Occupational Mobility Across Years, Decades and a Century

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Abstract

In this paper I document occupational mobility comparing the experiences of cohorts living one century apart: those captured in the Panel Study of Income Dynamics from 1968 to 2000 and a longitudinal census sample of individuals observed between 1880 and 1930. Considering different levels of aggregation with respect to occupations, as well as different definitions of what an occupation is, I uncover several facts which are remarkably stable in time: (i) occupational mobility is higher for younger workers, (ii) it is closely related to geographical mobility and (iii) over the life-cycle, individuals tend towards occupations with high cognitive, non-routine task requirements and away from manual-heavy tasks. A major difference between cohorts is the fate of geographical movers: for the 1880 cohort, interstate migrants were characterized with worse occupational outcomes than stayers, while the opposite is true for the 1968 cohort; additionally, the data shows that routine occupations are more prominent for the 1968 cohort.

Keywords: Occupations, geography, mobility, tasks, structural change.

JEL Codes: **J21,J24,J62,N31**

[PRELIMINARY AND INCOMPLETE]

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1 Introduction

Occupational mobility and the sorting of workers into occupations requiring different types of skill are two phenomena linked with the steady increase in income inequality experienced in the US economy over the last three decades. For example, Kambourov and Manovskii (2009) show that increased occupational mobility is linked to increases in wage inequality, while Acemoglu and Autor (2011), Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006) and others have linked the increase in inequality with changes in the types of jobs and required skills in different occupations, a phenomena also referred as *job polarization*.

This paper provides new facts in order to understand the relationship between polarization, occupational mobility and inequality, in the context of aggregate structural transformation. In doing so, I try to answer the question of whether and to what extend does economic development affect inequality through the rising menu of occupations available to workers. Furthermore, how is this related to forces that make individuals change occupations more often? To provide some guidance, I document occupational mobility comparing the experiences of male cohorts living one century apart: worker histories captured in the Panel Study of Income Dynamics from 1968 to 2000 and in a longitudinal census sample of individuals observed between 1880 and 1930.

Considering different levels of aggregation with respect to occupations, as well as different definitions of what an occupation is, I uncover several facts which are remarkably stable even one hundred years apart: (i) occupational mobility is higher at the beginning of a career (age of worker between 18 and 30), (ii) job mobility is closely related to geographical mobility in terms of inter-state reallocation and (iii) over the life-cycle, individuals tend to transit towards occupations with high cognitive, non-routine task requirements and away from occupations requiring manual-heavy tasks. The stability of all these facts across time provides important evidence that should help us understand how job discovery, search frictions, aggregate productivity and other factors that affect life-cycle occupational choices are evolving.

I also find that a major difference between cohorts is the fate of geographical/state movers: for the 1880 cohort, movers were characterized with worse occupational outcomes than stayers in terms of the abstract skill content of occupations: those who changed state of residence, ended up with less 'difficult' occupations. The opposite is true for the 1968 cohort. Additionally, occupations with highly routine tasks are more prominent for this latter cohort. Why are movers more *successful* in latter periods of time/cohorts? Does the relative prominence of routine-type occupations for the

latter cohort contradict the findings of recent literature (See for example, Autor and Dorn, 2013) which claims that technological changes have made routine tasks obsolete?

The findings I provide also are related to recent research linking occupations more closely with the tasks that define them, as in Yamaguchi (2012) and Jaimovich and Siu (2012). Since aggregate income inequality is closely linked to life-cycle inequality, understanding the sources of mobility and task learning over the life-cycle can improve our understanding of these processes for a macro perspective. In turn, the decomposition of earnings inequality into optimal remunerations to the amount of learned tasks by individuals can have first order implications to issues of optimal taxation of labor, aggregate inequality trends, intergenerational mobility of economic status, among many others.

