Supplementary Appendix B: Not for Publication

In this Appendix we investigate in detail the occupational mobility patterns of those workers who changed employers through spells of unemployment, complementing the empirical patterns documented in the paper. Section 1 documents the gross occupational mobility - unemployment duration profile. We show that gross occupational mobility is high and increases moderately with spell duration when considering different occupation classifications and types of non-employment spells. We also show that this profile is widely shared among demographic groups and individual occupations. The main message of Section 1 is that the aggregate mobility-duration profile documented in the main text is *not* driven by composition effects whereby some demographic groups and/or individual occupations are characterised by high mobility rates and short unemployment spells while, simultaneously, others are characterised by low mobility rates and longer unemployment spells. This finding motivates the assumption in our theoretical model of a common idiosyncratic (z-productivity) process shared across different occupations.

Section 2 investigates the extent to which excess and net mobility drive gross occupational mobility, once again using different alternative classifications and non-employment spells. The main message here is that excess occupational mobility is the main force behind the above gross occupational mobility - unemployment duration profile. Nevertheless, we find a clear pattern in the net mobility flows that is consistent with the job polarisation literature. These findings motivate the way we model workers' occupational choice in our theoretical model.

Section 3 investigates the cyclical patterns of occupational mobility among unemployed workers. We document that gross occupational mobility is procyclical. This pattern is present not only in the average mobility rate but also along the entire occupational mobility - unemployment duration profile. Here we show that the cyclicality of gross occupational mobility does not depend on occupational classifications or the inclusion of non-employment spells and that it is also present when controlling for demographic characteristics and individual occupation fixed effects. We also show that the procyclicality of gross occupational mobility is driven by excess mobility. In contrast, we document that net occupational mobility is countercyclical, once again showing a cyclical pattern consistent with the job polarisation literature.

Section 4 investigates the aggregate hazard functions of the unemployed and the non-employed in our sample. Our definition of unemployment implies that these hazard functions exhibit negative duration dependence but the degree of duration dependence is small. We then show that occupational movers take longer to leave unemployment than occupational stayers and that this difference increases in recessions and decreases in expansions. We argue that the difference in unemployment durations between movers and stayers is related to the process of mobility itself and not due to occupational or demographic composition effects.

In Section 5 we use the CPS and PSID to further investigate the extent and cyclicality of gross occupational mobility among the non-employed. Section 6 constructs occupational mobility rate using self-reported occupational and job tenure data obtained from the topical modules of the SIPP. The advantage here is that the information on occupational change does not use occupational codes, but relies on the workers own judgement of 'occupation', 'kind of work' or 'line of work'. Once again we find that gross occupational mobility among the unemployed is high and procyclical, increasing moderately with non-employment duration. Section 7 present the details of the data construction.

1 The occupational mobility - unemployment duration profile

Here we analyse the long-run relationship between occupational mobility and unemployment duration observed during the 1983-2013 period. We refer to this relation as the occupational mobility - unemployment duration profile or the mobility-duration profile for short. We provide further support to one of our main empirical findings: the extent of occupational mobility among those workers who changed employers through spells of unemployed is *high* and increases *moderately* with the duration of the unemployment spell. We use 'moderately' to indicate that at least 40% of long-duration unemployed workers return to their previous major occupation upon re-employment. We show that this pattern holds under alternative occupational classifications and when aggregating major occupations into task-based categories (see Acemoglu and Autor, 2011). This pattern also holds when considering non-employment spells instead of just unemployment spells, and can be found within gender, education and age groups as well as at the level of individual occupations. These findings are important as they counter concerns that the aggregate mobility-duration profile is driven by differences in the demographic or occupational composition of the outflows from unemployment at different durations. This suggests that there is a common underlying process shared across these subgroups which leads long-duration unemployed workers to be still significantly attached to their previous occupation.

Table 1 reports the estimated mobility-duration profiles across occupational categories and demographic groups. In particular, panel A reports the Γ-corrected mobility-duration profile, where the first row shows the average occupational mobility rates over all unemployment (non-employment) spells and the second row reports the OLS estimate of the linear relation between completed unemployment duration and occupational mobility, β_{dur}. To estimate the latter we compute the raw occupation transition matrix of all workers with the same unemployment duration. We then apply to this matrix our Γ-correction and compute the average corrected occupational mobility rate. This is done for each month of completed unemployment duration between 1 and 14 months. We estimate β_{dur} by regressing the set of average mobility rates on completed duration, weighing each monthly observation by the number of workers in the corresponding duration group (which itself involves summing the person weights by month).

Panel B reports the uncorrected mobility-duration profile in the same fashion as in panel A. However, since in the uncorrected data we can use individual workers' unemployment spells to estimate β_{dur}, we regress the following linear probability model (probits give nearly identical results)

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_{\text{dur}} \text{ duration of U (or N) spell} + \varepsilon, \tag{R1}$$

where $\mathbf{1}_{\text{occmob}}$ is a binary indicator that takes the value of one (zero) if a worker changed (did not change) occupation at the end of his/her unemployment (non-employment) spell, "duration of U (or N) spell" is the individual's *completed* unemployment (non-employment) spell and ε is the error term. The advantage of the individual-level uncorrected data is that we can take into account worker's characteristics and evaluate their role in shaping the mobility-duration profile. This is done in panels C, D and E.

Column (1) of Table 1 presents our benchmark result which is based on major occupational groups of the 2000 Census Classification of Occupations (or 2000 SOC). To consistently use the 2000 SOC throughout the period of study, we applied the IPUMS homogenisation procedure to convert previous classifications used in the SIPP. The 2000 SOC has 23 major occupational groups as its most aggregated classification, which we further reduce to 21 as we leave "army" and "agricultural occupations" out of our sample.

Figure 1a depicts the mobility-duration profile using this occupational classification, but based on an alternative formulation. Namely, for a given unemployment duration x, the figure depicts gross occupational mobility as the fraction of workers who had at least x months in unemployment and changed occupation at re-employment among those workers who had at least x months in unemployment before regaining employment. This way of presenting the profile allows to read directly from the graph the average occupational mobility rate of the sample of workers who had completed unemployment durations of at least x months. In what follows every time we graph the mobility-duration profile, we will be using this alternative formulation.

In both the table and figure the average (Γ-corrected and uncorrected) probability of an occupational change is high and increases moderately with unemployment duration. Further, note that the slope of the mobility-duration profile is slightly steeper with the corrected measures. This arises as miscoding (and hence spurious mobility) is more common among observations with short unemployment durations. The Γ-correction will then adjust more the shorter than the longer duration spells and yield a steeper profile relative to the uncorrected data. Also with considerably more short than long spells in the sample, the regression coefficient on duration is more representative of the slope at short completed durations.

The rest of the columns of Table 1 present the results for a number of different ways of classifying occupational mobility. Column (2) uses instead the major occupational groups of the 1990 Census Classification of Occupations (or 1990 SOC). Columns (3) to (5) aggregate occupations into task-based categories. Column (6) considers the case of simultaneous occupational and industry mobility as an alternative way to minimise the effects of coding errors in the occupational mobility rates. Column (7) considers industry mobility, as a comparison to occupational mobility. Column (8) uses the major groups of the 2000 SOC but instead considers non-employment spells that contain at least one month of unemployment ('NUN'-spells). We now discuss each one in turn. We then discuss the effects of worker demographics characteristic and the role of individual occupations.

