \sim N(\boldsymbol{\mu}_\xi, \Sigma_\xi).$$

The off-diagonal elements of Σ_ξ are all assumed to have the same value ρ_ξ, a parameter driving the correlation in overall ability. Let σ_H^2, σ_Q^2, and σ_{SS}^2 denote the three diagonal elements of this matrix. Finally, let the three elements of $\boldsymbol{\mu}_\xi$ be $-0.5\sigma_H^2$, $-0.5\sigma_Q^2$, and $-0.5\sigma_{SS}^2$.

It is likely that for individuals in our dataset the ability to acquire particular skills, $\boldsymbol{\xi}$, will be correlated with the signals of occupational aptitude, $\boldsymbol{\theta}$. Individuals who have a higher verbal ability than quantitative ability in school might perceive relatively more encouraging signals about their productivity in the legal profession. However, the relationship between schooling talent and occupational fit is not readily captured in a small number of parameters. There are three human capital types that get used in different ways in twelve occupations. Imposing a simplifying relationship could arbitrarily constrict the data in unintended ways and unintentionally sway the estimation. To avoid prejudicing the results in this way and to keep the number of parameters manageable, we maintain throughout that the two vectors are independent.[21]

This independence, however, does not imply zero correlation between abilities and the propensity of agents to work in particular occupations. For example, if writing well is a skill demanded from lawyers, students with high writing ability will tend to be lawyers, even though the correlation between writing ability and the noisy signal of the student's future productivity as a lawyer is zero. The reason is simply because high ability implies a relatively low cost of acquiring the skill. Choosing optimally, the student will put the skill to work in a profession where the skill is used intensively.

The cost function for acquiring skills is assumed to be additive and quadratic

$$C(\boldsymbol{\xi}, \boldsymbol{h}) = \sum_{k \in \{H,Q,SS\}} e^{\xi_k} h_k^2,$$

while the production technology is Cobb–Douglas

$$f_j(\boldsymbol{h}) = \prod_{k \in \{H,Q,SS\}} h_k^{\alpha_{j,k}}, \qquad \sum_{k \in \{H,Q,SS\}} \alpha_{j,k} = 1.$$

Set $\beta\gamma$ equal to 0.96 and fix γ to be consistent with average earnings growth observed in the data, around 8.4% per year, resulting in values for γ and β equal to 1.046 and 0.918, respectively.[22] As a result of these assumptions and normalizations, the vector of parameters for estimation is given by[23]

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

4.1. Estimation methodology

We use a Simulated Method of Moments (SMM) approach to estimate the 42 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 moments from the HS&B dataset, denoted by Υ, which describe statistics about occupational transitions, skills portfolios across occupations, the dispersion of (log) earnings, and correlations across skills. Given a value of the structural

[20] We also drop Homemakers as noted in the Online Appendix, Section 1.

[21] Section 4 of the Online Appendix reports results for model-generated simulations which partially address this issue.

[22] The appropriate amount of discounting is represented by the product $\beta\gamma$ and not just β.

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

Table 5
Elements of the vector $\hat{\Upsilon}$.

Occupation	Sample size	ω_H	ω_Q	% Switch
Clerical	280	0.256 (0.011)	0.284 (0.012)	0.262 (0.026)
Manager	500	0.225 (0.007)	0.300 (0.010)	0.176 (0.017)
Skilled operative	60	0.221 (0.025)	0.514 (0.036)	0.244 (0.054)
Professional – arts	90	0.504 (0.026)	0.174 (0.017)	0.157 (0.039)
Professional – medical	120	0.207 (0.010)	0.460 (0.018)	0.077 (0.024)
Professional – engineering	110	0.092 (0.009)	0.790 (0.013)	0.041 (0.019)
Professional – other	220	0.238 (0.013)	0.318 (0.015)	0.131 (0.023)
Sales	160	0.218 (0.011)	0.284 (0.014)	0.240 (0.033)
School teacher	90	0.348 (0.021)	0.283 (0.020)	0.158 (0.039)
Service	90	0.231 (0.020)	0.393 (0.026)	0.303 (0.050)
Technician – computer-related	150	0.147 (0.012)	0.602 (0.020)	0.114 (0.026)
Technician – non-computer-related	60	0.201 (0.020)	0.538 (0.035)	0.172 (0.050)
	Sample size			
Standard deviation (log) earnings				
First period	1940	0.539 (*0.009*)		
Standard deviation ω_H	1940	0.185 (0.003)		
Standard deviation ω_Q	1940	0.258 (0.004)		
Standard deviation $\omega_S S$	1940	0.218 (0.004)		
%"Stay-switch events"	1940	0.110 (0.007)		
$\rho(CRED_{SS}, CRED_Q)$	1940	−0.366 (0.020)		
$\rho(CRED_{SS}, CRED_H)$	1940	0.060 (0.023)		
$\rho(CRED_H, CRED_Q)$	1940	−0.531 (0.016)		
Switching rate	1940	0.408 (0.011)		