[to be completed]

2 Data Analysis

My main sources of data are the Panel Study of Income Dynamics and the US census. From the latter, I use a novel series of matched samples of individuals across decennial censuses, provided by the Integrated Public Use Microdata Series (IPUMS) website. These samples contain census information for individuals across decades, from which I can compute mobility and related statistics. On the other hand, the PSID has yearly information on a sample of US families, from where I can also construct statistics across decades. Table 1 shows the number of matched individual observations for each cohort between an initial period t_0 and period $t_0 + t$. The 1945 cohort refers to all individuals age 18-30 observed for the first time in the 1968 wave of the PSID; the 1855 cohort refers to all individuals age 18-30 observed for the first time in the 1880s US census. Given that I want to compare such different periods of time, where the role of women in the labor market changes dramatically, I focus only on male workers for the reminder of the paper. Also, given the importance of farming and agriculture for the earlier cohort, throughout I consider all sectors in the economy.

$t =$	1945 cohort	1855 cohort
10	1809	–
20	1413	4007
30	906	2793

Table 1: Matched sample size by cohort.

As seen from the table, the main benefit of the census sample is its size, which easily doubles that of the PSID. Table 1 also shows that information on the 1855 cohort is incomplete, given the absence of information on the 1890 US census from the IPUMS.

For all samples, I use the 1950 (3-digit level) census codes for occupations, which the Minnesota Population Center uses to recode all year-specific occupational codes to maintain comparability in time. I use a simple cross-walk to translate occupations in the PSID to these codes. Additionally, I use task data on different occupations from the fourth edition of the Dictionary of Occupational Titles. Following Autor, Katz, and Kearney (2006), I use three task indexes, measuring abstract, routine and manual tasks.[1]

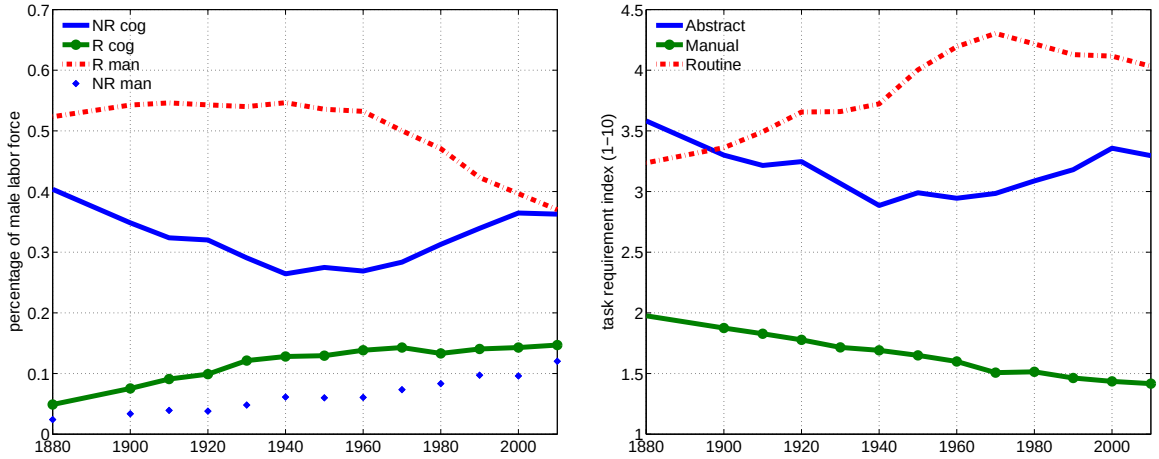

Figure 1: Occupations and average task content. Left panel shows share of male labor force, of four main occupational groups: non-Routine cognitive, routine (cognitive and manual) and non-routine manual occupations. The right panel shows average task content of occupations, using a 1-10 index of difficulty in tasks.

Figure 1 shows occupational choices and average task requirements of the male labor force using decennial census data. In the left panel of the figure, I present the share of male labor force in four major occupational categories spanning two dimensions/types of jobs: non-routine versus routine and cognitive versus manual. The right panel shows the average job task requirement of chosen occupations, in a $1-10$ index (higher numbers indicate more difficult tasks).