1.1 Gross occupational mobility under alternative occupational classifications

1990 Census Classification of Occupations The 2000 SOC provided a major revision of the 1990 SOC as a response to the changing structure of jobs in the US. The major difference between these two classifications relies on the former grouping occupations based on the concept of "job families" by placing individuals who work together in the same occupational group. The result was that some occupations that belonged to different groups in the 1990 SOC were pulled together in the 2000 SOC revision. This led to an increase in the size of occupations like "professional", "technical", "management" and "services".

Influential work, however, relies on the 1990 SOC to understand occupational change in the US (see Autor and Dorn, 2013, among others). To verify that our conclusions are not affected by the type of classification used, we compute the mobility-duration profile based on the 1990 SOC. In this case we apply the homogenisation procedure proposed by Autor and Dorn (2013). The 1990 SOC provides 13 major occupational groups from which we aggregate the services related occupations ("protective services", "private households" and "others") into one single major group. We do this as the "protective services" and "private households" occupations are very small in size. At the same time we expand the "precision, production, craft and repair" into three new major groups: "precision production", "mechanics and repair" and "construction trade occupations". This allows us to evaluate "construction" as a separate group.

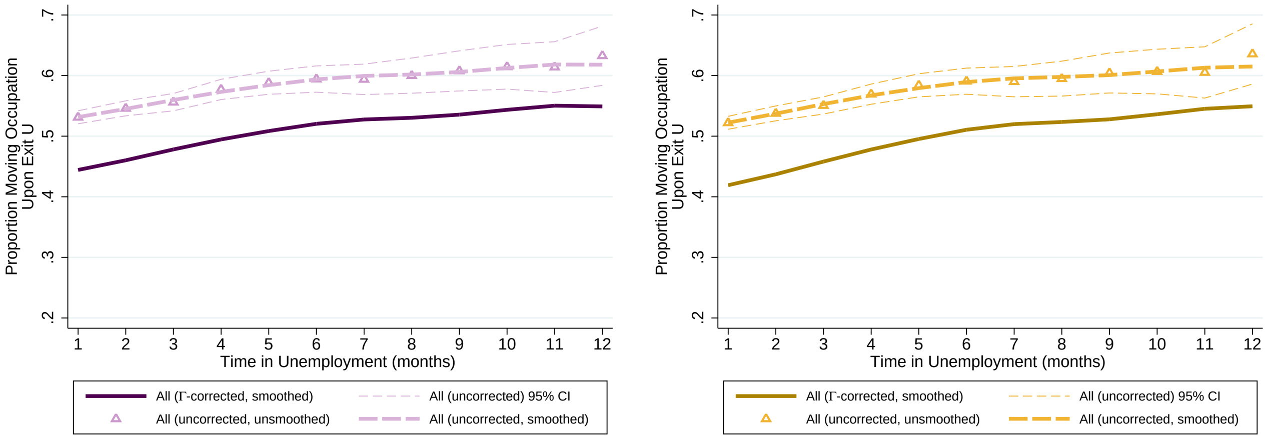
Column (2) of panel B in Table 1 shows that in the uncorrected data we obtain nearly identical results when using the 2000 SOC or the 1990 SOC. Applying the Γ-correction yields a slightly lower average mobility rate and a slightly larger duration coefficient when using the 1990 SOC. Despite these differences, Figure 1 shows the mobility-duration profiles and the associate 95% confidence intervals on uncorrected data. It shows that long-duration unemployed with completed spells of at least 9 months change occupations in 53% of cases in both the 1990 and 2000 classifications.

Table 1: The occupational mobility - unemployment duration profile

	2000 SOC (1)	1990 SOC (2)	NR/R-M/C (3)	NR/R-M/C* (4)	C/NRM/RM (5)	OCC*IND (6)	IND (7)	2000 SOC-NUN (8)
no. obs.	19,115	19,051	24,815	18,527	18,604	19,054	19,055	19,386
Panel A: miscoding corrected mobility, no demographic characteristics, no time, no occ/ind controls								
av occmob	0.444***	0.419***	0.271***	0.296***	0.227***	0.3838***	0.485***	0.469***
(s.e.)	(0.0043)	(0.0043)	(0.0037)	(0.0034)	(0.0035)	(0.0053)	(0.0039)	(0.0060)
dur coef	0.0173***	0.0197***	0.0111***	0.0123***	0.0098***	0.0116***	0.0146***	0.0184***
(s.e.)	(0.0017)	(0.0023)	(0.0018)	(0.0022)	(0.0023)	(0.0016)	(0.0012)	(0.0016)
Panel B: uncorrected, no demog, no time, no occ/ind controls								
av occmob	0.5312***	0.5221***	0.3391***	0.3659***	0.2809***	0.3838***	0.5285***	0.5504***
(s.e.)	(0.0054)	(0.0054)	(0.0052)	(0.0052)	(0.0049)	(0.0053)	(0.0055)	(0.0044)
dur coef	0.0142***	0.0149***	0.0093***	0.0103***	0.0086***	0.0116***	0.0131***	0.0149***
(s.e.)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0010)
Panel C: uncorrected, with demog, time controls, no occ/ind controls								
dur coef	0.0150***	0.0156***	0.0103***	0.0112***	0.0085***	0.0123***	0.0137***	0.0145***
(s.e.)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0010)
female	0.0208**	-0.0283***	0.0713***	0.0292***	-0.0273***	0.0012	0.0154*	0.0165**
(s.e.)	(0.0083)	(0.0083)	(0.0080)	(0.0081)	(0.0074)	(0.0082)	(0.0084)	(0.0069)
hs drop	-0.0421***	-0.0406***	-0.0545***	-0.0504***	-0.0379***	-0.0212*	-0.0309**	-0.0436***
(s.e.)	(0.0118)	(0.0118)	(0.0106)	(0.0110)	(0.0104)	(0.0116)	(0.0120)	(0.0099)
some col	0.0223**	0.0099	0.0364***	0.0312***	-0.0206**	0.0125	0.0287***	0.0235**
(s.e.)	(0.0108)	(0.0108)	(0.0104)	(0.0106)	(0.0101)	(0.0107)	(0.0109)	(0.0092)
col grad	0.0377***	-0.0151	0.0181	-0.0090	-0.1391***	0.0014	0.0047	0.0244**
(s.e.)	(0.0122)	(0.0122)	(0.0117)	(0.0117)	(0.0101)	(0.0119)	(0.0124)	(0.0102)
black	0.0315**	-0.0000	0.0265**	0.0159	0.0468***	0.0315**	0.0189	0.0247**
(s.e.)	(0.0124)	(0.0122)	(0.0119)	(0.0120)	(0.0116)	(0.0125)	(0.0126)	(0.0103)
time trend	0.0013***	0.0012***	0.0010***	0.0009***	0.0009***	0.0010***	0.0012***	0.0011***
(s.e.)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Panel D: uncorrected, additionally interactions of demog. with duration; demog. & time ctrls								
female*dur	-0.0014	-0.0013	0.0048	0.0034	0.0018	0.0008	0.0001	-0.0025
(s.e.)	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0029)	(0.0032)	(0.0031)	(0.0021)
hs drop*dur	-0.0022	-0.0051	-0.0000	-0.0023	-0.0037	0.0021	-0.0006	-0.0007
(s.e.)	(0.0043)	(0.0042)	(0.0041)	(0.0042)	(0.0040)	(0.0044)	(0.0044)	(0.0030)
(some col)*dur	0.0048	0.0019	-0.0011	-0.0001	0.0022	0.0074*	0.0004	0.0025
(s.e.)	(0.0037)	(0.0037)	(0.0039)	(0.0039)	(0.0038)	(0.0039)	(0.0039)	(0.0026)
(col grad)*dur	0.0045	0.0005	0.0005	-0.0017	-0.0032	0.0081*	0.0054	0.0047
(s.e.)	(0.0043)	(0.0043)	(0.0045)	(0.0045)	(0.0041)	(0.0045)	(0.0045)	(0.0030)
black*dur	0.0020	0.0005	0.0022	0.0027	0.0064	0.0002	-0.0012	0.0010
(s.e.)	(0.0043)	(0.0043)	(0.0044)	(0.0045)	(0.0045)	(0.0045)	(0.0044)	(0.0030)
Panel E: F-test equality duration coefficient across gender, educ and race								
p-value	0.756	0.904	0.852	0.7	0.382	0.621	0.906	0.453