Notes: Each cell reports a sample moment, either a mean or a standard deviation, and in parentheses an estimate of the standard deviation of that sample moment. In the upper panel we report, for each occupation, the mean portfolio shares in Humanities and Quantitative Skills, and the fraction of Switchers in the first period. In the lower panel, we report the standard deviations of (log) earnings in the initial period, the cross-sectional standard deviation for the portfolio shares in each skill type, the fraction of "Stay-Switch Events" (see main text for an explanation of how the statistic is computed), the cross-sectional correlations among the different human capital types, and the overall Switching Rate. We also report the sample size used to compute each sample moment.

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

$$\hat{\Lambda} = \arg\min_{\Lambda} (\Upsilon - \hat{\Upsilon})' W (\Upsilon - \hat{\Upsilon})'.$$

The matrix W is a weighting matrix that places more weight in moments with the lowest amount of uncertainty. It is a diagonal matrix where each diagonal element is the inverse of the variance of the moment itself. 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):

$$\hat{\Omega} = \left(\hat{H}'_{\Lambda} W \hat{H}_{\Lambda}\right)^{-1} \hat{H}'_{\Lambda} W \Omega_{\hat{\Upsilon}} W \hat{H}'_{\Lambda} \left(\hat{H}'_{\Lambda} W \hat{H}_{\Lambda}\right)^{-1}, \tag{2}$$

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

Table 5 displays the statistics found for Υ. 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. The column ω_Q corresponds to "Share of Quantitative " in Table 1.[24] The last column of Table 5 reports the share of individuals that began their labor market career in a given occupation but switched in the second year. These shares range from a high of nearly one third in Service to a low of 4.1% for Engineers.

The two vectors of average shares for the two human capital types, ω_H and ω_Q, identify the 24 technological parameters $\alpha_{j,H}$ and $\alpha_{j,Q}$, $j = 1, ..., 12$. The fractions of individuals who leave an occupation after one year identify the 12 variances, $\sigma^2_{\epsilon_j}$, associated with each occupation $j = 1, \dots, 12$. Occupations in which updates to the initial 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.

Nine aggregate moments complete the set of moments that comprise the parameter vector Υ. The standard deviation 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

[24] 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 and Homemakers.

Table 6
Estimation results.

Occupation	$\hat{\alpha}_H$	$\hat{\alpha}_Q$	$\hat{\sigma}_\epsilon$
Clerical	0.241 (0.020)	0.418 (0.058)	0.263 (0.047)
Manager	0.186 (0.077)	0.489 (0.038)	0.184 (0.063)
Skilled operative	0.242 (0.054)	0.729 (0.020)	0.685 (0.014)
Professional – arts	0.443 (0.033)	0.141 (0.042)	0.380 (0.029)
Professional – medical	0.116 (0.082)	0.572 (0.033)	0.102 (0.040)
Professional – engineering	0.029 (0.019)	0.958 (0.029)	0.097 (0.035)
Professional – other	0.173 (0.046)	0.442 (0.043)	0.214 (0.036)
Sales	0.169 (0.044)	0.490 (0.041)	0.236 (0.037)
School teacher	0.336 (0.025)	0.409 (0.063)	0.213 (0.044)
Service	0.056 (0.024)	0.523 (0.033)	0.456 (0.033)
Technician – computer-related	0.099 (0.039)	0.783 (0.049)	0.215 (0.034)
Technician – non-computer-related	0.280 (0.039)	0.635 (0.023)	0.337 (0.058)
Estimate (std. error)			
σ_θ	0.216 (0.040)		
$\sigma^2_{\xi_H}$	0.912 (0.017)		
$\sigma^2_{\xi_Q}$	0.387 (0.055)		
$\sigma^2_{\xi_{SS}}$	1.646 (0.034)		
π	0.891 (0.031)		
ρ_ξ	−0.279 (0.024)		

Notes: This table reports the estimated value for each element in the vector of structural parameters $\hat{\Lambda}$. In parentheses, we report numerical standard errors computed using (2).

different skills helps identify the three diagonal elements of Σ_ξ. The moment labeled percentage of "Stay-Switch Events" is defined as the fraction of workers whose occupational choice is the same in periods 1 and 2 but different in period 3. That fraction in the data is 11% (of all workers, not of all switchers). Finally, we also target the three cross-correlations in credits across skills and the overall switching rate.