[1]The task information, codes and cross-walks are provided by David Dorn in his webpage: http://www.cemfi.es/~dorn/data.htm. I follow Autor, Katz, and Kearney (2006) who use three aggregate tasks, who in turn follow Autor, Levy, and Murnane (2003).

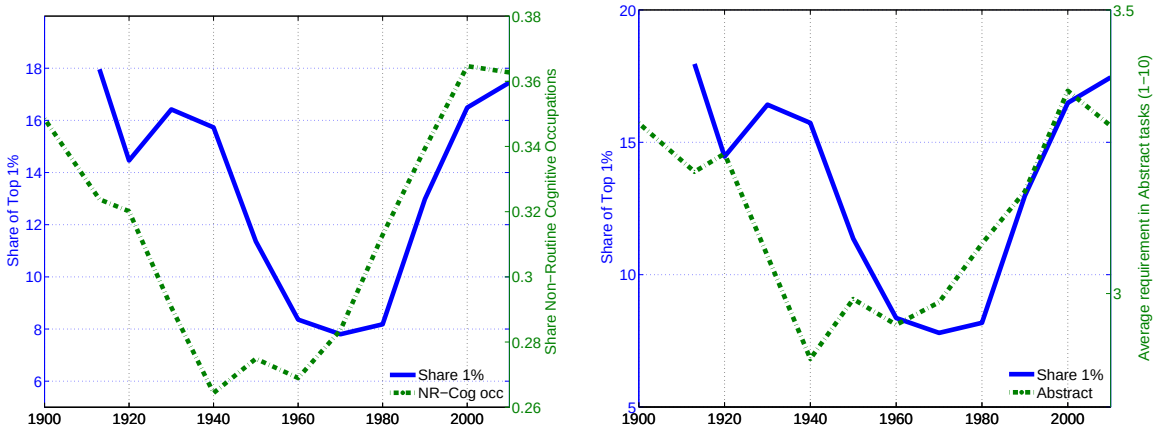

Figure 2: Inequality, occupations and tasks. Both panels depict the share of income going to the 1% of the population (From *The World Top Incomes Database*). The left panel also depicts the share of non-routine cognitive occupations, while the right panel shows the average level of abstract task over all occupations.

Figure 2 shows that the amount of inequality in the US economy (which shows a U-shape during the last century), measured as the share of income going to the top 1% of earners, from *The World Top Incomes Database*[2]. From the figure we see that inequality is closely linked to the availability of occupations which are characterized for being non-routine and requiring cognitive ability. This is mirrored in both panels of the figure, with the left panel showing the share of these types of occupations and the right panel showing the level of abstract skill requirements over all occupations.

3 Results

Tables 2 and 3 show occupational mobility figures of both cohorts, for different time spans. In the tables I present the probability that an individual observed in a certain occupation in the initial period (1968 and 1880 for each cohort) is observed in a different occupation at different times past that initial period. Table 2 shows occupational mobility figures considering a 3-digit level of disaggregation (around 270 occupations) while table 3, considers the four occupational aggregates described above.

Both tables show that occupational mobility is a very stable phenomenon for both cohorts, even considering that aggregate conditions were likely very different for both of them. In table 2 we see that mobility is overall higher for the latter cohort, although differences are never higher than 20%. For both cohorts, the probability that an individual ends up with a different occupation code after

[2]Available online at http://topincomes.g-mond.parisschoolofeconomics.eu/

$t =$	1945 cohort	1855 cohort
10	0.56	–
20	0.71	0.52
30	0.76	0.62

Table 2: Probability of occupation at time $t_0 + t$ being different from the occupation at time t_0 (3-digit level).

$t =$	1945 cohort	1855 cohort
10	0.27	–
20	0.35	0.42
30	0.40	0.48

Table 3: Probability of occupation at time t_0+t being different from the occupation at time t_0 (4 categories).

30 years is north of 50%. On the other hand, table 3, which considers only four aggregate categories, shows that occupational mobility is lower the coarser the definition used. However, the numbers are still considerable and the table shows that the probability of changing major occupations earlier in life has remained more or less stable over time. In relative terms, the older cohort exhibits a larger probability of changing major occupational categories.