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Routine vs Non-Routine, Cognitive vs Manual Occupational Categorization A related set of important work has documented a pattern of job polarization during our period of study (1983-2013). This pattern is characterised by a decline in the employment shares and levels of occupations that have a high content of routine tasks (see Autor et al., 2003, Goos and Manning, 2007, and Acemoglu and Autor, 2011, among others). Although at the heart of this evidence lies the changing direction of net flows across occupations (a topic we address in Section 2 below), it is important for our study to first investigate whether the mobility-duration profile documented above is also observed when aggregating the major occupations into the task-based categories suggested by the job polarization literature. In particular, we aggregate the 13 major occupational groups of the 1990 SOC into routine manual (RM), non-routine manual (NRM), routine cognitive (RC) and non-routine



(a) 2000 SOC

(b) 1990 SOC

Figure 1: Extent of mobility by unemployment duration - Major occupational groups

cognitive (NRC).

Column (3) of Table 1 shows the estimates based on the RM/NRM/RC/NRC grouping. In this case we follow Cortes et al. (2016) and define the RM occupations to be (i) "precision production", (ii) "machine operators and assemblers", (iii) "mechanics and repairers", (iv) "laborers and helpers", (v) "transportation and material moving" and (vi) "construction and extractive". The NRM occupations to be the "service occupations". The RC occupations to be (i) "sales occupations" and (ii) "administrative support and clerical occupations". The NRC occupations to be (i) "management occupations", (ii) "professional specialties" and (iii) "technicians and related support occupations".

Column (4) considers an alternative classification in which we move the "transportation and material moving" occupation to the NRM group (see Autor et al., 2003). This is done mainly because this occupation exhibits a low routine-intensity score. Table 2 illustrates this feature by reporting the average routine task-intensity (together with the abstract and manual task intensity) of each major occupation of the 2000 SOC, using the occupation-task intensity crosswalk of Autor and Dorn (2013). Its third column reports the average routine task intensity of the pre-separation three-digit occupation held by unemployed workers. It is clear that "transportation and material moving" has one of the lowest routine task-intensity scores.[1] Additional reasons to include "transportation and material moving" into the NRM groups are that this occupation exhibits net inflows, while the other conventional RM occupations are net losers of workers; and that it also behaves cyclically similar to other NRM occupations.

Table 1 shows that under both task-based categorizations the average occupational mobility rates is high: 26% (33%) and 29% (35%) of all unemployment spells in the Γ-corrected (uncorrected) data involved workers changing task-based occupational categories. It also shows that the duration coefficient implies a modestly increasing profile. Figures 2a and 2b present the mobility-duration profiles and the associate confidence intervals. It shows that workers who had unemployment spells of at least 9 months experience about a 34% and 37% probability of changing task-based groups. Figure 2c shows the mobility-duration profile by assigning "transportation and material moving" into the NRM category, using the 2000 SOC. Once again we observe that choosing the 2000 SOC or the 1990 SOC to classify occupations makes little difference.

[1]A similar ranking occurs when using the 1990 SOC. We use the 2000 SOC in Table 2 to refer back to the results presented in the main text, which are based in the latter classification.

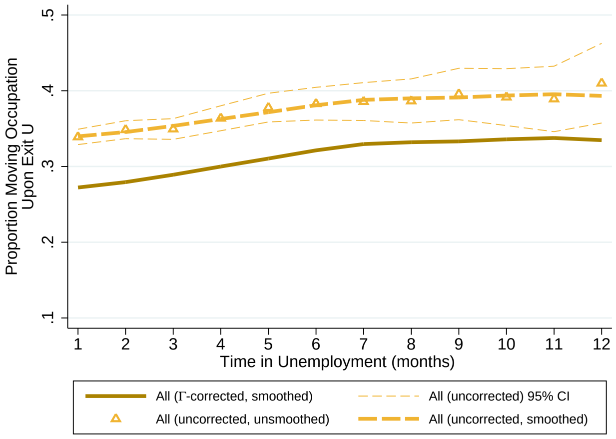
Table 2: Routine (Abstract, Manual) task intensity for source occupations of U inflow

Occupation	U inflow distr	Routine Int.	Abstract Int.	Manual Int.	Class.
Protective service	1.30	1.52	0.87	0.83	NRM
Management	6.22	1.91	6.95	0.29	NRC
Educ, training, and library	2.84	2.17	3.97	1.22	NRC
Personal care/Service	1.51	2.21	1.54	0.97	NRM
Transportation & Mat moving	11.58	2.35	0.84	2.92	NRM
Comm & Social service	0.64	2.60	4.89	0.17	NRC
Building/Grounds clean & maint.	4.97	2.97	0.93	2.30	NRM
Food prep/Serving & rel.	6.85	3.00	1.38	1.01	NRM
Legal	0.31	3.39	3.23	0.28	NRC
Healthcare support	2.08	3.53	1.70	1.67	NRM
Computer and Math. occ	1.12	3.62	5.78	1.22	NRC
Arts/Dsgn/Entrtmnt/Sports/Media	1.21	3.69	3.61	0.97	NRC
Sales & related occ	10.42	3.79	2.92	0.65	RC
Buss & Financial operations	2.67	3.86	6.50	0.43	NRC
Life, phys, and social science	0.68	4.74	4.67	0.84	NRC
Architect & Eng.	1.62	5.96	6.52	1.29	NRC
Production	12.88	6.03	1.40	1.20	RM
Office/Admin Support	13.04	6.16	2.03	0.30	RC
Construction/Extraction	12.53	6.37	1.76	3.02	RM
Healthcare pract & Tech	1.72	6.64	3.17	1.22	NRC
Install/Maint/Repair	3.80	6.65	2.05	1.79	RM

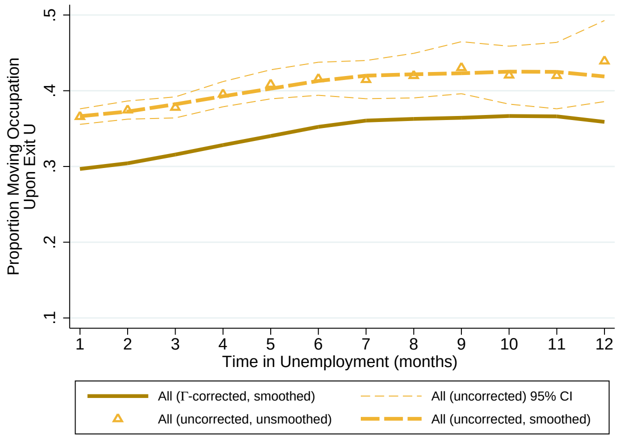
Column (5) of Table 1 presents the results for another task-based classification. In this case we merge the routine cognitive and non-routine cognitive categories together, to focus on transitions between routine manual and non-routine manual, relative to all other (cognitive) occupations. This aggregation is motivated by the observed direction of the net flows across the task-based occupations, which we discuss in detail in Section 2. It aims to highlight the disappearance of routine manual jobs and the rise of non-routine manual jobs as a key feature of unemployed workers' occupational mobility, and reduce the role of "management occupations" which accounts for the vast majority of net outflows from non-routine cognitive occupations. Nevertheless, we again observe that, even with this very coarse subdivision, there remains substantial occupational mobility (over 20%) which modestly increases with unemployment duration. Figure 2d presents graphically the mobility-duration profile and the associate confidence intervals.

