CLOSER Conference

Economic 1: Labour market

Chair: **Dick Wiggins**

• Turbulent transitions and labour market outcomes in Canada

Michael R Smith

 Forecasting Life Cycle Outcomes using Childhood Skills

Chase Corbin

 Onwards and Upwards? The Role of Internal Migration in the UK for Graduates' Social Mobility in the Context of Different Career Paradigms

Bozena Wielgoszewska



Twitter: WIFI:

#CLOSERConf **BL-GUEST-CONF**

Password: BLgue5T23



Turbulent transitions and labour market outcomes

Xiaoyu Gong (McGill University)

Qiaoling He (McGill University)

Laurence Lessard-Phillips (University of Birmingham)

Michael R. Smith (McGill University0

The route from schooling to employment is often depicted nowadays as long and perilous, unlike the short and direct routes presumed available to previous generations - as if Powell's expedition on the Colorado river were to replace a ride on the Staten Island Ferry. (Paul Ryan. "The school-to-work transition: A cross-national perspective." *Journal of Economic Literature* 39. 2001, p.34.)

The weight of opinion in the literature ...

- The transition is problematic for some significant proportion of young persons (Marquardt, Enter at your Own Risk, 1998; Hammer, Youth Unemployment and Social Exclusion, 2003)
- Things have got worse (Blanchflower and Freeman in Youth Unemployment and Joblessness in Advanced Countries, 2000; Fuller, American Sociological Review, 2008, Choi, Janiak and Villena-Roldán, Economic Journal, 2014).
- It is more problematic in Canada and the US than in other countries for example, Germany and Japan (Ryan, *Journal of Economic* Literature, 2001)
- ➤ Mostly, assessed using youth unemployment rates.

Approaches to the transition that go beyond the unemployment rate

- NEETs (particular interest in the UK and Japan, but some interest in most rich countries)
- Turbulence multiple transitions between educational programs, employment, unemployment, and residual NLF

Canadian data suggest that the NEET approach is unpromising (Marshall, Perspectives on Labour and Income, 2012)

There are quite a lot of them but ...

- From the mid 1970s to the beginning of the 2000s the proportions of them fell by about a third.
- In the later years most of them were unemployed.
- For most, that unemployment had lasted for less than six months.
- Of those residually NLF rather than unemployed, the bulk would have taken a job if they could have found one.
- Of those not looking work the principal reasons for not doing so were:
 - gaps between acceptance of a job and the beginning of employment;
 - disability;
 - childcare;
 - forms of schooling not included in OECD definition of 'education'.

So, the turbulence approach, informed by the idea that multiple statuses are of interest

- Turbulence might reflect either exploration or floundering
- Evidence of which is the best characterization comes from post school labour market performance, particularly earnings.
- Articles by Fuller (American Sociological Review, 2008) and Krahn, Howard, and Galambos (Youth and Society, 2015) suggest that floundering is the best characterization.
- Policy implication of floundering? Counsel students to complete school on schedule.

Another possibility

■ The floundering hypothesis assumes the following:

turbulence → earnings

An alternative floundering hypothesis:

turbulence

7

Personal characteristics

 \mathbf{k}

earnings

Further complexities

- There are different forms of turbulence: education, employment, unemployment, residual NLF.
- Young people can exit their schooling at different levels in particular, secondary (about 30%) or postsecondary (the rest).
- Turbulence can occur before a schooling stage is completed or after it. The effects of turbulence need not be the same at each stage.

The Youth in Transition Survey (YITS)

- Sample of 15 years olds who were part of the 2000 Programme for International Student Assessment (PISA).
- Parents were interviewed.
- Then young people were interviewed every 2 years during which monthly information on schooling and labour market status collected along with other relevant information.
- So we have ten years of monthly data covering ages 16 to 25, going from 2000 to 2009.
- The survey started with 14,460 respondents. By 2009 70% of the sample was available to us because of attrition or missing values.

Our dependent variables

- Earnings age 25.
- Unemployment after schooling level exit.

Our research design

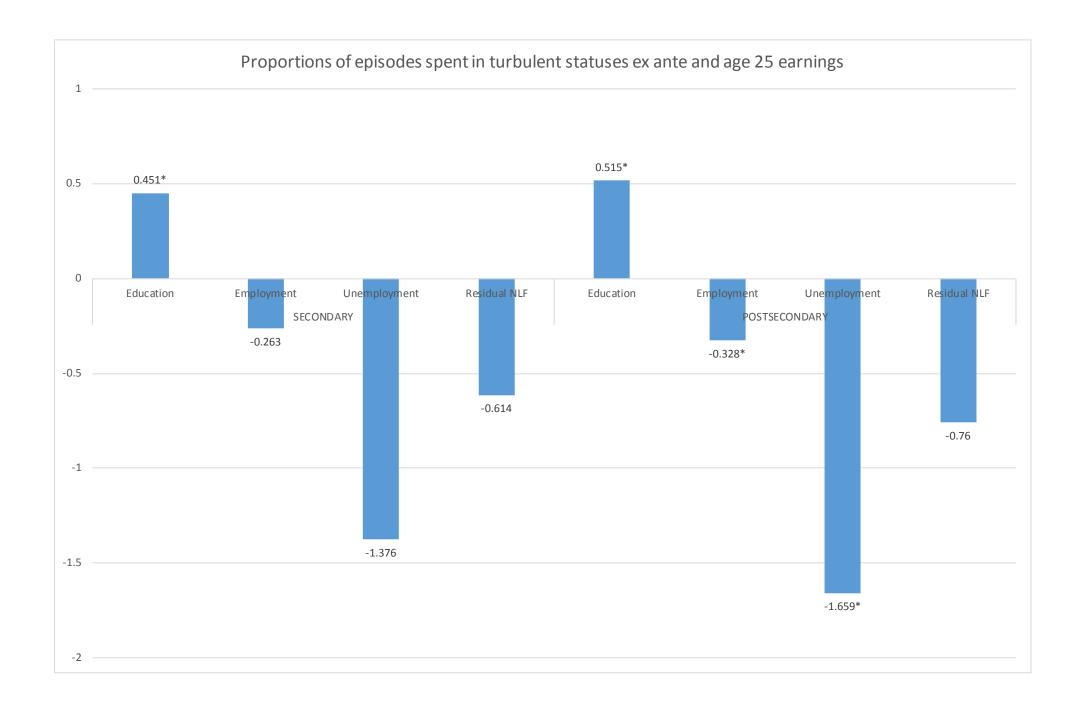
- Describe the amount of turbulence before (ex ante) and after (ex post) exiting an educational level
- Construct two independent variables before and after exiting an educational level:
 - number of transitions in aggregate and status;
 - Proportion of time spent in each state.
- For before and after exiting an educational level, regress age 25 earnings on i) number of transitions (in aggregate and by status) and ii) proportion of time spent in each state in each case using OLS.
- Because of the striking results where unemployment is a predictor of earnings, analyze the association between unemployment before exiting an educational level and unemployment after exiting an educational level. Because our number of transitions variable is a count we i) run a logistic regression where the dependent variable is experienced or did not experience any post education exit unemployment and ii) for those who experienced post education exit unemployment, a Poisson regression with number of post education exit episodes as the dependent variable.

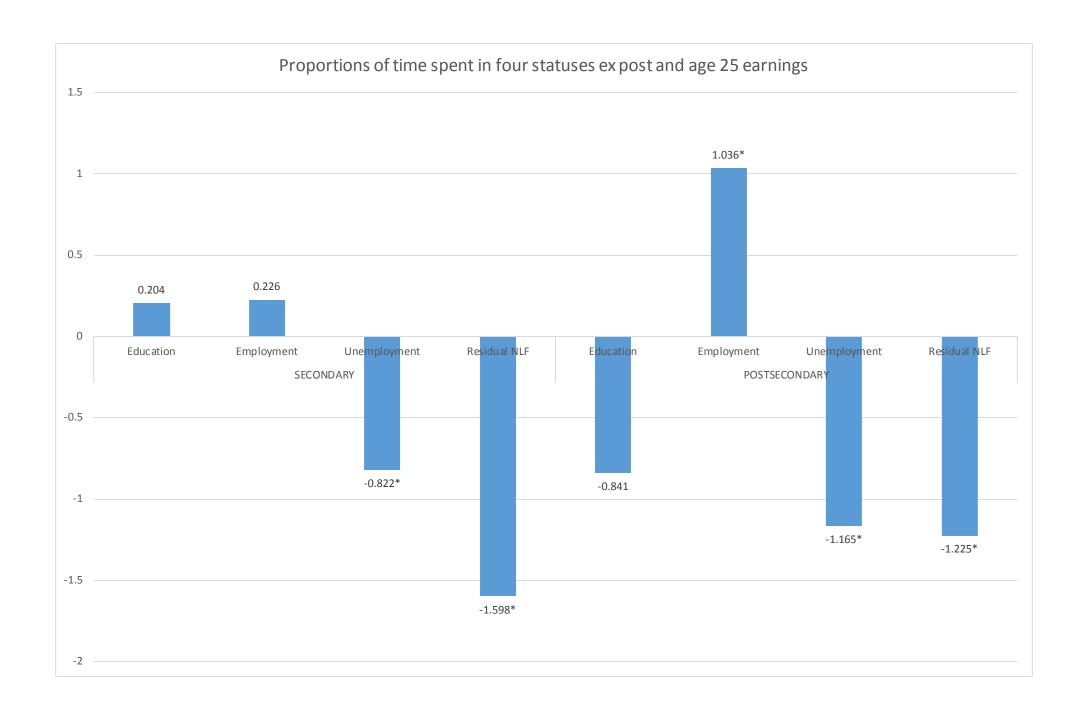
How much turbulence was there in the sample?