In principle one could include the model-analog coefficients shown in Table 3 as additional moments in the estimation and formally test the over-identifying restrictions. We decided to leave these regression coefficients outside of the estimation procedures as they involve the variable δ. Instead, in the next section, we examine the model-analog to the reduced-form coefficients in Tables 3 and 4 using our estimated structural parameters.

Given a vector of structural parameters Λ, we simulate labor market histories for a large number of individuals by taking a $(\boldsymbol{\xi}, \boldsymbol{\theta})$ 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. Repeating those steps for a large number of individuals provides the model-analog to the moments in the vector $\Upsilon(\Lambda)$.

5. Results

5.1. Parameter values

Table 6 reports the elements of $\hat{\Lambda}$, along with their estimated numerical standard errors. These parameters tend to be tightly estimated. Overall, the standard errors of the parameters are generally small relative to the estimates.

Production displays substantial variation in the use of skills across occupations. There is also an emphasis on technical, quantitative skills. The estimated Cobb–Douglas quantitative parameter for the production technology, $\hat{\boldsymbol{\alpha}}_{\boldsymbol{Q}}$, ranges from 0.14 to 0.96 with a mean of slightly more than a half. The ranges for humanities and social science are respectively $(0.03, 0.44)$ and $(0.01, 0.42)$. The mean for humanities is less than a fifth. Unsurprisingly, Engineers have the highest quantitative and lowest humanities components whereas Arts Professionals have the highest humanities and lowest quantitative components.

The estimated Cobb–Douglas technology parameters are more dispersed than the portfolios. Compare $\hat{\boldsymbol{\alpha}}_{\boldsymbol{H}}$ and $\hat{\boldsymbol{\alpha}}_{\boldsymbol{Q}}$ with ω_H and ω_Q in Table 5. Although the technology parameters are more dispersed than the average portfolio shares across occupations observed in the data, the $\hat{\boldsymbol{\alpha}}$ follow the pattern seen in the portfolio shares. The correlations between these figures are 0.86 for humanities and 0.96 for quantitative skills respectively.

The compressed portfolio weights in Table 5 relative to the technology parameters result from hedging. Increasing marginal costs also contribute to balancing out these portfolios. As a student accumulates skills in a particular area, the cost of acquiring more of these skills rises, inducing the student to acquire skills in other fields. Given these complementary motives, we compare the distance of the estimated production parameters to the portfolios implied by our estimates, with and without uncertainty, in the post-probation fit. The specification without uncertainty is described in Section 5.3. The difference in these two distance measures is highly correlated ($\rho = 0.7$) with uncertainty as measured by $\hat{\sigma}_\epsilon$. In other words, hedging on average appears to increase with volatility in the occupation fit and its associated turnover.

Table 7
Income growth distribution summary – model vs. data.

	Min.	1st. quart.	Median	Mean	3rd quart.	Max.	Std. dev.	Skew.	Kurt.
Data	−0.417	0.004	0.058	0.084	0.131	1.137	0.175	1.594	8.895
Model	−0.275	0.027	0.068	0.084	0.127	1.031	0.094	1.474	7.871

Notes: The table compares several statistics of interest of the income growth distribution found in the HS&B dataset with a model-simulated (150 000 individuals) income growth distribution. The sample of students used to compute the Data moments are the same 1940 individuals reported in Table 5.

The volatility of the post-probation fit, $\hat{\sigma}_\epsilon$ (which is related to the probability of exiting an occupation) itself also varies substantially across occupations. Engineers encounter the least uncertainty whereas Skilled Operatives, Service and Arts Professionals workers experience the most uncertainty. Note as well that uncertainty in the occupational fit is higher in those professions that emphasize humanities skills, i.e. those with highest $\hat{\alpha}_{j,H}$.'s. Although not especially pronounced, occupational uncertainty correlates best with humanities components. The correlation between the first and third column in Table 6 is 0.32, and 0.50 if we omit the outlying observation of Service.