1.2 Industry Mobility, and Simultaneous Occupation and Industry Mobility

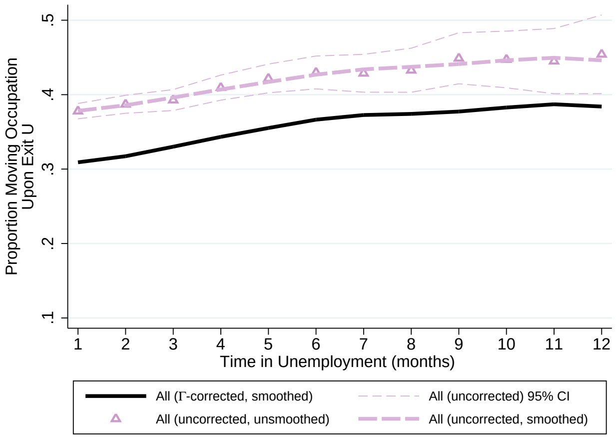
Next we consider the case of simultaneous occupational and industry mobility as an alternative way to minimise the effects of coding errors in the occupational mobility rates in the raw data. This approach follows Neal (1999), Moscarini and Thomsson (2007), Kambourov and Manovskii (2008) and Pavan (2011), and it is based on the assumption that workers who are observed changing occupations, are more likely to be true movers when they are also observed changing employers and industries. Column (4) of Table 1 shows the average mobility rate and duration coefficient for the sample of workers for which we have valid (and non imputed) occupation and industry information. In this case we use the major occupational groups of the 2000 SOC and the 15 major industry groups of the 1990 Census Bureau industrial classification system. Since simultaneous occupational and industry mobility can be taken as an alternative measure of true occupational mobility (see references above), we report this measure both in panels A and B without any further adjustment. Once again we observe that the extent of occupational mobility among those who changed employers through spells of



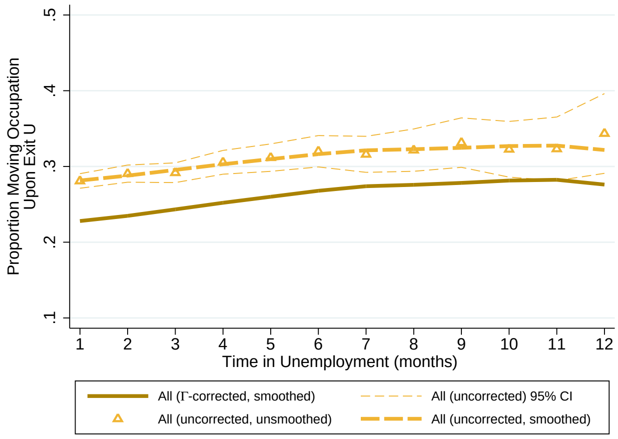
(a) RM/NRM/RC/NRC (1990 SOC-based, Transport in RM)



(b) RM/NRM/RC/NRC (1990 SOC-based, Transport in NRM)



(c) RM/NRM/RC/NRC (2000 SOC-based, Transport in NRM)



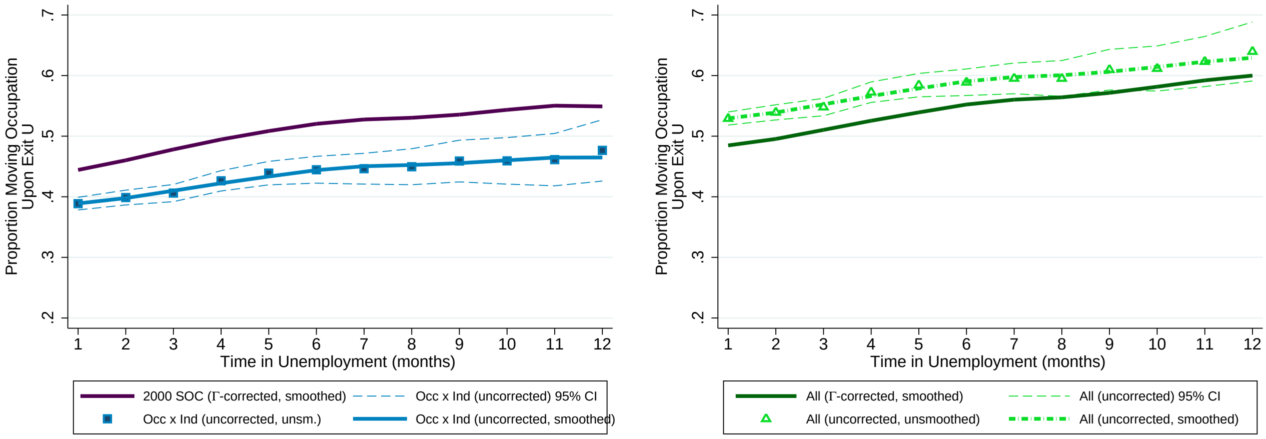
(d) RM/NRM/C (1990 SOC-based, Transport in NRM)

Figure 2: Extent of mobility by unemployment duration - Task based categorisation

unemployed is high and increases moderately with unemployment duration.

The mobility-duration profile obtained from simultaneous occupational and industry mobility is depicted in Figure 3a, together with the Γ-corrected mobility-duration profile depicted in Figure 1a for comparison and the associate confidence intervals. The former shows that about 38% of workers who had unemployment spells of at least one month changed major occupations and industries at re-employment, while about 46% of workers who had unemployment spells of at least 9 months changed major occupations and industries at re-employment. These rates are around 5 percentage points lower but not too dissimilar from the ones obtained from the Γ-corrected profile for occupational mobility. This suggests that conditioning on simultaneous industry and occupational transitions can provide a useful alternative to gauge the level of gross occupational mobility rates.

Caution is advised, however, when constructing statistics that lean more heavily on occupational identities or capture measurement of change in occupational mobility rates. When using the occupation/industry cross-product to inform true occupational mobility, two mistakes will be made. (i) True occupational movers who are true industry stayers will be mistakenly left aside. This issue might be more prevalent in some occupations and less so in others, and hence can *unevenly* affect the measurement of net mobility. For this reason, in what follows we will use simultaneous industry and occupation transitions to construct gross mobility rates



(a) Simultaneous Occ and Ind. mob

(b) Industry mobility

Figure 3: Extent of mobility by unemployment duration - Relation with industry mobility

and not net mobility measures. (ii) For true industry movers who are also true occupational stayers, there will be a (on average) 20% probability of mistakenly considering them as simultaneous occupation and industry movers. It is not clear whether the size of these two types of errors will stay constant when, for example, measuring differences between subsamples with different true mobility rates.[2] Nevertheless, it is evident that the simultaneous mobility measure also indicates a high level of occupational mobility that moderately increases with unemployment duration.