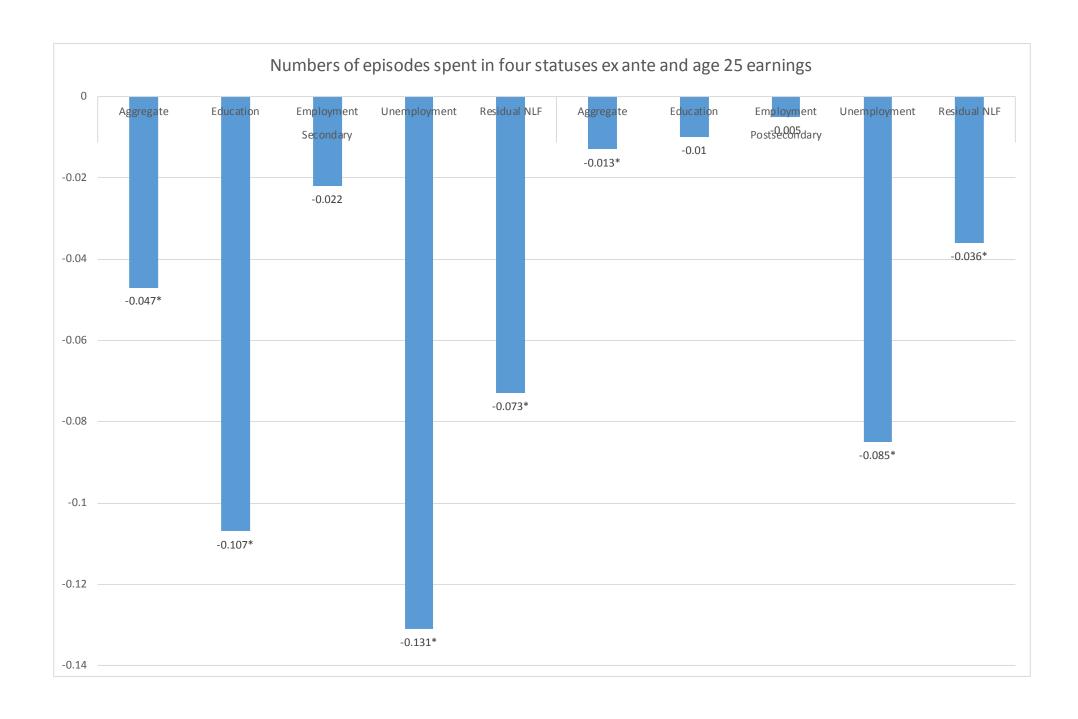
- Not much but some among the secondary finishers *ex ante*.
- A great deal among the secondary finishers ex post.
- A lot among the postsecondary sample ex ante.
- Quite a lot among the postsecondary sample ex post:
 - About 3% had uncompleted education episodes;
 - 21% had more than one employment episode;
 - 27% had one or more unemployment episodes;
 - 22% had one or more episodes of residual NLF.

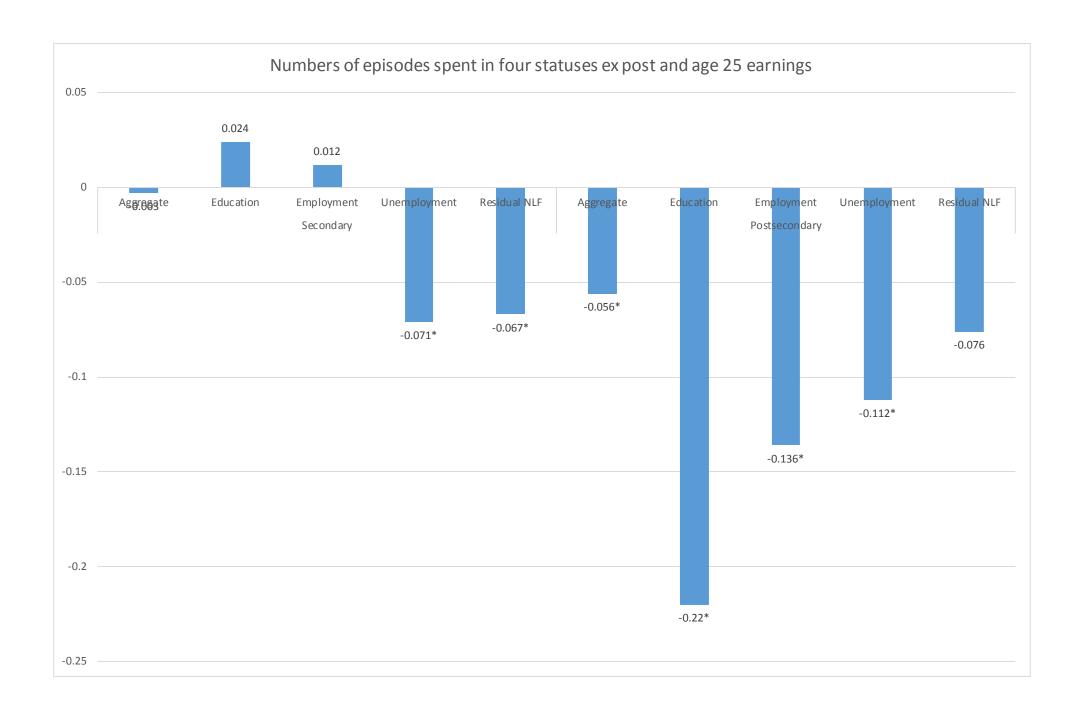
A brief summary of the results describing turbulence

- Ex ante, a plurality of the sample at both educational levels spends about the proportion of time in education and other statuses that one would expect, given school holidays. The same is true of numbers of episodes of each status.
- However, ex ante, a significant minority of postsecondary completers had 40% or more of their time in employment, 7% experienced unemployment, and 20% residual NLF.
- Ex post, lots of turbulence among the secondary sample (55% one or more episodes of unemployment, 46% one or more episodes of residual NLF, 68% uncompleted educational episodes, lots of job-changing.
- Ex post, quite a lot of turbulence within the postsecondary sample: 27% one or more episodes of unemployment, 23% one or more episodes of of residual NLF, 3% uncompleted educational episodes, more than 20% more than one job.







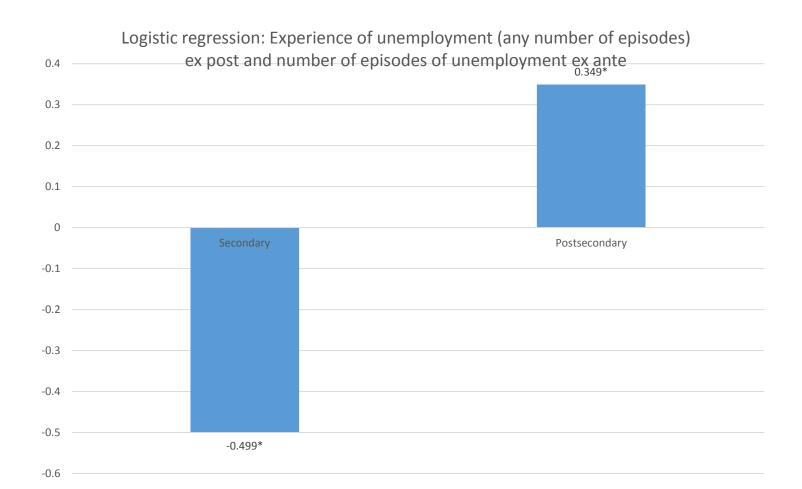


What the charts show

- Aggregating statuses produces misleading results.
- Spending a larger proportion of time in education ex ante increases earnings.
- Proportionally or in terms of episodes more unemployment ex ante reduces earnings by a lot. So does
 proportionally more time spent employed for the postsecondary completers.
- Ex post unemployment and, mostly, residual NLF reduce earnings.
- Ex post educational and employment episodes reduce earnings of postsecondary completers.

What interpretation do these results suggest?