Consider one of the riskiest occupations, Arts Professional. It not only has a relatively high estimated standard deviation of shocks, $\hat{\sigma}_{\epsilon_{Prof.Arts}} = 0.38$, but the technology is also tilted towards humanities with $\hat{\alpha}_{Prof.Arts,H} = 0.44$. A high weight in humanities is not very portable across occupations. The profession with the second highest $\hat{\alpha}_{j,H}$ is School Teacher, with a much smaller value of 34%. The average $\hat{\alpha}_H$ is only 0.19. The low portability of humanities counteracts to some extent the high volatility of shocks in this profession. In other words, although Arts Professionals do not find much use in other occupations for their high proportion of humanities skills, they also experience relatively high volatility in their ϵ shocks which makes occupational shifts likely. Hence, from Table 5, the percentage of switching in this occupation is about average.

Dispersion in abilities to acquire a skill type, the $\hat{\sigma}_{\xi_{H,Q,SS}}$, differs across types of human capital. The ability to acquire quantitative skills is highly concentrated (the variance is 0.39) relative to the ability to study humanities (0.91) and especially social science (1.65). Workers appear to learn about their true productivities relatively fast: the estimated value of π is 0.89. Finally, the estimate of $\hat{\rho}_\xi$ is -0.28. At first, this estimate might appear peculiar. The sample, however, focuses on college students. As shown in Table 2 the distribution of credits is concentrated. As a result, more credits in a given type of human capital will generally imply fewer credits in other types (consistent with the three correlations shown in Table 5). The estimated covariance reflects this feature of the data.

5.2. Goodness of fit

The estimates in Table 6 map out an explicit as well as involved trade-off between specialization and hedging. Before considering this trade-off further, we now examine how well the estimated model replicates outcomes observed in the labor market that were not targeted as part of the estimation procedure. Since occupational switching and dispersion in initial earnings were targets of the estimation, the focus turns to earnings in 1991 to assess the performance of the model. In simulations of the model, income levels depend upon arbitrary normalizations of parameters, hence comparing income distributions is not insightful. We therefore compare the distributions of income growth in the data and the model.

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 slightly more than half that seen in the data. The maximum simulated growth is approximately 90% of the maximum observed whereas the minimum growth in the simulated data is approximately two thirds of the smallest growth in the data. This difference is not surprising. In reality individual earnings vary after workers settle in an occupation. The construction of the model rules out such shocks and changes to earnings that occur after exploration of occupations in the labor market ends.[25]

The model rules out other possibilities. Students do not update their beliefs on their occupational calling while at university. They also cannot update their skill set when they switch professions. Students, of course, change majors and workers can improve the alignment of their skills after they settle on an occupation. On the other hand, such career learning while studying may well occur early on and thus not drastically alter the desired make-up of acquired of skills. Many changes in majors occur when students are just beginning their studies. Intended majors can change even before first year enrollment. Likewise, workers who do not switch also acquire on-the-job skills. Acquiring fundamental skills when young is often less costly, more enduring and easier to build upon. The impact of poorly aligned skills may be long lasting. There are many possibilities yet little direct evidence guiding these abstractions.

Despite these limitations, 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 model does not replicate the extremes exceptionally well but does very well replicating the core of the distribution. The first quartile, the median, and the third quartile all line up well, especially considering the lower dispersion in the simulated model. Skewness

[25] The mean income growth reported in Table 7, 8.4%, differs slightly from that reported in Table 2, 8.3%. The reason is minor differences in sample selection. For the purpose of estimating the model, we eliminate individuals belonging to two occupations (*Owner* and *Laborer/Homemaker*). See the Online Appendix for details.

Table 8
Regression results – model-simulated final wage ($\log(Y_{91})$).

	Model		Data	
	(1)	(2)	(1)	(2)
$\log(Y_{91-T})$	0.734	0.595	0.286*** (14.98)	0.271*** (13.95)
$\log(CRED)$	0.217	0.348	−0.117* (−1.82)	−0.138** (−2.15)
δ	0.115	0.363	0.053 (0.90)	0.235*** (2.81)
CAREER		−0.008		0.159*** (3.66)
STAY		0.245		0.185*** (4.34)
$\delta \times STAY$		−0.386		−0.265** (−2.34)
Intercept	0.232	0.062	5.521*** (14.35)	5.632*** (14.70)
N	150 000	150 000	1940	1940
R^2	0.706	0.722	0.269	0.280

Notes: The table reports coefficient estimates (and estimated t-statistics in parentheses) from an OLS regression of final earnings ($\log(Y_{91})$) on the variables displayed on the first column. $\log(Y_{91-T})$ denotes initial earnings, $\log(CRED)$ is the log of credits (in the model this variable is calculated as $\log(\sum_{k=1}^{K} h_k)$), δ denotes our measure of distance described in the text, and *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise. The first two columns report values found using model-simulated data and the last two columns correspond to columns 1 and 4 of Table 3.