Column (5) of Table 1 report the Γ-corrected and the uncorrected average mobility rates and the duration coefficients of workers who changed employers through unemployment, using only the 15 major industry groups of the 1990 Census Bureau industrial classification system. Figure 3b also presents the Γ-corrected and the uncorrected mobility-duration profiles. This evidence confirms that many unemployed workers also changed industries at re-employment. In the uncorrected data we observe that around 53% of workers who had unemployment spells of at least a month changed industries at re-employment, while about 60% of workers who had unemployment spells of at least 9 months changed industries at re-employment. These rates are remarkably close to the raw occupational mobility rates reported in columns (1) and (2). The Γ-correction mobility-duration profile of industry mobility, however, drops by less than the occupation profiles, with an average mobility of 48.5%. This is consistent with the well-known fact that industry mobility rates are less prone to measurement error than occupational mobility rates (as also reported in Table 5 of Supplementary Appendix A).

1.3 Occupational mobility through non-employment spells

The above analysis restricts attention to non-employment spell in which workers where unemployed every month, categorised as “no job/business - looking for work or on layoff” in the SIPP. We now consider the case in which workers spend part of their non-employment spell outside of the labor force, categorised as “no job/business - not looking for work and not on layoff” in the SIPP. This allows us to investigate whether the mobility-duration patterns documented above are also present when we include joblessness periods in which workers reported no active job search. This case also allows us to investigate whether the mobility-duration

[2] It is relatively straightforward to verify that the (uncorrected) slope of the mobility-duration profile can suffer from attenuation bias arising from miscoding. While our Γ-corrections pushes against this bias, this does not seem to be the case when using the simultaneous mobility measure. In this case we observe that the mobility-duration profile has a somewhat lower slope than both the raw occupational and industrial mobility-duration profiles, and therefore even lower than the Γ-corrected slopes.

profile based on "pure" unemployment spells is driven by a composition effect based on workers' differential propensities to drop out of the labor force. In particular, if workers had ex-ante different propensities to change occupations and if these propensities were negatively associated with the probability of dropping out of the labor force after long periods of joblessness (for example, due to discouragement effects), a restriction to "pure" unemployment spells could be effectively selecting occupational movers at higher unemployment durations. This would then lead to a different interpretation of the mobility-duration profile than the one proposed by our theoretical framework.

To address this concern we compute the mobility-duration profile for workers with different degrees of labor market attachment: (1) 'U' spells, our baseline, where the individual is "looking for work" every month of the non-employment spell. (2) 'UNU' spells, where the worker starts the non-employment spell "looking for a work" and ends it also "looking for a work", but can have intervening months outside the labor force. (3) 'UN' spells, where the worker starts the non-employment spell "looking for work" and this can be followed by periods out of the labor force, before regaining employment (not necessarily reporting unemployment just before re-employment). (4) 'NU' spells, where the worker might or might not be "looking for work" after separation, but eventually "looks for work" and finds one shortly thereafter. (5) 'N*' spells, where the worker loses his job for economic reasons tied in with the job (as indicated by the 'reason for ending previous job', or starts looking for a job when he becomes non-employed.[3] (6) 'NUN' spells, where the worker "looks for work" at least one month during the non-employment spell. (7) 'N' spells, covering all non-employment spells in the sample that are completed within 18 months.

Table 3: Non-employment spells - basic statistics

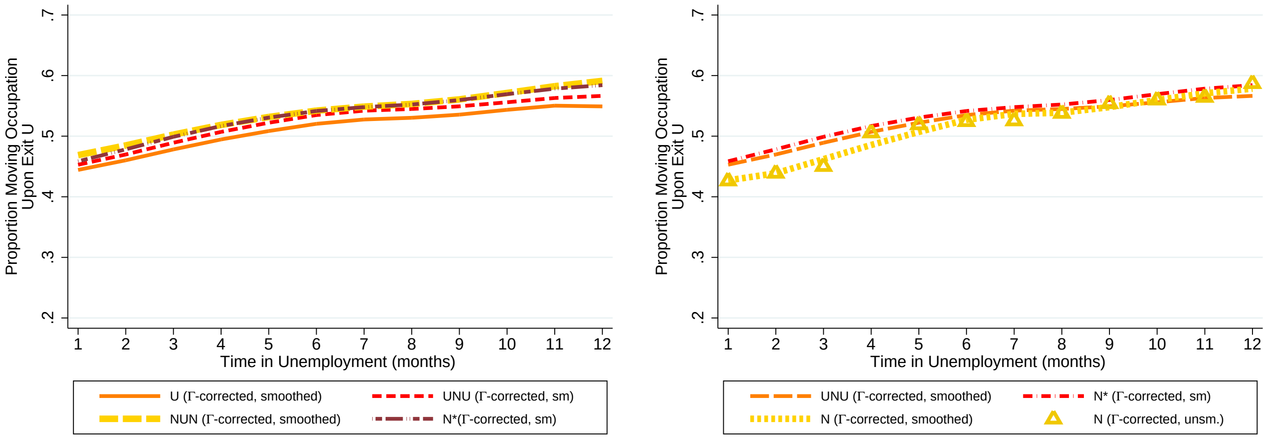
	Num. obs	Occ. mobility (%)	Job finding rate (%)
(1) U	12,278	44.4	23.1
(2) UNU	14,861	45.3	19.7
(3) UN	16,106	45.9	18.1
(4) NU	17,579	46.4	17.2
(5) N*	18,559	46.0	17.5
(6) NUN	19,060	47.0	15.9
(7) N	27,931	43.2	16.7

Column (8) of Table 1 reports the average mobility rate and duration coefficient for the 'NUN' case using the major occupation categories of the 2000 SOC. It shows that the mobility-duration profile is very similar to the one obtained when considering only unemployment spells in between jobs. Table 3 then compares the 'NUN' case with the rest of the cases described above. The first column shows the amount of eligible spells for the 1983-2013 period, where we have arranged the number of spells in ascending order. The number of eligible spells takes into account that we do not want to create a bias because of left-censoring. Therefore we only count those spells that end after more than 16 months into the sample. At the same time we want to ensure that the relevant observations are not too close to the end of the panel, at least 1 year away from it, to avoid biases due to right-censoring.[4] Analogously to our treatment of unemployment spells, we consider workers to enter non-employment only if they have not been employed for more than a month.

The second column of Table 3 shows the Γ-corrected average occupational mobility rates of all those

[3]The reasons we consider in this case are: (i) employer bankrupt, (ii) employer sold business; (iii) job was temporary and ended, (iv) slack work or business conditions, (v) unsatisfactory work arrangements (hours, pay, etc), (vi) quit for some other reason. We do not consider: quit to take another job, retirement or old age, childcare problems, other family/personal obligations, own illness, own injury, school/training.

[4]When controlling for non-/unemployment duration in the regressions, censoring is less of an issue. In that case we use a less stringent selection criterion, and as a result we have more observations, as can be seen in the first line of Table 1.



(a) U, NUN, UN, NU

(b) UNU, N*, N

Figure 4: Extent of mobility by non-employment duration - Γ corrected

workers who had at least one month in non-employment before regaining employment. We can readily observe very similar and high average occupational mobility rates across different degrees of labor market attachment. Figure 4 shows the Γ-corrected mobility-duration profiles for all these cases. It is immediate that these profiles are also very similar to each other. Overall, this means that the concern that our baseline restriction to (pure) unemployment is selecting occupational movers at long unemployment durations appears not to be supported by the data. Workers who spend part of their non-employment spell outside the labor force have very similar mobility-duration profiles as those who spend all their non-employment spell actively looking for work.[5]

Although not shown in the figure, we also observe that when using non-employment spells the Γ-corrected and uncorrected mobility-duration profiles relate to each other in a similar way as documented when using pure unemployment spells. For example, in the case of the 'UNU' spells we find a 7.1 percentage points average difference between the corrected and uncorrected profiles, while for the 'NUN' spells the average difference is of 6.7 percentage points.