- Those who took the conventional route spent proportionally more time in education *ex ante* do better. Doing things other than education would constitute exploration. That seems not to pay-off.
- Postsecondary completers who spend time in anything other than paid employment do badly this looks like floundering having failed to get a reasonable job.
- Ex ante unemployment is particularly negatively associated with earnings. This may reflect floundering at the postsecondary level (including negative symbols to potential employers). But why would that be the case for ex ante unemployment at the secondary level?



How to interpret these and the previous results?

- The negative association between ex ante unemployment and earnings is very strong at both educational levels.
- This looks like floundering. The absence of a direct route from school to work reduces earnings. But what does floundering mean?
 - Uncertainty about suitable labour market choices?
 - Difficulty finding a job for personal reasons, both ex ante and ex post?
- Two observations lead us to think that the second mechanism plays some role.
 - The negative association between *ex ante* unemployment and earnings for secondary exiters. Is it reasonable to think that *ex ante* unemployment among secondary school exiters originates with poor decision-making with respect to labour market options?
 - The strong association between numbers of episodes of unemployment *ex ante* and whether or not unemployment is experienced *ex post* for postsecondary completers.

Some apparent puzzles

- From the logistic regressions, the negative association between *ex ante* episodes and *ex post* unemployment (whatever the number of episodes) among secondary school students. But the expectation that a secondary school student has to have a job is modest. Those who looked for work may be showing more gumption.
- From the Poisson regressions, the absence of an association between *ex ant*e and *ex post* episodes of unemployment, among those who experienced unemployed. This may reflect the alternative adaptations available to those who looked for a job but didn't find one. They could take extra courses, exit the labour market, or move from unsatisfactory job to unsatisfactory job which seems to happen for a part of the postsecondary sample.

Why does this matter?

- The two conclusions about floundering imply different policies.
 - If floundering reflects uncertainty counsel students that they should focus on completing school more or less on a standard schedule.
 - If floundering reflects personal characteristics the solutions are less obvious, but the previous one won't work.

Some methodological issues

- Direct measurement of disadvantageous traits.
- Age 25 earnings.
- Attrition.

Using Childhood Skills to Forecast Lifecycle Outcomes

Chase Corbin
Jun Hyung Kim
Supervisor: James J. Heckman

University of Chicago cocorbin @uchicago.edu junhyung @uchicago.edu

November 1, 2017

Research reported in this publication was supported by the National Institute On Aging of the National Institutes of Health under Award Number R24AG048081.

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Research Questions

- How predictive are the cognitive and non-cognitive skills measured at early childhood, relative to those measured at later ages?
- What is the best forecasting model based on childhood skill measures for each of adult outcome?
- How does the predictive power of skills vary across outcome distribution?

Method I

We address question one using simple OLS regression for the outcome, Y_i , on the inputs of θ^c , θ^{nc} controlling for the baseline characteristics of gender and race. We regress outcomes taken at ages 23, 33, 42, and 50 and using measures of skill taken at ages 6-8, 10-12, and 16.

We measure cognitive skill as being a single factor extracted from the normalized math and reading test scores for each age.

We construct measures of non-cognitive skill both as a single factor, and as and internalizing factor and externalizing factor based on the teachers report of child's behavioral problems in the classroom.

We consider labor market outcomes, including wages, hours worked, and duration of unemployment spells. We consider measured health outcomes, including self-perceived general health, obesity, and a binary indicator based on the Malaise index.

We estimate all combinations of skill and age of the form:

$$y_{i,33} = \alpha x_i + \beta \theta_7^C + \beta \theta_7^{nc} + \varepsilon_i$$
 (1)



Method II

We address question two using receiver operator characteristic (ROC) analysis and using quantile regression

We measure cognitive and non-cognitive skill using the same factor methods as above.

ROC plots true positive rate vs. false positive rate, we show results by decile of outcome, using both cognitive and non-cognitive skill,, and measures how well each type of skill performs as a classifer, where each quantile of outcome represents one class.

Quantile regressions measure the contribution of cognitive and non-cognitive skill to the observed outcome:

Quantile regressions are of estimated of the form, where $q \in \{1, ..., 10\}$:

$$y_{i,33}^{q_i=q} = \alpha x_i + \beta \Theta + \beta \theta_7^{nc} + \varepsilon_i$$
 (2)

Data

- Our analysis takes advantage of two nationally representative surveys with comparable outcome measures and measures of childhood skill.
 - National Childhood Development Survey, a sample of 17,415 men and women born during 1958 and followed through the current date.
 - The Children of the National Longitudinal Study of Youth (1979). A survey of the 11,521 children born to mothers who participated in the National Longitudinal Study of Youth as of 2014.
 - Our sample is restricted to only those participants for whom there exist at least two childhood measurements of skill and at least two periods of observable outcomes.

Data I – NCDS

- Sample of men and women born during one week in march of 1958
- Perinatal and family history data was collected from the parents during 1958 (original aim of study was to investigate perinatal mortality in the UK)
- Follow ups completed in 1965 (age 7); 1969 (age 11), 1974 (age 16), 1981, (age 23), 1991 (age 33), 2000 (age 42), 2004 (age 46), 2008 (age 50), 2013 (age 55), and an age 60 follow up scheduled for 2018. Supplemental surveys by mail (or phone) in 1978 (age 20) and 2002 (age 44).

Data II - NCDS

- The 1978 survey collected exam scores as the participants completed the secondary education and the 2002 survey collected biomedical data and cognitive skill measures
- During waves 1-3 (ages 6-16), individual ability was reported by both teachers and parents with identical questions. Academic performance, measures of general aptitude and specific ability were also rated by both teachers and parents.
- In wave 3, the individuals also self-reported measures of ability and academic performance. Both teachers and the individual were asked about their expectations for the individual with respect to the upcoming national exams.

Data I – CNLSY

- 11,521 children born to NLSY79 mothers as of 2014. (5,882 males and 5,638 females)
- Born between 1970 and 2014. At the time of the first interview in 1986, child ages ranged from 0-23 years.
- Annual follow ups collected between 1987 and 1994, with biennial follow ups since 1994.

Data II - CNLSY

- The 1978 survey collected exam scores as the participants completed the secondary education and the 2002 survey collected biomedical data and cognitive skill measures
- Cognitive Skill measures include the Digit Span scale of the Wechsler, the Peabody Picture Vocabulary Test-Revised (PPVT-R), and the Peabody Individual Achievement Tests (PIAT) for math and reading
- Non-cognitive skill measures include Motor and Social Development reports and the Behavior Problems Index

Outcomes

Labor and earnings

Log weekly earnings, tenure on job, avg. hours worked per week, number of years unemployed, professional skills)

Classification by quintiles of earnings, hours worked, number of unemployment spells

Educational outcomes

Educational attainment at 23 & 33, National exam scores (A / Higher levels, O levels, GSE), no. of years of schooling beyond age 16, continuing professional or vocational training

Involvement in own child's education (wave 5, age 33) / Child's educational attainment (wave 7, age 46)

Health

Body mass index, self reported general health, # of days hospitalized. Classification of obesity, malaise index indicator

Outcome & Skill Correlation - Males

Math + Reading Test, 7									
0.699	Math + Reading Test, 11								
0.654	0.824	Math + Reading Test , 16							
-0.132	-0.108	-0.115	Behavior Report,						
-0.149	-0.125	-0.150	0.460	Behavior Report, 11					
-0.132	-0.193	-0.291	0.050	0.087	Behavior Report, 16				
-0.287	-0.340	-0.363	0.112	0.162	0.236	Bristol Social Adj. Score, 11			
0.151	0.195	0.216	-0.056	-0.047	-0.063	-0.096	(log) - Weekly Gross Income		
0.433	0.560	0.640	-0.090	-0.092	-0.286	-0.254	0.210	Highest Level of Education	
-0.117	-0.163	-0.162	0.076	0.079	0.100	0.126	-0.056	-0.131	std. Malaise Index Score

Outcome & Skill Correlation - Females

Math + Reading Test, 7									
0.690	Math + Reading Test, 11								
0.626	0.794	Math + Reading Test , 16							
-0.102	-0.121	-0.149	Behavior Report, 7						
-0.140	-0.154	-0.191	0.464	Behavior Report,					
-0.132	-0.183	-0.302	0.088	0.102	Behavior Report, 16				
-0.286	-0.328	-0.335	0.133	0.151	0.234	Bristol Social Adj. Score, 11			
0.168	0.220	0.245	-0.058	-0.070	-0.070	-0.098	(log) - Weekly Gross Income		
0.402	0.533	0.620	-0.147	-0.153	-0.259	-0.255	0.290	Highest Level of Education	
-0.102	-0.141	-0.168	0.116	0.123	0.111	0.114	-0.081	-0.154	std. Malaise Index Score