* Coefficient significantly different from zero at least at the 0.1 level.
** Coefficient significantly different from zero at least at the 0.05 level.
*** Coefficient significantly different from zero at least at the 0.01 level.

and kurtosis are likewise close in the data and the simulated model. Even with less dispersion than in the data, the model is able to generate a substantial mass of negative earnings growth rates. These are associated with occupational switchers.

To further explore the relationships among income, 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 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 there are no analogs to GPA, type of degree and major. Hence, *SEX*, GPA and type of degree and major dummies do not appear in the simulated regressions. The remaining variables – $\log(Y_{91-T})$, $\log(CRED)$, δ, *STAY*, and *CAREER* along with occupational dummies – are constructed the same way as in the actual data. 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 two columns display results with model-generated data.

In Table 8, the coefficient estimates from simulated data compare favorably to those estimated from the observed data. Although the simulated data abstract from a number of factors (some are mentioned above while others involve familiar variables related to wage determination), the estimates are all roughly in line with the HS&B empirical estimates. As one might expect, the coefficients from using simulated data are in general somewhat higher than in the noisier data, as is the R^2.

The model generates large and positive coefficients on initial earnings (0.73 and 0.60) because those with high initial earnings have strong signals and hence portfolios targeted to the first occupation. They are less likely to switch, accruing growth for a larger number of periods resulting in higher earnings. The model generates a positive relationship between credits and income whereas in the data this relationship is negative. When we further condition on switching, the positive coefficient on *STAY* (0.25 which is higher than the empirical counterpart of 0.19) reflects simple selection. Those who stay in the job receive good ϵ draws and earn more relative to similar workers who try other occupations.

Now consider the relationship between hedging, earnings, and occupational exploration. Note first that the coefficient on δ displays the same pattern as found in HS&B data. Without controls for occupation switches, the coefficient estimates in the observed and simulated data are positive. Adding the control for mobility increases the magnitude of this coefficient by a factor of three in the model and four in the data. For an individual who switches occupations ($STAY = 0$), the coefficient of δ on (log) earnings is about 0.36, again somewhat higher than that found in the data (0.24). The coefficient on the interaction term $\delta \times STAY$ is also higher (−0.39) in absolute value than its empirical counterpart (−0.27) but implies that, everything else constant, portfolio distance decreases stayers' earnings.

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 distance measure and other observables, including occupational dummies. The first two 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 simple model again matches up fairly well. The coefficients based on simulated data are once again higher than those from the (noisier) data but the general pattern in the coefficients appear in both sets of regressions.

Table 9
Probit regression results – model-simulated occupational stayers vs. switchers (*STAY*).

	Model		Data	
	(1)	(2)	(1)	(2)
δ	−3.036	−2.589	−0.803*** (−4.69)	−0.677*** (−3.88)
$\log(Y_{91-T})$		0.960		0.519*** (8.68)
Intercept	−0.140	−2.747	0.729 (1.39)	−2.920** (−2.50)
N	150 000	150 000	1940	1940

Notes: The table reports coefficient estimates (and estimated t-statistics in parentheses) from a Probit regression of *STAY* on the variables displayed on the first column. *STAY* is defined as 1 if a worker does not switch occupations and 0 otherwise. $\log(Y_{91-T})$ denotes initial earnings, and δ denotes our measure of distance described in the text. The first two columns reflect values found in model-simulated data and the last two columns correspond to the first two columns of Table 4.
* Coefficient significantly different from zero at least at the 0.1 level.
** Coefficient significantly different from zero at least at the 0.01 level.
*** Coefficient significantly different from zero at least at the 0.05 level.

5.3. Counterfactual earnings distributions

The $\hat{\Lambda}$ estimates in Table 6 shape the trade-offs an individual confronts when choosing a portfolio of skills to acquire before entering the labor market. Personalized circumstances embedded in the $\boldsymbol{\xi}$ and $\boldsymbol{\theta}$ draws pin down these trade-offs precisely for each individual. When deciding what and how much to study, each agent weighs up and balances a number of idiosyncratic uncertain options.