1.4 Demographics

We now investigate the extent to which different demographic groups have different propensities to change occupations and how these propensities change with unemployment (non-employment) duration. In particular, we want to know whether there is evidence of a demographic composition effect driving the aggregate mobility-duration profile. To analyse the impact of demographic characteristics we use the uncorrected, individual-based, data and augment equation (R1) by including dummies for gender, race and education, a quartic in age, a linear time trend, and dummies for the classification used to report occupations (industries) in each panel. The

[5]Note, however, that including non-employment spells that are spent wholly outside of the labor force ('N' spells), leads to a somewhat steeper mobility-duration profile. This is visible especially when we consider the non-smoothed observations in Figure 4b. This difference originates entirely by the set of short completed spells ($\leq$ three months) in which workers were exclusively out of the labor force and exhibited a significantly lower probability of changing occupation at re-employment. These short 'pure N'-spells may reflect employer-to-employer moves with a delayed start. After three months the'N' mobility-duration profile then follows the other profiles.

resulting regression is then given by

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_{\text{dur}} \text{ duration of U (or N) spell} + \beta_{\text{educ}}\text{dum}_{\text{Education}} + \beta_{\text{race}}\text{dum}_{\text{Race}} \\ + \beta_{\text{sex}}\text{dum}_{\text{Gender}} + \beta_{\text{time}}\text{Quarter} + \beta_{cls}\text{dum}_{\text{classification}} + \beta_{\text{age}}(\text{Quartic in Age}) + \varepsilon, \qquad \text{(R2)}$$

where as a baseline we chose white high school educated male individuals. The demographic dummies attempt to capture any fixed characteristics that differentiate the average probability of an occupational change across these groups. Further, if some demographic characteristics are associated with higher (lower) propensities to move occupations at re-employment and if these propensities are positively associated with longer (shorter) unemployment durations, the inclusion of the demographic dummies will also capture any composition effects that could be driving the slope of the mobility-duration profile. Hence significant changes to the estimated value of the duration coefficient, β_{dur}, when using equation (R2) instead of (R1) would suggest that demographic composition effects are at work.

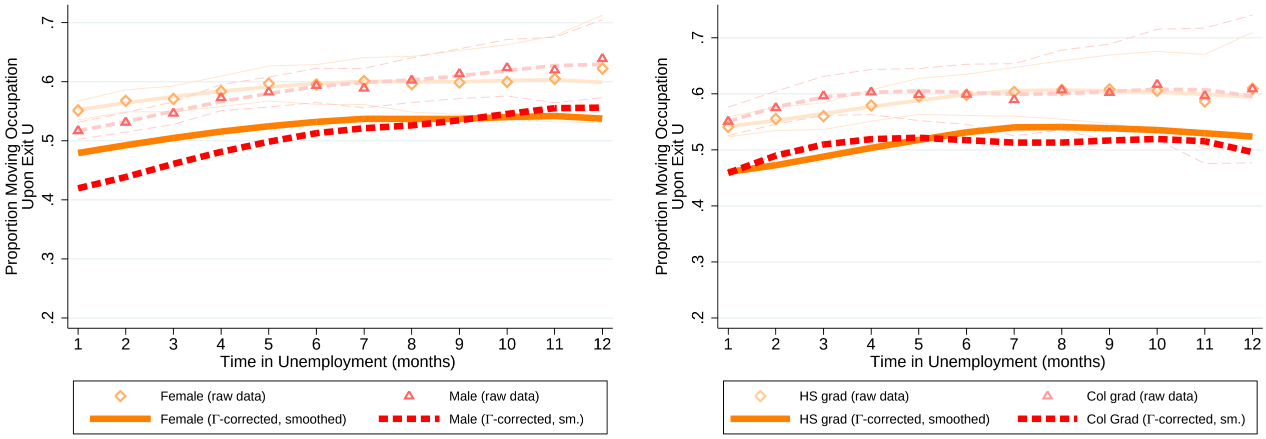
Gender and Education The first row of panel C of Table 1 shows that the inclusion of the gender and education dummies do not meaningfully affect the coefficient on unemployment duration. Across all columns, the point estimates of the duration coefficient are marginally higher relative to the point estimates in panel B and their differences are not statistically significant. Therefore we do not find evidence that the increase in occupational mobility with unemployment duration is a result of different demographic composition among those that re-gain employment at different unemployment durations. The rest of the estimated coefficients in panel C show that the average probability of an occupational change only differs a few percentage points across gender and education groups. For example, using the 2000 SOC the average occupational mobility rate of females is 2.1 percentage points higher than for males; while the average occupational mobility rate of a high school graduate is around 4.2 percentage points higher than for high school dropouts and 3.4 percentage points lower than college graduates.[6]

Panel D shows the estimates of augmenting equation (R2) by interactions between the completed unemployment duration, gender and education. This is done to investigate whether the different demographic groups exhibit different slopes in their respective mobility-duration profiles. The lack of statistical significance of the interaction terms then suggests that the mobility-duration profiles specific to the gender and educational subgroups exhibit similar slopes. This is further confirmed in panel E, where we test the joint equality of the duration coefficients across these demographic groups. We cannot reject that the duration coefficients are equal, even at higher p-values.

Figure 5 depicts the mobility-duration profiles by gender and two education subgroups. Figure 5a depicts the occupational mobility-duration profile by gender, while Figure 5b depicts the profiles for high school graduates and college graduates. We observe that across these demographics occupational mobility is high, above 40%. Moreover, although the slope is somewhat stronger for males, the increase of occupational mobility with unemployment duration is moderate, in the sense longer-term unemployed more often change occupations, yet between 45-50% will still return to the previous occupation, across gender and education.

Linear Time Trend The last two rows of panel C of Table 1 shows that the average occupational mobility rate of the unemployed has been increasing over time. The estimated coefficients are statistically significant

[6]The exception is the college graduates group in the 3-category task-based classification (see column (8)). This arises because in this case we have aggregated all cognitive occupations, which represent the bulk of occupations chosen by college graduates, into one task-based group. The remaining mobility of these workers is therefore mostly into (or from) manual occupations. Around 10% of college graduates (Γ-corrected measure) move across these task-based groups rising to about 15% for long-term unemployed workers.