NCDS - Q1 Income

main							
auc	0.409***	0.421***	0.421***	0.411***	0.413***	0.410***	0.409***
	(30.30)	(36.11)	(35.52)	(28.93)	(31.44)	(31.32)	(30.30)
ncogall_std							
auc	0.525***						0.525***
	(85.76)						(85.76)
ncog_std7							
auc		0.514***					
		(108.04)					
ncog_std11							
auc			0.514***				
			(99.88)				
ncog_std16							
auc				0.504***			
				(76.17)			
ncog_std7_11							
auc					0.521***		
					(102.11)		
ncog_std11_16							
auc						0.515***	
						(71.67)	
N	32935	64120	57690	56555	46265	40675	32935

4

t statistics in parentheses

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

NCDS - Q5 Income

main							
auc	0.691***	0.653***	0.686***	0.708***	0.680***	0.704***	0.691***
	(35.09)	(57.11)	(50.99)	(45.06)	(45.72)	(35.16)	(35.09)
$ncogall_std$							
auc	0.451***						0.451***
	(51.88)						(51.88)
neog_std7							
auc		0.466***					
		(65.47)					
neog_std11							
auc			0.455***				
			(71.47)				
neog_std16							
auc				0.415***			
				(34.35)			
ncog_std7_11							
auc					0.452***		
					(53.53)		
ncog_std11_16							
auc						0.422***	
						(32.67)	
N	32935	64120	57690	56555	46265	40675	32935
t statistics in parentheses			8				

NLSY – Measure Comparison (Age 8)

			p					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
var	model1	model2	model3	model4	model5	model6	model7	model8
piatmath8	0.05**	0.05**	0.05**					
P	(0.00)	(0.00)	(0.00)					
piatrec8	, ,	, ,	` ′	0.04**	0.04**	0.04**		
				(0.00)	(0.00)	(0.00)		
nco_ext8		0.30**			0.30**			
		(0.04)			(0.04)			
nco_int8			0.20**			0.22**		
_			(0.04)			(0.04)	0 1044	O 1144
cog8							0.49**	0.41**
0							(0.04)	(0.04)
nco8								0.32** (0.04)
female	0.33**	0.34**	0.32**	0.36**	0.38**	0.37**	0.42**	0.39**
1011010	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)
white	0.33**	0.35**	0.32**	0.41**	0.43**	0.40**	0.39**	0.42**
	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
black	0.23**	0.25**	0.32**	0.29**	0.29**	0.36**	0.25**	0.27**
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)
$_{ m cons}$	7.70**	7.77**	7.70**	7.78**	7.91**	7.83**	9.06**	9.05**
	(0.14)	(0.15)	(0.15)	(0.14)	(0.15)	(0.15)	(0.10)	(0.10)
N	4,716	3,958	3,958	4,698	3,939	3,939	4,411	4,093
$r2_a$	0.05	0.07	0.06	0.04	0.06	0.05	0.05	0.06

A */** next to the coefficient indicates significance at the 10/5% level.

General Framework

$$Y_{i,t'} = \beta_t X_i + \gamma_t \theta_{i,t}^c + \gamma_t \theta_{i,t}^{nc} + \varepsilon_t$$
 (4)

Childhood at 7, 11, 16 and adult life from 23 to 60.

Cognitive and noncognitive skills during childhood are used to predict adult outcomes

Test different age and skill combination of childhood predictors:

7, 11, 16, 7-11, 11-16, 7-11-16

cog. only, noncog. only, both – at each of the age combinations above

Use minimal set of other covariates: gender and ethnicity

adj R2 values for Log Weekly Earnings - average over all specifications.

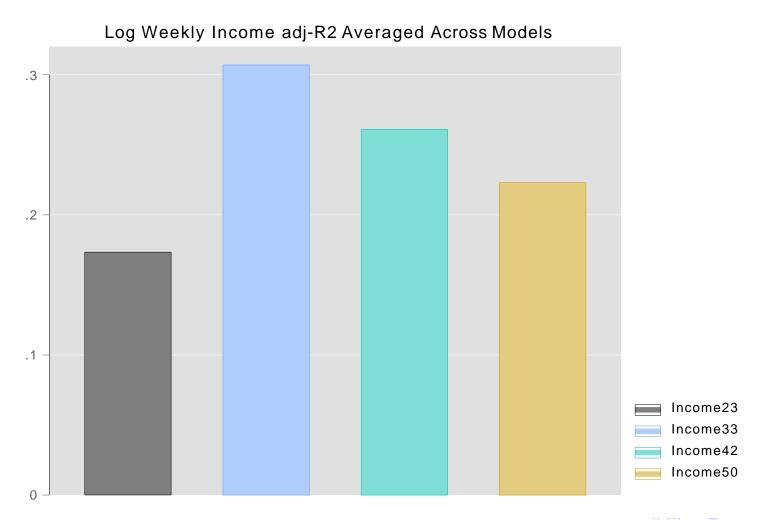


Figure: Log weekly income at age 33, predicted by child skills at different ages

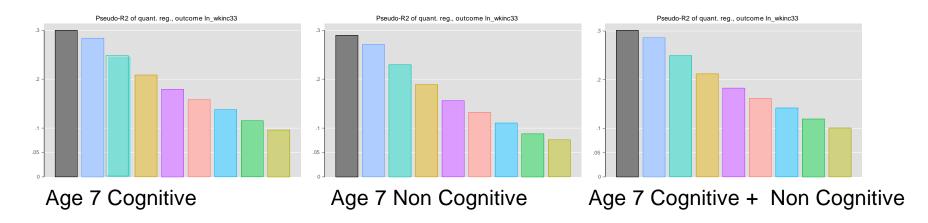
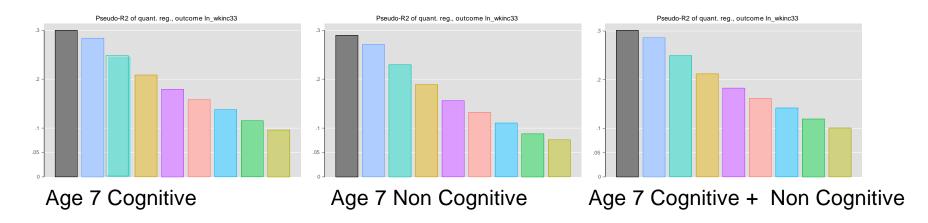
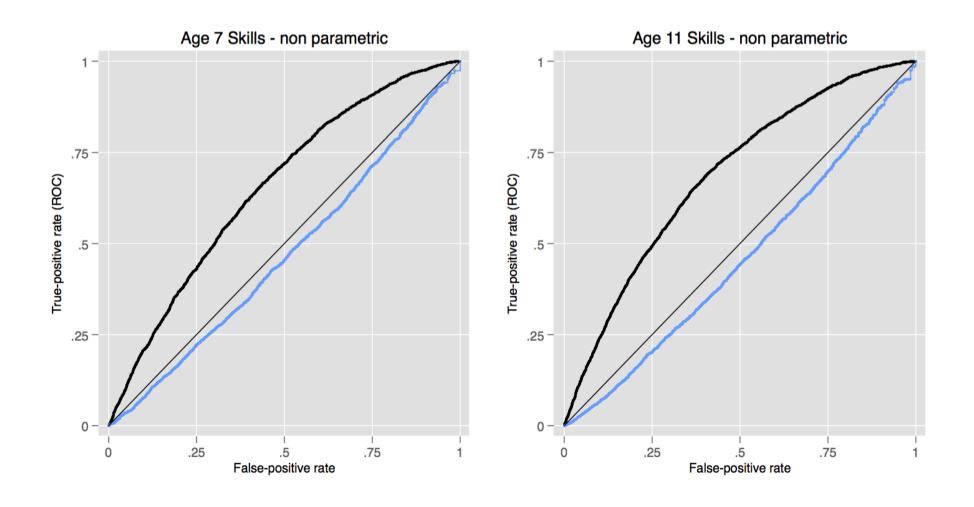


Figure: Log weekly income at age 33, predicted by child skills at different ages

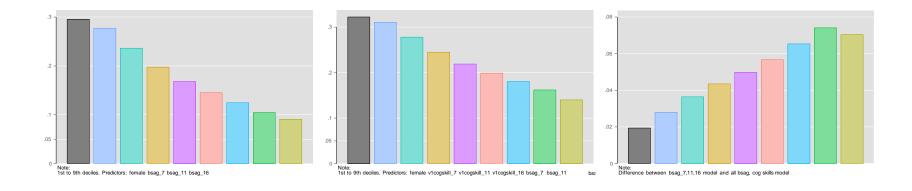


Pred. validity of skills for Q5 of Log Earnings



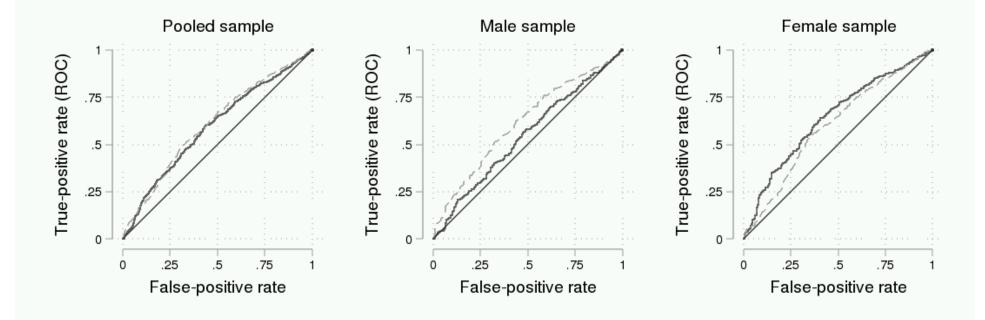
Consistent with prior literature, income at higher deciles are harder to predict with early childhood skills, suggesting greater volatility. Overall there aren't huge differences among skill measurements at different ages. Measures taken at later age provide slightly better fit. This improvement is greater at higher deciles than at lower deciles, although the magnitude of improvement remains small.