Two thought experiments aim to condense and abstract from the individual-specific components of occupational uncertainty. The first considers the impact on the income distribution of removing uncertainty. Suppose agents know their $\boldsymbol{\epsilon}$ before investing thus making the investment and occupation choices straightforward. This perfect information scenario, labeled "no uncertainty", provides a natural benchmark for assessing the impact of hedging.

The aim of the second policy experiment is to assess the impact of the relative inflexibility associated with European higher educations systems in diversifying across areas of study. A European student wishing to become a biologist is offered a curriculum from which there is little freedom to deviate. In contrast, the baseline model resembles an American system in which students have a relatively large degree of freedom to diversify across areas of study. The comparison between a relatively inflexible education system and one that allows tailoring portfolios to a students' characteristics is related to work by Bordon and Fu (2013). They compare a system in which students have to state a major in their college application with an alternative system in which a planner allocates students to colleges and then students choose majors after they learn about their abilities.

Capturing institutional features that tailor choices is elusive. Given the heterogeneous costs of acquiring skills, no one bundle ideally suits every student entering a given occupation. On the other hand, a training regime targeting an occupation will try to align with the technological parameters of that occupation. To succinctly mimic the choice of a rigid training option in an uncertain labor market, the second experiment specifies that agents choose their portfolios as if $\boldsymbol{\epsilon} = 0$. As such, students choose human capital portfolios stressing their first choice but are then sent out into a world with uncertainty.

More specifically, in the experiment (labeled "Specialization"), agents specialize by choosing their optimal portfolios as if they were to remain in that occupation forever. 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 $\boldsymbol{h}'$. We give $\boldsymbol{h}'$ to individuals in the stochastic world, and construct earnings distributions.

Table 10 presents descriptive statistics from simulations of the estimated baseline model and from the two experiments, each broken down for three groups: all workers, those who switch occupations, and those who are non-switchers. The figures for the experiments are expressed as percentage deviations from the corresponding group in the baseline case.

The first column reports the aggregate number of switchers under each regime. Occupational switching, a target in the estimation, is widespread in the baseline case with 43.3% of all workers experiencing job change. In contrast, there are no shocks in the certain world, so workers never change occupations. More interestingly, in the world in which individuals choose portfolios under the restriction that they must specialize, the fraction of switchers falls by nearly a fifth. This reduction is expected. Having a portfolio of skills tailored to a particular occupation reduces the attraction of trying a new one.

The next two columns report average income levels and average income growth in the three scenarios. The cross-sectional average of earnings growth, $\mathbb{E}(\Delta Y)$, in the baseline case for "All" corresponds to the number reported in Table 7, 8.40%. In the baseline case, non-switchers enjoy earnings growth for two reasons. The first channel is the self-selection mechanism discussed previously that makes switching optimal only in the event of a relatively low productivity shock.

Table 10
Baseline and counterfactual earnings distributions.

		% Switchers	Earnings (level)	Earnings (growth)	Earnings (Gini)	$p(99)/p(50)$	Cost
Baseline	All	43.3	21.817	0.084	0.308	4.212	236.312
	Non-switchers		26.133	0.099	0.302	4.032	254.245
	Switchers		17.219	0.065	0.252	3.072	212.805
% Change from baseline							
No uncertainty	All	−100.0	32.6	−45.6	29.0	73.3	73.3
	Non-switchers		10.7	−53.7	31.7	81.1	38.3
	Switchers		–	–	–	–	–
Specialization	All	−19.1	−5.2	−11.1	−0.1	−1.5	−7.9
	Non-switchers		−8.2	−19.8	−1.0	−1.4	−7.0
	Switchers		−8.9	2.3	0.8	−1.0	−14.3

Notes: The table reports selected moments from three model simulations. The upper panel ("Baseline") corresponds to simulations using our estimated parameters and the model described in the text. The middle panel ("No Uncertainty") corresponds to the case in which individuals choose portfolios under the knowledge of θ and ϵ. The lower panel ("Specialization") corresponds to the case in which individuals with specialized portfolios experience the labor market of the "Baseline" scenario. $p(99)/p(50)$ denotes the ratio of the 99th percentile to the median of the earnings distribution. All model-generated distributions come from the same cross-section of 150 000 individuals.

Occupational switches are often associated with a drop in earnings, more so in cases where the portfolio is tailored to the departing occupation. The second channel is the earnings growth of γ. Switchers experience lower earnings and earnings growth because they enjoy the geometric growth rate for a shorter period of time.