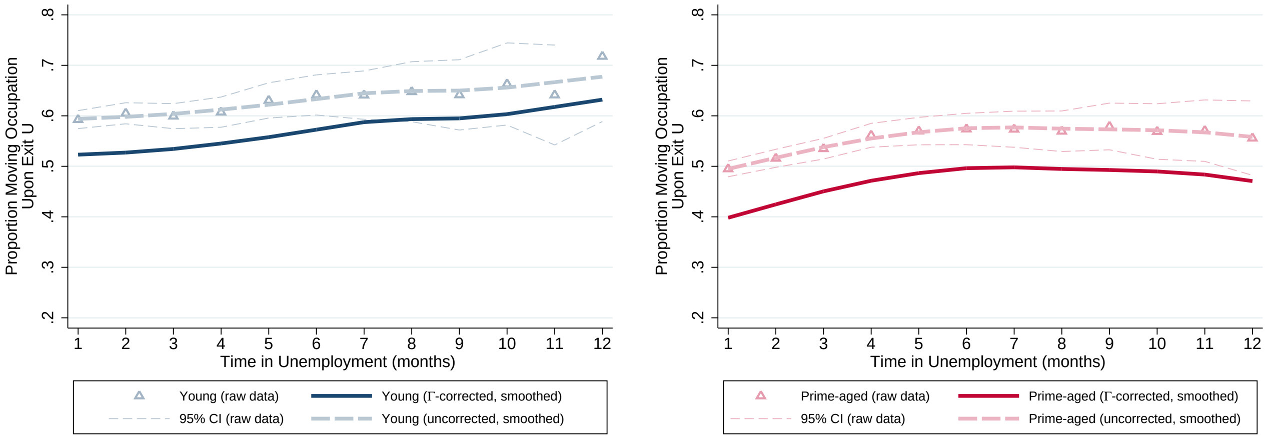
(a) Gender

(b) High school graduates and college graduates

Figure 5: The mobility-duration profile by gender and education groups

and economically meaningful. This is consistent with the rise in *overall* occupational mobility documented by Kambourov and Manovskii (2008). As the main focus of our paper is on the cyclical patterns of occupational mobility, we leave the investigation of these long-run increase for future research. However, we note that controlling for a linear time trend does not have a major impact on the documented behavior of the mobility-duration profile and its cyclical responsiveness.

Age groups The most significant difference across all the demographic groups considered is between young and prime-aged workers. We define young workers as those who left education (and hence fully entered the labor market) and are between 20-30 years. Prime-aged workers are those workers who are between 35 and 55 years of age. Figure 6 depicts the uncorrected and Γ-corrected mobility-duration profiles of these workers.



(a) Young workers

(b) Prime-aged workers

Figure 6: The mobility-duration profile by age groups

Panel A of Table 4 reports the average occupational mobility rate of young and prime-aged workers, after correcting for miscoding. The first two rows show that across classifications the difference between young and prime-aged workers' average occupational mobility rates is about 10 percentage points. The second two rows show that this difference diminishes somewhat with unemployment duration. The last two rows summarise all this information by showing the ratio between the occupational mobility rate of those long-term unemployed (with spells of at least 9 months) and the occupational mobility rate of all those unemployed of the same age group. In particular, we observe that across the different classifications young workers with unemployment spells of at least 9 months have an occupational mobility rate that is about 15% higher than the average mobility rate of all young unemployed workers. In the case of prime-aged workers, this ratio is about 20%. Panel B shows very similar conclusions for the uncorrected data.

Table 4: Occupational mobility of young and prime-aged

	2000 SOC (1)	1990 SOC (2)	NR/R-M/C (3)	NR/R-M/C* (4)	C/NRM/RM (5)	OCC*IND (6)	IND (7)	2000 SOC-NUN (8)
Panel A: Overall mobility of different age groups (corrected)								
young -all	0.521	0.489	0.335	0.365	0.305	0.443	0.533	0.528
prime -all	0.398	0.375	0.229	0.250	0.179	0.344	0.447	0.428
young -9+ months	0.585	0.582	0.383	0.439	0.354	0.511	0.636	0.598
prime -9+ months	0.499	0.489	0.300	0.331	0.255	0.435	0.562	0.531
relative mobility increase Unemp 9mth+ / All Unemp								
young	0.114	0.173	0.136	0.185	0.148	0.143	0.176	0.124
prime-aged	0.225	0.265	0.270	0.278	0.349	0.235	0.229	0.214
Panel B: Overall mobility of different age groups (uncorrected for miscoding)								
young -all	0.593	0.583	0.598	0.443	0.571	0.393	0.424	0.350
prime -all	0.495	0.485	0.518	0.344	0.497	0.303	0.327	0.238
young -9+ months	0.642	0.647	0.655	0.511	0.663	0.432	0.485	0.393
prime -9+ months	0.579	0.569	0.600	0.435	0.597	0.363	0.396	0.304
Panel C: Regression, uncorrected, no demog, no time controls, no occ/ind controls								
prime-aged dum	-0.1032***	-0.1031***	-0.0938***	-0.1006***	-0.0714***	-0.0891***	-0.0944***	-0.1087***
(s.e.)	(0.0092)	(0.0091)	(0.0077)	(0.0091)	(0.0094)	(0.0088)	(0.0089)	(0.0084)
Panel D: Regression, uncorrected, demog and time controls, no occ/ind controls								
prime-aged dum	-0.1121***	-0.1077***	-0.1004***	-0.1038***	-0.0783***	-0.1001***	-0.1014***	-0.1002***
(s.e.)	(0.0093)	(0.0093)	(0.0078)	(0.0093)	(0.0095)	(0.0089)	(0.0090)	(0.0085)
Panel E: Regression, uncorrected, interactions with demog, time controls, and occ/ind controls								
prime-aged dum	-0.1359***	-0.1188***	-0.1212***	-0.1454***	-0.1138***	-0.0846***	-0.0989***	-0.1043***
(s.e.)	(0.0164)	(0.0168)	(0.0143)	(0.0163)	(0.0165)	(0.0153)	(0.0159)	(0.0155)
gender*prm age	0.0252	0.0187	0.0354**	0.0356*	0.0420**	-0.0055	-0.0015	-0.0126
(s.e.)	(0.0182)	(0.0183)	(0.0153)	(0.0184)	(0.0182)	(0.0178)	(0.0181)	(0.0168)
hs drop*prm age	-0.0150	-0.0322	-0.0112	0.0180	-0.0046	-0.0251	-0.0209	-0.0145
(s.e.)	(0.0254)	(0.0254)	(0.0213)	(0.0256)	(0.0255)	(0.0225)	(0.0240)	(0.0229)
some col*prm age	0.0256	-0.0061	0.0200	0.0342	0.0281	0.0003	-0.0003	0.0171
(s.e.)	(0.0231)	(0.0232)	(0.0196)	(0.0236)	(0.0237)	(0.0223)	(0.0230)	(0.0225)
col grad*prm age	0.0267	0.0075	-0.0085	0.0348	0.0164	-0.0094	-0.0029	0.0668***
(s.e.)	(0.0266)	(0.0268)	(0.0220)	(0.0268)	(0.0266)	(0.0267)	(0.0269)	(0.0221)
black*prmage	0.0176	0.0091	0.0114	0.0412	0.0285	-0.0269	-0.0118	0.0012
(s.e.)	(0.0266)	(0.0261)	(0.0221)	(0.0273)	(0.0269)	(0.0254)	(0.0262)	(0.0253)
Panel F: Regression, uncorrected, no demog, no time and no occ/ind controls, interaction coeff dur and age								
dur*prm. age	0.0060*	0.0039	0.0073***	0.0076**	0.0056	0.0053	0.0049	0.0060*
(s.e.)	(0.0034)	(0.0034)	(0.0023)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0033)
Panel G: Regression, uncorrected, with demog, time and occ/ind controls, interaction coeff dur and age								
dur*prm. age	0.0048	0.0032	0.0066***	0.0071**	0.0045	0.0051	0.0047	0.0073**
(s.e.)	(0.0033)	(0.0033)	(0.0022)	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0033)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Panel C reports the estimated difference between young and prime-aged workers' average occupational mobility rates obtained from regressing $\mathbf{1}_{\text{occmob}}$ on a constant and a dummy that takes the value one if the worker belongs to the prime-age group and zero otherwise. In this case we restrict to the sample that only contains either young or prime-aged workers. As in panel A, we find that the difference between the occupational mobility rates of young and prime-aged workers is of about 10 percentage points. Panel D shows the estimated coefficient of the prime-age dummy when augmenting this regression with controls for demographic characteristics (gender, race, education) and a linear time trend. In this case we find that adding these additional regressors does not meaningfully affect the estimated difference between the average occupational mobility rates of young and prime-aged workers.