Next, table 4 shows how individuals transit across occupations with different skill requirements: in the table I compute the percentage change in occupational tasks indexes across time. Positive numbers imply that individuals are on average moving to occupations with higher difficulty in that particular task.

The table shows that for both cohorts, individuals tend to move upwards in terms of the abstract task requirements in occupations (e.g., from office clerk to office manager) moving away from both jobs requiring routine and manual skills. Considering that farming and agricultural sectors are included in the sample for the earlier cohort, it is remarkable that the transition away from manual work over the life-cycle seems to be quite stable in time.

I present a more detailed view in figures 3 and 4, which show life-cycle profiles of occupations and skills, for synthetic cohorts constructed using decennial US data. Figure 3 shows how individuals choose different occupational categories (between cognitive/manual and routine/non-routine occupational dimensions) for the two cohorts. On the other hand, figure 4 shows the skill requirements of occupations over the life-cycle.

$t =$	1945 cohort	1855 cohort
	Abstract skills	
10	0.22	–
20	0.31	0.30
30	0.27	0.41
	Routine skills	
10	-0.12	–
20	-0.19	-0.14
30	-0.20	-0.16
	Manual skills	
10	-0.05	–
20	-0.11	-0.19
30	-0.19	-0.25

Table 4: Percentage change in task difficulty index ($1-10$ scale, higher means more difficult task) between t_0 and $t_0 + t$.

Both figures show that individuals tend towards occupations requiring non-routine, cognitive skills over the life-cycle and that this fact is very robust across cohorts. This can be seen for both the fraction of workers in non-routine cognitive occupations (figure 3) and the level of abstract skills required by chosen jobs (figure 4) over the life-cycle: for both cohorts, both statistics increase with age.

Figure 3 also shows that the main tension in terms of occupations over the life-cycle is between non-routine cognitive and routine manual type of occupations: the majority of workers start in routine and manual intensive jobs, but they transit towards other types of occupations with age. Note that these types of occupations lose predominance in the second cohort (right panel). Surprisingly, for the this last cohort there is an increase of routine cognitive jobs, which sounds counterintuitive given the preponderance of new technologies making routine tasks less important. In terms of non-routine manual occupations, the fraction of individuals in them has stayed very stable in time, maybe because its specificity (e.g., high end carpenters). On the other hand, figure 4 shows that individuals tend to move towards occupations with high abstract skill requirements over the life-cycle, mirroring the profile for non-routine cognitive occupations described above, and

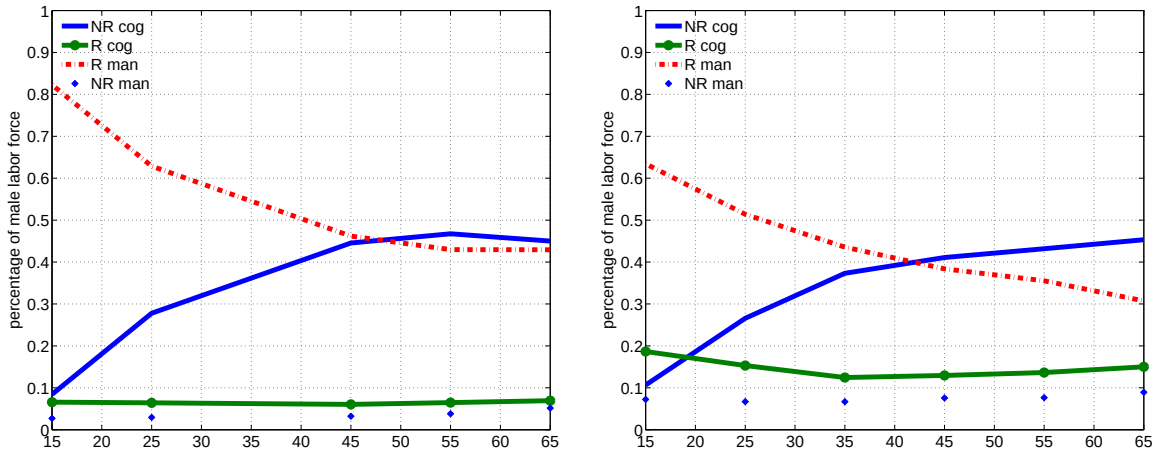

Figure 3: Occupations over the life-cycle (4 aggregate categories). 1855 cohort (left) and 1945 cohort (right)