Figure: Log weekly income at age 33, predicted by cognitive and noncognitive skills



Cognitive skills contribute more to predicting income at higher deciles. Note that the right-most figure has different scale from the other two.

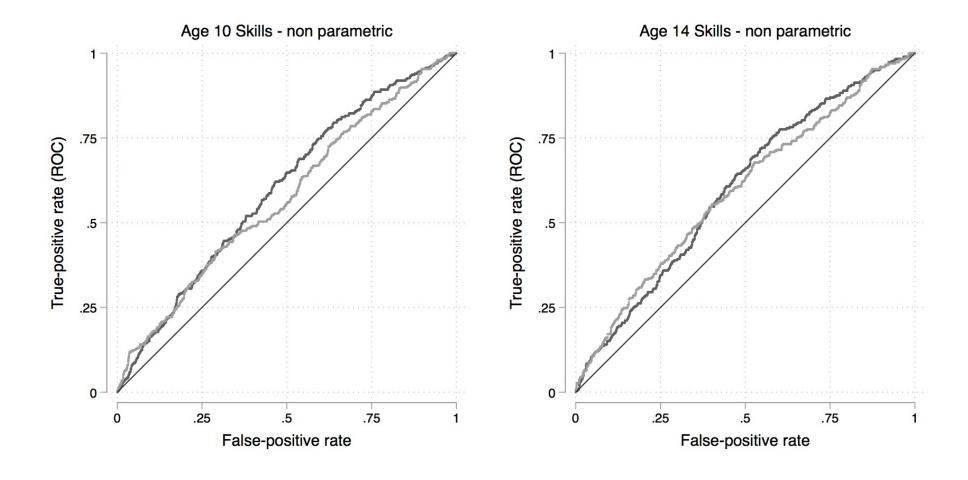
Pred. validity of skills for self-rated health for ages 26-30



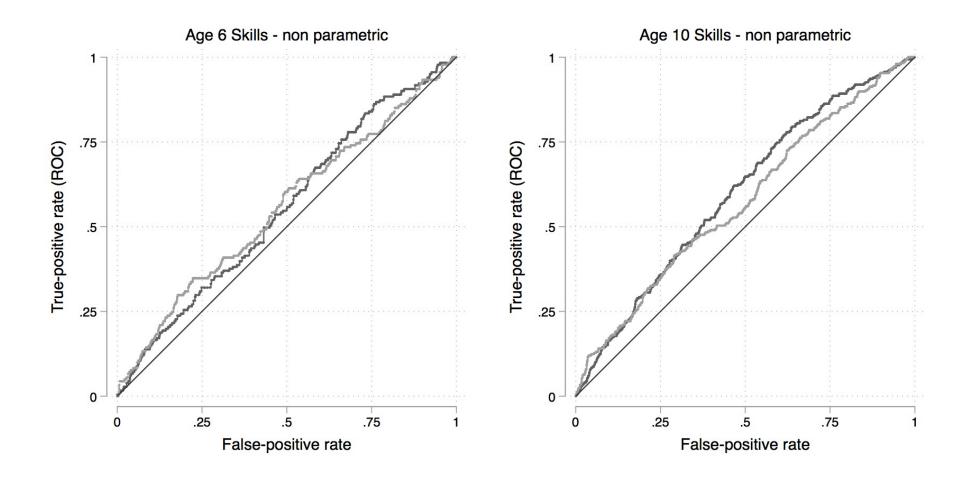
- Cognitive skill factor score at age 12
- Socio-emotional skill factor score at age 12

Note: Cognitive vs. noncognitive skills at age 12.

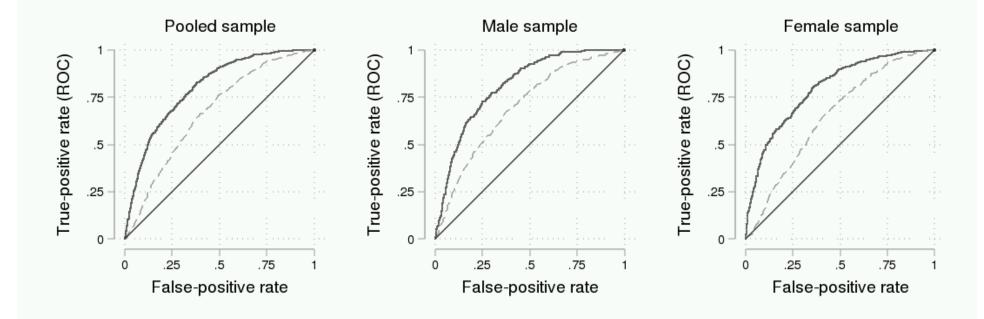
Pred. validity of skills for Q5 of childwage30



Pred. validity of skills for Q5 of childwage30



Pred. validity of skills for college graduation by age 26

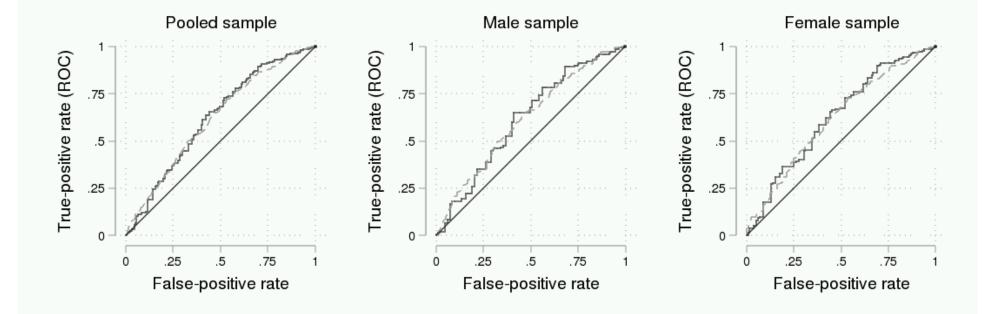


- Cognitive skill factor score at age 12
- Socio-emotional skill factor score at age 12

Note: Cognitive vs. noncognitive skills at age 12.



Pred. validity of skills for college graduation by age 26

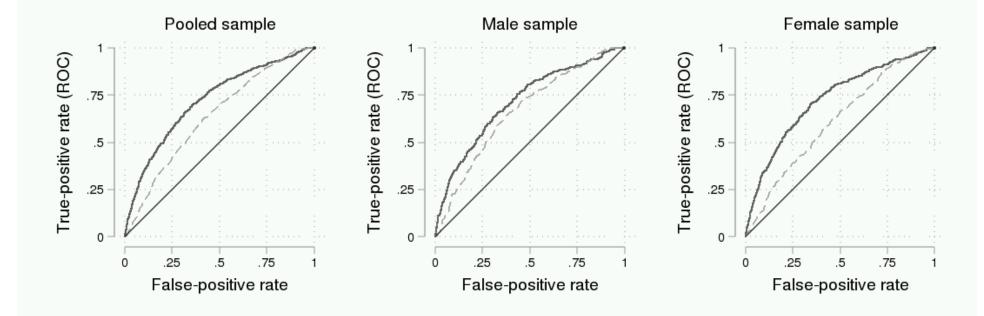


- Cognitive skill factor score at age 4
- Socio-emotional skill factor score at age 4

Note: Cognitive vs. noncognitive skills at age 4.



Pred. validity of skills for college graduation by age 26

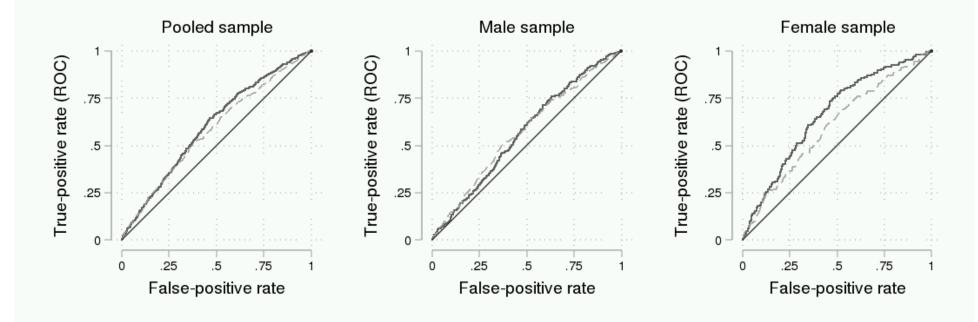


- Cognitive skill factor score at age 8
- Socio-emotional skill factor score at age 8

Note: Cognitive vs. noncognitive skills at age 8.