In a certain world, there are no bad investment outcomes so aggregate earnings rise by nearly a third while education expenditure (in the right most column) increases by more than two thirds. Comparing all of these non-switchers with just the non-switchers in the baseline case reduces the difference in earnings levels to just over 10% as these baseline non-switchers receive better than average draws in their occupation. The picture for earnings growth is somewhat different. Earnings growth in the certain world equals γ for all workers. In the baseline case, good draws in occupational fit supplement such growth. As a result, non-switchers in the uncertain world experience more than double the income growth which in turn generates substantially higher earnings growth for all workers.

In the forced specialization economy, individual portfolios tend to be tailored to the initial choice of occupation. Moreover, individuals in the specialized case more frequently select portfolios aimed at less risky occupations. When choosing portfolios in the baseline case, students know they will have the option of leaving bad draws behind. This option value makes investing in risky occupations more attractive.[26] More cautious behavior in the specialized economy generates lower aggregate earnings levels, lower aggregate earnings growth and lower expenditure (−5.2%, −11.1% and −7.9% respectively) as workers become more tethered to their occupations through more specific portfolios.

For non-switchers these earnings losses are slightly higher. Interestingly, specialized workers who do switch experience slightly higher earnings growth than switchers in the baseline case. In both economies, a few individuals will invest in a portfolio linked closely with one occupation but initially choose a very risky occupation in the hope that luck is more important than skill. Low draws lead these workers back to the occupation more closely aligned with their initial portfolio. When such a switch occurs, the specialized individual turns out to have better back up skills than in the baseline case. In the specialized world, as noted far fewer job changes occur so the switchers into the tailored occupation play a more prominent role which helps explain the higher earnings growth of switchers.

The next two columns present the Gini and the 99–50 percentile difference in the earnings distributions. The model delivers an earnings distribution for "Non-Switchers" with more dispersion than that of the "Switchers". This is a common feature of the simulations: switchers experience lower growth in earnings and their distribution is relatively less disperse. On the other hand, earnings of those who remain in their initial occupation grow faster on average and their earnings distribution is more disperse. The Gini of earnings for all individuals is 0.308; for non-switchers this figure is 0.302 and for switchers 0.252.

Dispersion in the model is considerably lower than dispersion in the certain world where all differences among individuals are known from the outset. Good draws increase investment and hence magnify differences relative to the baseline case. Considerably higher earnings dispersion emerges. On the other, the specialized world is only marginally less dispersed than the baseline case. The proposed channel does not appear a likely explanation for European income dispersion relative to the US.

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

[26] This implication is similar to the induced risk loving in search models where searchers prefer mean preserving spreads of the offer distribution.

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 is higher for the more specialized individuals who do not switch occupations whereas income is higher for more diversified individuals who switch occupations.

To further evaluate the 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 the level and growth of labor market earnings.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.red.2014.09.001.