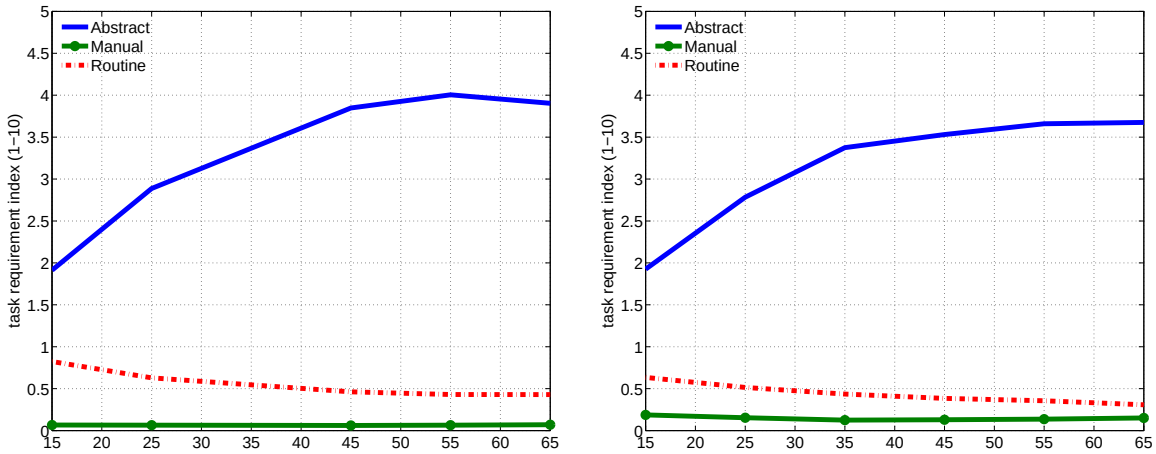

Figure 4: Skills and jobs over the life-cycle. 1855 cohort (left) and 1945 cohort (right)

away from jobs requiring high levels of routine tasks. Comparing the left and right panels of figure 4, we see that the profiles across cohorts have remained almost identical.

Next, tables 5 and 6 show occupational mobility for two levels of aggregation (3-digit and four aggregate occupations, respectively) considering the initial occupation. To maintain simplicity, we consider as initial occupations only the four aggregate categories described above: non-routine cognitive, routine cognitive, routine manual and non-routine manual.

Both tables show that, across cohorts, individuals starting in non-routine cognitive occupations show less tendencies to switch occupations in the life-cycle. This is true when using both levels of aggregation in terms of occupation. The main difference found across cohorts, is the fact that individuals of the latter cohort are much more likely to change occupations if they start at a non-

	1945 cohort (PSID)				1855 cohort (census)			
$t =$	NR cog	R cog	R man	NR man	NR cog	R cog	R man	NR man
10	0.42	0.50	0.47	0.49	–	–	–	–
20	0.63	0.76	0.70	0.70	0.30	0.83	0.71	0.77
30	0.70	0.80	0.79	0.82	0.39	0.86	0.80	0.84

Table 5: Occupational mobility (3-digit) given initial occupation category. *NR*: non routine, *R*: routine, *cog*: cognitive, *man*: manual.