Pred. validity of skills for age 24-30 wage income in top decile



- Cognitive skill factor score at age 12
- Socio-emotional skill factor score at age 12

Note: Cognitive vs. noncognitive skills at age 12.

Unobserved heterogeneity

Liu, Moon and Schorfheide (2015) estimates the following random coefficient model

$$y_{it} = \lambda_i w_{it-1} + \rho y_{it-1} + \gamma z_{i,t-1} + E_{it}, \lambda_i \sim F, E_{it} \sim G$$
 (5)

projection, which are provided as

$$Y_{it}^* = \lambda_{i, t-1} + W_{t-1} + \gamma Z_{i, t-1} + \rho^{\gamma}$$

Unobserved heterogeneity in forecasting life outcomes

We consider two forms of unobserved heterogeneity:
Heterogeneity of individual skill dynamics
Heterogeneity of income dynamics

Within the NCDS data, we find no role for either type of heterogeneity.

Next Steps

- Recently began duplicate analysis using GSEOP data
- Exploring additional nationally representative longitudinal data sets for cross-national comparison
- Improve analysis of health outcomes.
- Out of sample validation using data from policy interventions (Perry Preschool, Abcedarian Prooject)

Onwards and Upwards?

The Role of Internal Migration for Graduates' Social Mobility in the Context of Different Career Paradigms

by Bozena Wielgoszewska







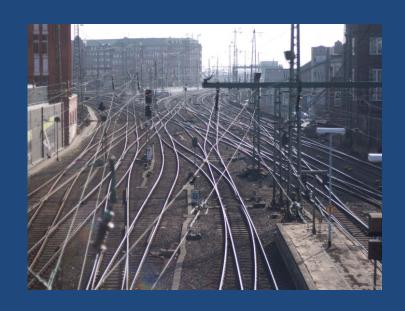


Supervisors:

Dr. Zhiqiang Feng

Dr. Darja Reuschke

The Role of Migration



Smoke lingers 'round your fingers;
train Heave on - to Euston

Do you think you've made the right decision this time?

You left your tired family grieving and you think they're sad because you're leaving, but did you see jealousy in the eyes of the ones who had to stay behind?

And do you think you've made the right decision this time?

You left your girlfriend on the platform with this really ragged notion that you'll return, but she knows that when he goes he really goes

And do you think you've made the right decision this time?

"London" the Smiths

Escalators in the UK

The seminal work of Fielding (1992) recognised London as upward social class escalator:

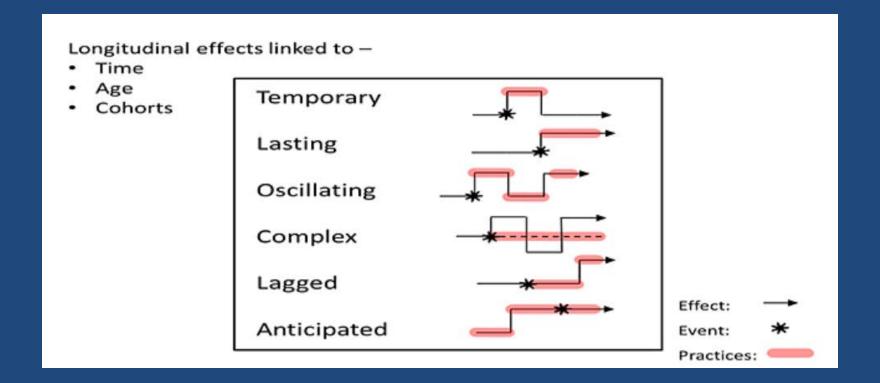
- it attracts more than proportional share of upwardly mobile adults,
- it promotes both in-migrants and the local labour at a faster rate than other regions,
- people who achieved higher status "step off" the escalator by migrating away

Champion and Townsend (2013), Champion, Coombes et al. (2014), and Van Ham, Findlay et al. (2012) expand this theory to other big cities in the UK – second order escalators.

University graduates, who are both highly educated and highly mobile (Abreu et al., 2015), are expected to utilise this strategy effectively.



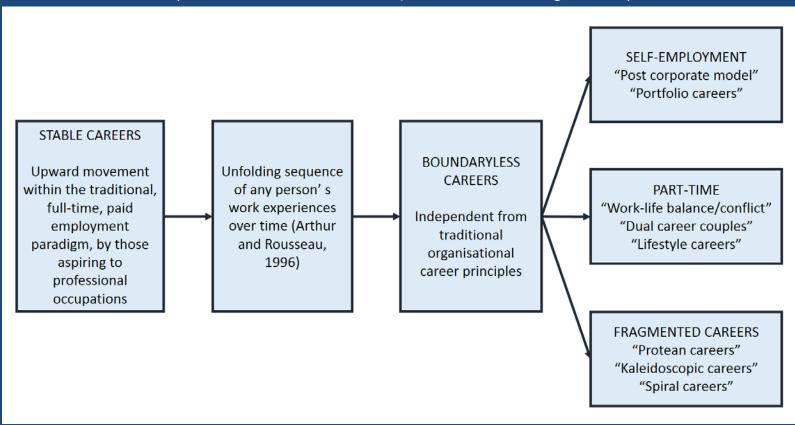
Mobility through longitudinal lens



"(...) we have mapped a shift from researchers analysing a single migration event, to adopting life course theory to explore the fluidity of modern day mobility trajectories." (Findlay et al., 2015, p.392)

Evolution of the Career Literature

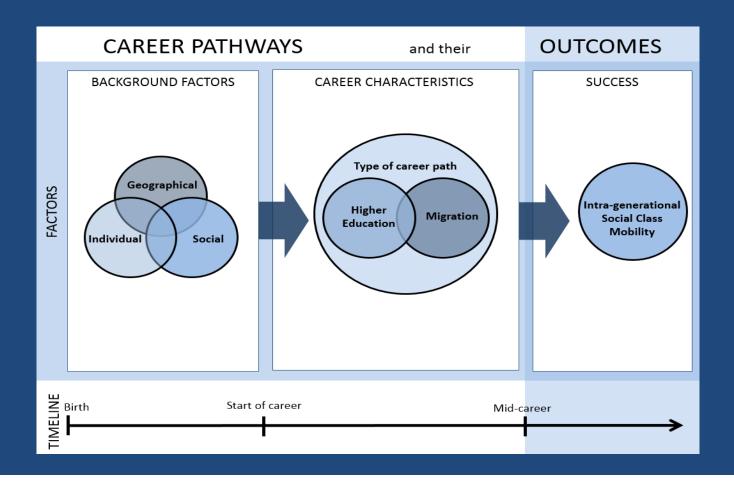
Careers became more varied and complex (Sullivan and Baruch 2009; Valcour and Ladge 2008)



The literature review of career studies conducted by Mulhall (2011) shows that 97 % of career studies concern only those in paid employment.

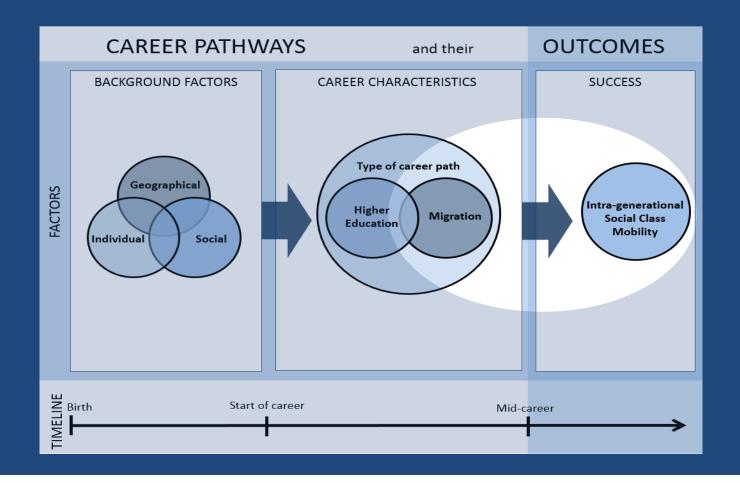
Conceptual Framework

Life course approach is primarily concerned with the unfolding of individual lives as embedded in social structures and economic context (Dykstra and van Wissen, 1999; Smith et al., 2016)



Research question

What role does internal migration play for UK graduates' social mobility in the context of different career paradigms?