References

Altonji, J.G., 1993. The demand for and return to education when education outcomes are uncertain. Journal of Labor Economics 11 (1), 48–83.
Antonovics, K., Golan, L., 2012. Experimentation and job choice. Journal of Labor Economics 30 (2), 333–366.
Arcidiacono, P., 2004. Ability sorting and the returns to college major. Journal of Econometrics 121 (1–2), 343–375.
Becker, G.S., 1994. Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, 3rd edition. NBER Books. National Bureau of Economic Research, Inc.
Ben-Porath, Y., 1967. The production of human capital and the life cycle of earnings. Journal of Political Economy 75 (4 Pt. 1.), 352–365.
Bordon, P., Fu, C., 2013. College-Major Choice to College-Then-Major Choice. Discussion paper. The University of Wisconsin–Madison.
Gathmann, C., Schönberg, U., 2010. How general is human capital? A task-based approach. Journal of Labor Economics 28 (1), 1–49.
Gervais, M., Livshits, I., Meh, C., 2008. Uncertainty and the specificity of human capital. Journal of Economic Theory 143 (1), 469–498.
Gittins, J., Jones, D., 1972. A Dynamic Allocation Index for the Sequential Design of Experiments. University of Cambridge, Department of Engineering.
Gourinchas, P.-O., Parker, J.A., 2002. Consumption over the life cycle. Econometrica 70 (1), 47–89.
Groes, F.N., Kircher, P., Manovski, I., 2009. The U-shapes of occupational mobility. 2009 Meeting Papers, no. 26. Society for Economic Dynamics.
Heckman, J.J., Sedlacek, G., 1985. Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market. Journal of Political Economy 93 (6), 1077–1125.
Heckman, J.J., Sedlacek, G.L., 1990. Self-selection and the distribution of hourly wages. Journal of Labor Economics 8 (1), S329–S363.
Huggett, M., Ventura, G., Yaron, A., 2011. Sources of lifetime inequality. The American Economic Review 101 (7), 2923–2954.
James, J., 2012. Learning and occupational sorting. Working Paper 1225. Federal Reserve Bank of Cleveland.
Jovanovic, B., 1979. Job matching and the theory of turnover. Journal of Political Economy 87 (5), 972–990.
Kambourov, G., Manovskii, I., 2009. Occupational mobility and wage inequality. Review of Economic Studies 76 (2), 731–759.
Keane, M.P., Wolpin, K.I., 1997. The career decisions of young men. Journal of Political Economy 105 (3), 473–522.
Kinsler, J., Pavan, R., 2012. The specifity of general human capital: evidence from college major choice. Discussion paper. The University of Rochester.
Lazear, E.P., 2009. Firm-specific human capital: a skill-weights approach. Journal of Political Economy 117 (5), 914–940.
Levhari, D., Weiss, Y., 1974. The effect of risk on the investment in human capital. The American Economic Review 64 (6), 950–963.
Malamud, O., 2010. Breadth versus depth: the timing of specialization in higher education. Labour 24 (4), 359–390.
Miller, R.A., 1984. Job matching and occupational choice. Journal of Political Economy 92 (6), 1086–1120.
Neal, D., 1999. The complexity of job mobility among young men. Journal of Labor Economics 17 (2), 237–261.
Papageorgiou, T., 2009. Learning your comparative advantages. 2009 Meeting Papers, no. 1150. Society for Economic Dynamics.
Papageorgiou, T., 2011. Worker sorting and agglomeration economies. Meeting Papers, no. 660. Society for Economic Dynamics.
Robst, J., 2007. Education and job match: the relatedness of college major and work. Economics of Education Review 26 (4), 397–407.
Roy, A., 1951. Some thoughts on the distribution of earnings. Oxford Economic Papers 3 (2), 135–146.
Sanders, C., 2011. Skill uncertainty, skill accumulation, and occupational choice. Discussion paper. Washington University at St. Louis.
Sanders, C., Taber, C., 2012. Life-cycle wage growth and heterogeneous human capital. Annual Review of Economics 4 (1), 399–425.
Schoellman, T.K., 2010. The occupations and human capital of U.S. immigrants. Journal of Human Capital 4 (1), 1–34.
Smith, A., 1776. An Inquiry into the Nature and Causes of the Wealth of Nations. History of Economic Thought Books. McMaster University Archive for the History of Economic Thought.
Stigler, G.J., 1962. Information and the labor market. Journal of Political Economy 70 (5), 94–105.
Stinebrickner, T., Stinebrickner, R., 2013. Academic performance and college dropout: using longitudinal expectations data to estimate a learning model. NBER Working Papers 18945. National Bureau of Economic Research, Inc.
Stinebrickner, R., Stinebrickner, T.R., 2014. A major in science? Initial beliefs and final outcomes for college major and dropout. Review of Economic Studies 81 (1), 426–472.
Sullivan, P., 2010. A dynamic analysis of educational attainment, occupational choices, and job search. International Economic Review 51 (1), 289–317.
Topel, R.H., Ward, M.P., 1992. Job mobility and the careers of young men. The Quarterly Journal of Economics 107 (2), 439–479.
Wasmer, E., 2006. General versus specific skills in labor markets with search frictions and firing costs. The American Economic Review 96 (3), 811–831.
Weitzman, M.L., 1979. Optimal search for the best alternative. Econometrica 47 (3), 641–654.
Whittle, P., 1982. Optimization Over Time, Dynamic Programming and Stochastic Control. Applied Probability and Statistics. Wiley Series in Probability and Statistics, Applied Probability and Statistics Section. John Wiley & Sons.
Willis, R.J., 1987. Wage determinants: a survey and reinterpretation of human capital earnings functions. In: Ashenfelter, O., Layard, R. (Eds.), Handbook of Labor Economics, vol. 1. Elsevier, pp. 525–602. Chap. 10.
Yamaguchi, S., 2012. Tasks and heterogeneous human capital. Journal of Labor Economics 30 (1), 1–53.