	1945 cohort (PSID)				1855 cohort (census)			
$t =$	NR cog	R cog	R man	NR man	NR cog	R cog	R man	NR man
10	0.22	0.35	0.16	0.29	–	–	–	–
20	0.30	0.51	0.26	0.39	0.24	0.66	0.51	0.72
30	0.33	0.56	0.33	0.50	0.27	0.70	0.57	0.72

Table 6: Occupational mobility (4 categories) given initial occupation category. *NR*: non routine, *R*: routine, *cog*: cognitive, *man*: manual.

routine cognitive occupations. The other main salient fact from the tables is related to the fate of non-routine manual occupations: across time and levels of aggregation of occupations, individuals starting in these occupations are the ones most likely to end up switching.

3.1 Occupational and Geographical Mobility

Below I consider facts regarding geographical mobility as well as occupational and skill transitions over time and over the life-cycle. First, consider table 7 which shows state mobility rates for both cohorts.

$t =$	1945 cohort	1855 cohort
10	0.18	–
20	0.22	0.19
30	0.45	0.23

Table 7: Probability that state of residence at time $t_0 + t$ being different from the state of residence at time t_0.

As seen from the table, inter-state mobility has seen an increase in magnitude from the earlier to the latter cohort. The probability that an individual age 18 to 30 in the 1968 PSID had changed state of residence over a span of 30 years is 45%, while the probability for its 1855 cohort counterpart was almost half of that (23%).

Below, tables 8 and 9 show estimates for occupational mobility across the four aggregate occupation categories, conditioning on whether individuals were *stayers* (did not change state of residence) or *movers* (state of residence in time $t_0 + t$ was different than that in t).

	1945 cohort		1855 cohort	
$t =$	stayers	movers	stayers	movers
10	0.54	0.69	–	–
20	0.71	0.77	0.49	0.65
30	0.75	0.82	0.59	0.72

Table 8: Occupational mobility (3-digit level) and geographical mobility. *Stayers* and *Movers* are defined by changes in the state of residence.

	1945 cohort		1855 cohort	
$t =$	stayers	movers	stayers	movers
10	0.26	0.36	–	–
20	0.33	0.55	0.41	0.47
30	0.38	0.56	0.46	0.53

Table 9: Occupational mobility (4 categories) and geographical mobility. *Stayers* and *Movers* are defined by changes in the state of residence.

For movers, both tables show that occupational mobility is higher than for stayers. In terms of cohorts, movers in the PSID cohort exhibit larger occupational switch rates than the ones in the 1880 cohort. While the difference between stayers and movers in terms of occupations is relatively constant across cohorts using a 3-digit level of disaggregation (8), considering aggregate categories (table 9) tells a different story: the differences in outcomes for stayers and movers in terms of occupational mobility rates are significantly higher for the 1945 cohort.

In term of "acquired" abstract skills, table 10 shows the percentage change in the level of abstract task requirements across occupations for both cohorts.

	1945 cohort		1855 cohort	
$t =$	stayers	movers	stayers	movers
10	0.19	0.41	–	–
20	0.29	0.65	0.33	0.18
30	0.25	0.44	0.43	0.35

Table 10: Percentage change in abstract task requirement ($1 - 10$ scale, higher means more difficult task) and geographical mobility. *Stayers* and *Movers* are defined by changes in the state of residence.

Although one should expect a close relationship between geographical and occupational mobility, in the sense that interstate moves are very likely accompanied with a change in jobs, and with some probability, a change in occupations. However, not much can be said whether geographical movers are chasing better jobs or settling down because lack of opportunity in their initial location of residence. Table 10 answers in part some of these questions: it shows that the fate of movers has changed in time, since movers in the 1855 cohort were more likely to end up with an occupation requiring *less* abstract skills than stayers. For the 1945 cohort, the opposite is the case: movers are the ones climbing up the ladder of the top 1% occupations.

4 Conclusions

In this paper I document several facts with regard to occupational mobility. Using longitudinal data for cohorts one century apart, I provide occupational mobility rates over the life-cycle at several levels of aggregation and I also link occupational choices with the degree of task requirements needed at each occupation. My results shed light on several strands of the literature studying income inequality (both at the aggregate level and for the cross-section), life-cycle inequality and occupational choices and work focusing on regional mobility and economic outcomes.

[to be completed]

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