Data and Methodology

Secondary longitudinal data obtained from 1970 British Cohort Study

This study follows a birth cohort of 17,287 individuals born in the UK

The information has been collected in 9 sweeps, when the Cohort Members were age 0, 5, 10, 16, 26, 30, 34, 38, and 42

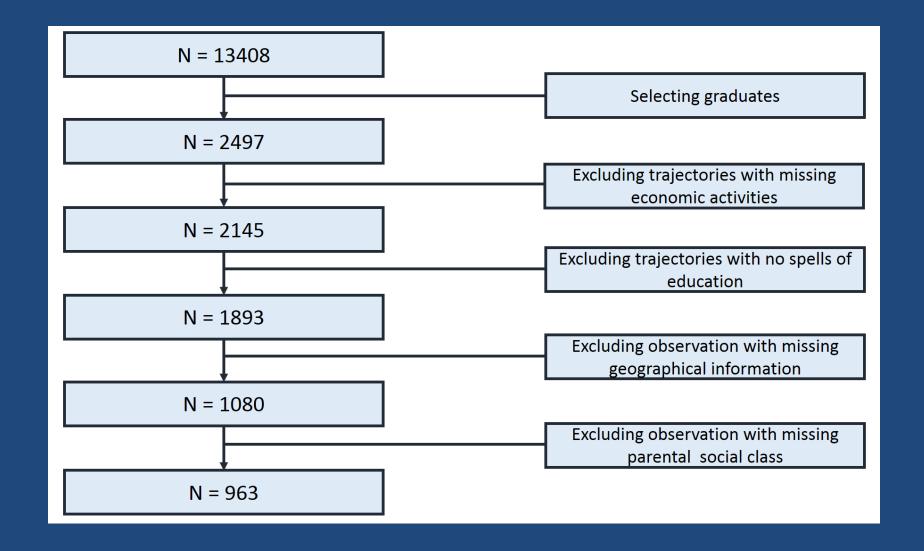
				Variables		
		Y	X1	X2	Х3	X4
SN	Study Description	Social Mobility	Parental Class	Gender	Career Typology	Migration
3723	Ten-Year Follow-Up, 1980		✓			
5585	Thirty-Four-Year Follow-Up, 2004-2005			✓		
6943	Activity Histories, 1986-2013	✓			✓	
5537	County Data, 1986-2012: Special Licence Access					✓

Sequence Analysis is used to derive indicators of the three longitudinal aspects of graduates' career: Social Mobility, Migration and Career Typology

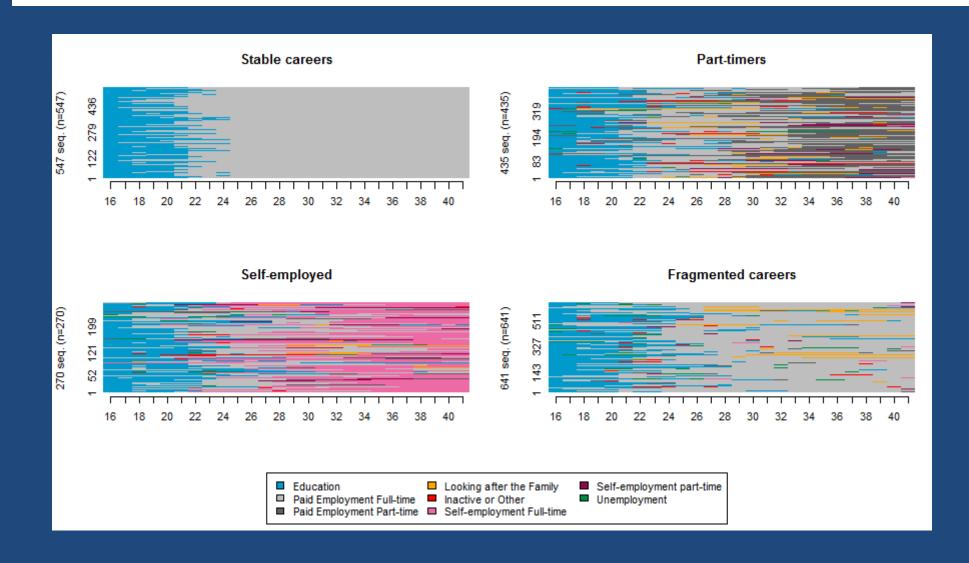
Marginal Effects Model is used for statistical inference of the relationships between them

$$\log \left[\frac{P(Y=1)}{1 - P(Y=1)} \right] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_3 X_4$$

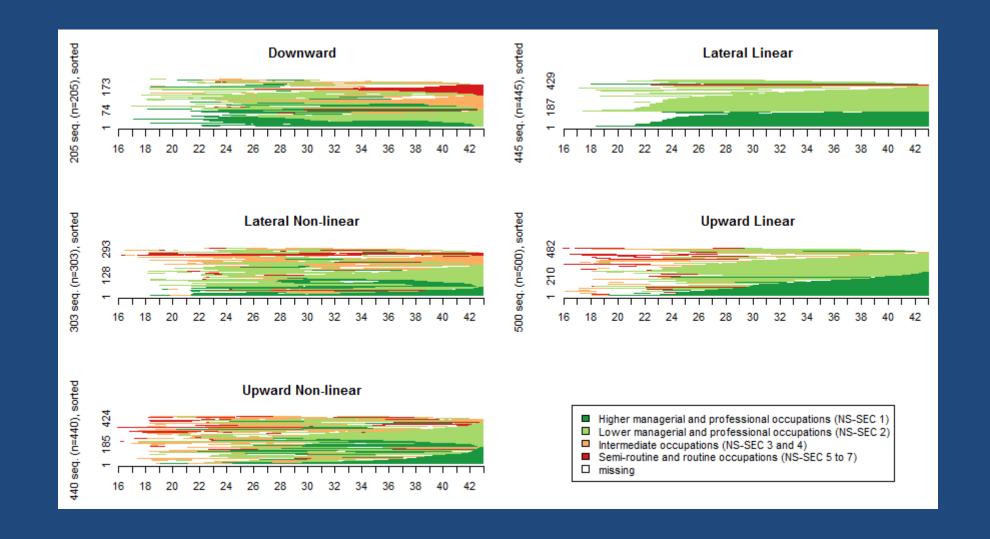
Sample size



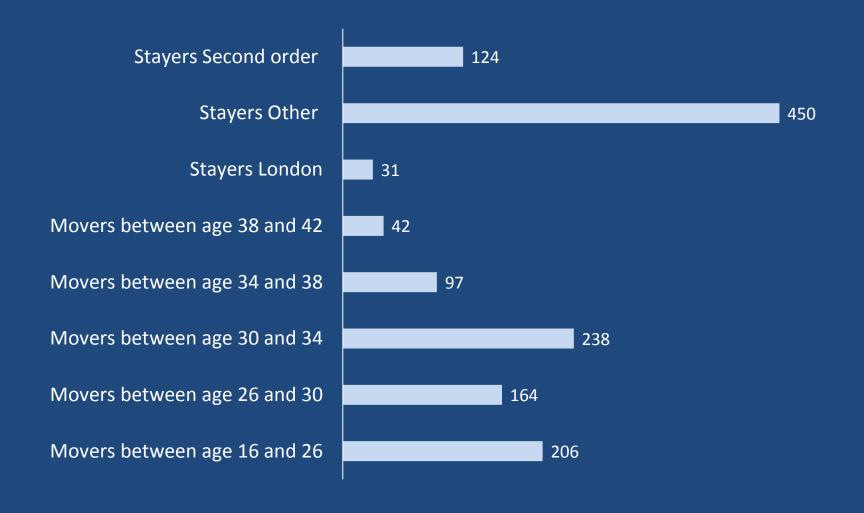
Career Typology



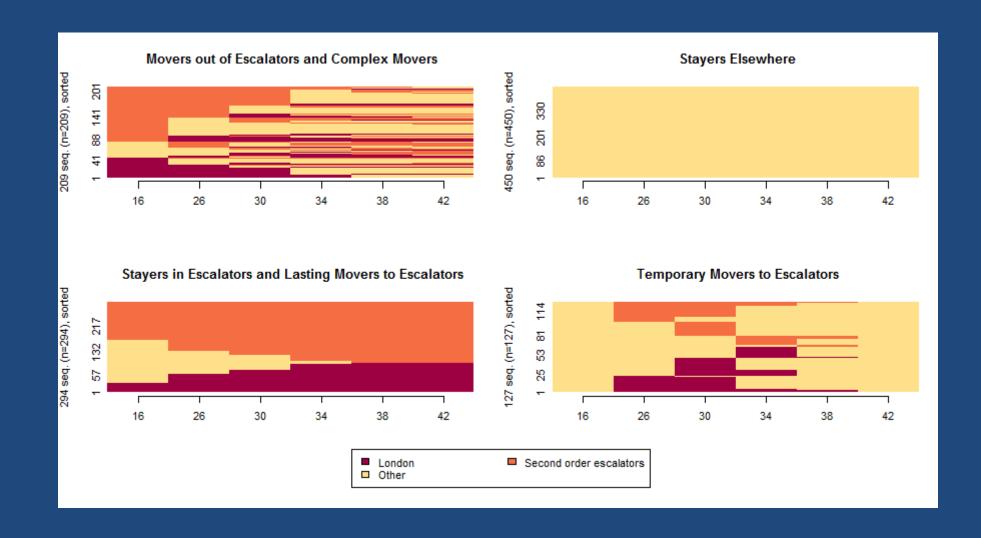
Intra-generational Social Mobility



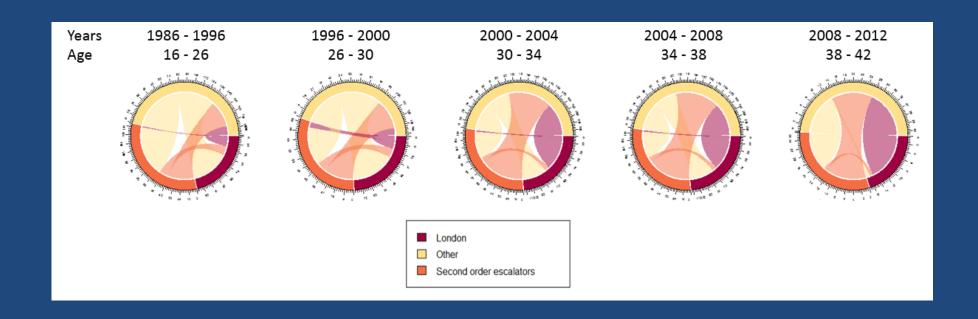
Stayers and Movers



Migration biographies



Migration flows



- During early stages of career main flow occur to escalators regions, which is consistent with the theory.
- From the age of 30 onwards the proportion of graduates moving out of escalators increases, which the escalator region theory does not account for.

Regression Results

						Dependent variable						
Explanatory Variable	Reference Category			Downward	Lateral Non-linear	Lateral Linear	Upward Non-linear	Upward Linear				
Parental Social Class	NS-SEC 5-7	NSSEC 1 NSSEC 2 NSSEC 3-4		0.266 -0.088 -0.136	0.409 0.844***	0.454* 0.250 -0.104	-0.398 -0.340 -0.001	-0.422* -0.412* -0.284				
Gender	Female	Male		0.393	-0.128	-0.266	0.176	0.016				
Career type	Stable	Fragmented careers Part-timers Self-employed		0.597 1.121** 0.419	0.721* 1.073*** 0.513	-0.839*** -0.663** -0.456	1.041*** 0.418 0.249	-0.693** -0.831*** -0.072				
Migration	Stayers elsewhere		ators and Complex Movers s and Lasting Movers to Escalators Escalators	0.369 -0.237 0.898	0.726 0.579 0.709	-0.794** -0.167 -0.559	0.480 0.333 0.679	-0.092 -0.260 -0.762				
	Challa W	Fragmented careers Part-timers Self-employed Fragmented careers	* Movers out of Escalators and Complex Movers * Movers out of Escalators and Complex Movers * Movers out of Escalators and Complex Movers * Stayers in Escalators and Lasting Movers to Escalators	-0.739 -0.493 1.107 -1.381	-0.984 -0.912 -0.862 -0.543	0.518 0.600 0.497 -0.665	-0.422 -0.359 -0.629 -0.369	0.586 0.452 -0.487				
Career type * Migration	Stable * Stayers elsewhere	Part-timers Self-employed	* Stayers in Escalators and Lasting Movers to Escalators * Stayers in Escalators and Lasting Movers to Escalators * Stayers in Escalators and Lasting Movers to Escalators	-0.254 0.930	-0.993 -0.291	0.526	-0.269 0.128	0.504				
		Fragmented careers Part-timers Self-employed	* Temporary Movers to Escalators * Temporary Movers to Escalators * Temporary Movers to Escalators	-0.607 -1.266 -0.837	-0.805 -1.175 -0.336	1.248* 1.307** 1.244	-1.214* -0.745 -0.855	0.464 0.431 -0.281				
Constant				-2.948***	-2.804***	-0.662**	-1.707***	-0.300				
Observations				963	963	963	963	963				
Log Likeliho				-290.22 620.441	-417.136 874.272	-518.557 1,077.12	-493.173 1,026.35	-543.347 1,126.69				

Onwards and Upwards?

Stable careers are not as common as often assumed (less than 30% of the UK graduates who participate in the British Cohort Study)

Escalator Regions Theory does not account for complex or temporary movers (31% of the UK graduates who participate in the British Cohort Study)

The "stepping off" stage starts during later 30s and early 40s, especially if they do not follow the stable careers, and is not necessarily related to achieving higher status.

Temporary movers on fragmented and part-time careers, are more likely to have "travellator" (lateral linear) careers.

While graduates from lower social class background are more likely to climb the social class ladder, those from highest social class are more likely to experience "Glass Floor" (Milburn et al., 2015, Friedman and Macmillan, 2017).

Parental social class plays a significant role in terms of graduates social mobility, which contradicts the assumption of meritocracy.



b.wielgoszewska@ed.ac.uk

@MeBozena



Skills Development **Scotland**





Supervisors:

Dr. Zhiqiang Feng

Dr. Darja Reuschke

Inequalities: a longitudinal perspective, November 2017

References

ARTHUR, M. B. & ROUSSEAU, D. M. 1996. A career lexicon for the 21st century. The Academy of Management Executive, 10, 28-39.

Butler, N., Bynner, J.M., University of London. Institute of Education. Centre for Longitudinal Studies. (2016). 1970 British Cohort Study: Ten-Year Follow-Up, 1980. [data collection]. 6th Edition. UK Data Service. SN: 3723, http://doi.org/10.5255/UKDA-SN-3723-7

CHAMPION, T., COOMBES, M. & GORDON, I. 2014. How Far do England's Second-Order Cities Emulate London as Human-Capital 'Escalators'? *Population, Space and Place*, 20, 421-433.

CHAMPION, T. & TOWNSEND, A. 2013. Great Britain's second-order city regions in recessions. Environment and Planning A, 45, 362-382.

DYKSTRA, P. A. & VAN WISSEN, L. J. 1999. Introduction: The life course approach as an interdisciplinary framework for population studies. Population Issues. Springer.

FIELDING, A. J. 1992. Migration and social mobility: South East England as an escalator region. Regional studies, 26, 1-15.

FINDLAY, A., MCCOLLUM, D., COULTER, R. & GAYLE, V. 2015. New mobilities across the life course: A framework for analysing demographically linked drivers of migration. *Population, Space and Place,* 21, 390-402.

FRIEDMAN, S. & MACMILLAN, L. 2017. Is London really the engine-room? Migration, Opportunity hoarding and Regional social mobility in the UK. National Institute Economic Review, 240, R58-R72.

MILBURN, A., SHEPHERD, G., ATTWOOD, T., CLEAL, P., GREGG, P., GUY, C., HAMILTON, D., JOHNSTON, D. & WILLIAMS, C. 2015. Downward mobility, opportunity hoarding and the 'glass floor'.

MULHALL, S. 2011. CSI: Career success investigation. Irish Journal of Management, 30, 67-93.

SMITH, D. P., FINNEY, N. & WALFORD, N. 2016. Internal Migration: Geographical Perspectives and Processes, Routledge.

SULLIVAN, S. E. & BARUCH, Y. 2009. Advances in career theory and research: A critical review and agenda for future exploration. *Journal of management*, 35, 1542-1571.

University of London. UCL Institute of Education. Centre for Longitudinal Studies. (2017). 1970 British Cohort Study: Activity Histories, 1986-2013. [data collection]. 3rd Edition. UK Data Service. SN: 6943, http://doi.org/10.5255/UKDA-SN-6943-3

University of London. Institute of Education. Centre for Longitudinal Studies. (2016). 1970 British Cohort Study County Data, 1986-2012: Special Licence Access. [data collection]. 3rd Edition. UK Data Service. SN: 5537, http://doi.org/10.5255/UKDA-SN-5537-1

University of London. Institute of Education. Centre for Longitudinal Studies. (2016). 1970 British Cohort Study: Forty-Two-Year Follow-Up, 2012. [data collection]. 2nd Edition. UK Data Service. SN: 7473, http://doi.org/10.5255/UKDA-SN-7473-2

VALCOUR, M. & LADGE, J. J. 2008. Family and career path characteristics as predictors of women's objective and subjective career success: Integrating traditional and protean career explanations. *Journal of vocational behavior*, 73, 300-309.

VAN HAM, M., FINDLAY, A., MANLEY, D. & FEIJTEN, P. 2012. Migration, occupational mobility, and regional escalators in Scotland. *Urban Studies Research*, 2012.

Migration in the context of career