The first row of panel E reports the estimated coefficient on the prime-age dummy when augmenting the regression underlying panel D with occupational/industry controls and interactions between gender, education and race with the prime-age dummy. In this case we find a slightly larger difference between the occupational mobility rates of young and prime-aged workers, with the exception of the task-based classification. The remainder rows of panel E show the estimated coefficients of the interaction terms. The interaction terms allow us to investigate whether the lower occupational mobility rate of prime-aged workers can be explain by life-cycle shifts towards certain occupations, or is concentrated in certain demographic groups. Given the lack of statistical significance of most of the coefficients, we do not find strong evidence for either explanation.[7]

Panels F and G consider the interaction between age and unemployment duration. In panel F (G) we add an interaction term between the prime-aged dummy and unemployment duration to the regression underlying the estimates in panel C (E). In both cases, we observe that the point estimates indicate a steeper slope for prime-aged workers, as suggested by the last two rows of panel A. However, the estimated coefficients are small and are not always statistically significant.

1.5 Occupation identities

We now turn to investigate whether the aggregate mobility-duration profile is driven by composition effects at the level of individual occupations. In particular, we want to know to what extent a subset of occupations is associated with high occupational mobility rates and longer non-employment durations, while another subset is associated with lower mobility rates and shorter non-employment durations. If this were to be the case, one could potentially explain the aggregate mobility-duration profile as a result of selection effects across occupations.

Figures 7 and 8 (in Section 2) show the average gross occupational mobility rates by major occupations and task-based occupations together with the corresponding overall average occupational mobility rate. The height of each light colored bar corresponds to the average gross occupation(industry)-specific mobility rate, while the width of each bar corresponds to the proportion of the inflow into unemployment that originate from a given occupation (industry). The light colored horizontal line depicts the Γ-corrected occupational (industry) mobility rate.

The graphs in Figure 7 show that across the vast majority of occupations (and industries) the extent of gross mobility is high. The Γ-corrected occupation-specific mobility rate in nearly all occupations is either close or above 40%, covering over 80% of all unemployment spells. Figures 28a and 28b use the 2000 SOC and show that this feature is robust to whether we consider pure unemployment spells or ‘NUN’ spells. Figure 7c shows that this feature is also robust to using the 1990 SOC instead of the 2000 SOC. Figure 7d shows that this feature is also found across major industries. In both industry and occupations, however, the main exception is

[7] An exception being for gender in the cases of ‘NUN’ spells, industry mobility and simultaneous occupation and industry mobility. Here we find a drop of 2 to 3 percentage points. Another exception is for college graduates in the case of the 3 task-based category classification. Here all cognitive occupations are merged into one task-based group, limiting overall occupational mobility and its responsiveness of college graduates.

"construction", which exhibits a mobility rate of around 25%. Figure 8 shows that gross occupational mobility is also high and nearly identical across all task-based occupational categories.

To analyse the impact of occupational identities on the slope of the mobility-duration profile, we estimate regressions of the general form:

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_{\text{dur}} \text{ u.duration} + \beta_{\text{occ}}\text{occ.dum} + \beta_{\text{age}}(\text{Quartic in Age}) + \beta_{\text{dm}} \text{ demog.ctrls} + \varepsilon, \qquad \text{(R3)}$$

where "occ.dum" denotes occupation identity dummies and the demographic controls include dummies for gender, education and race. If a subset of occupations are associated with higher (lower) mobility probabilities and if these probabilities are positively associated with longer (shorter) unemployment durations, the inclusion of occupation identity dummies will capture composition effects that could be driving the slope of the aggregate mobility-duration profile. We consider two cases when evaluating these occupation dummies: (i) source and (ii) destination occupations. The former are the occupations that were performed by workers immediately before becoming unemployed (non-employed), while the latter are the occupations to which workers got re-employed into. For comparability, panel A of Table 5 reports the estimated duration coefficient based on regression (R2) without occupation identity dummies, as reported in the first row of panel C of Table 1. If significant changes to the estimated value of the duration coefficient, β_{dur}, were observed when adding occupation identity dummies, this would suggest the presence of composition effects across occupations.

Table 5: The role of individual occupations

	2000 SOC (1)	1990 SOC (2)	NR/R-M/C (3)	NR/R-M/C* (4)	C/NRM/RM (5)	OCC*IND (6)	IND (7)	2000 SOC-NUN (8)
Panel A: baseline regression, with demog, time controls, but no occ/ind controls								
dur coef	0.0150***	0.0156***	0.0103***	0.0112***	0.0085***	0.0123***	0.0137***	0.0145***
(s.e.)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0010)
Panel B: uncorrected, source occupation controls, time and demographic controls								
dur coef	0.0136***	0.0145***	0.0106***	0.0113***	0.0088***	0.0109***	0.0116***	0.0136***
(s.e.)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0010)
female	-0.0144	-0.0315***	0.0042	-0.0059	-0.0286***	-0.0166*	0.0097	-0.0073
(s.e.)	(0.0094)	(0.0092)	(0.0091)	(0.0088)	(0.0081)	(0.0098)	(0.0091)	(0.0079)
hs drop	-0.0311***	-0.0306***	-0.0386***	-0.0389***	-0.0426***	-0.0160	-0.0268**	-0.0346***
(s.e.)	(0.0116)	(0.0117)	(0.0103)	(0.0109)	(0.0105)	(0.0115)	(0.0116)	(0.0098)
some col	0.0047	0.0014	0.0056	0.0097	-0.0159	0.0088	0.0314***	0.0104
(s.e.)	(0.0107)	(0.0107)	(0.0103)	(0.0106)	(0.0102)	(0.0107)	(0.0106)	(0.0091)
col grad	-0.0200	-0.0391***	-0.0692***	-0.0743***	-0.1219***	-0.0147	0.0078	-0.0166
(s.e.)	(0.0137)	(0.0138)	(0.0139)	(0.0138)	(0.0116)	(0.0138)	(0.0123)	(0.0113)
black	0.0299**	0.0116	0.0241**	0.0169	0.0362***	0.0291**	0.0128	0.0240**
(s.e.)	(0.0123)	(0.0120)	(0.0118)	(0.0120)	(0.0116)	(0.0124)	(0.0123)	(0.0102)
time (qtr)	0.0011***	0.0012***	0.0008***	0.0008***	0.0009***	0.0010***	0.0012***	0.0010***
(s.e.)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Panel C: uncorrected, destination occupation controls, time and demographic controls								
dur coef	0.0137***	0.0144***	0.0103***	0.0112***	0.0088***	0.0112***	0.0117***	0.0132***
(s.e.)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0016)	(0.0015)	(0.0010)
Panel D: F-test source occupation-specific duration slopes (demog &time & source occ controls)								
p-value	0.545	0.77	0.494	0.679	0.85	0.913	0.808	0.188

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Panel B reports the results from regression (R3) based on workers' *source* occupations. By comparing the duration coefficients of panels A and B, it is immediate that across all occupational classifications the slopes of the mobility-duration profile are hardly affected when adding source occupation fixed effects. The rest of the coefficients in panel B show a similar pattern as the one reported in Table 1. Panel C reports the results from regression (R3) based on workers' *destination* occupations. Note that the duration coefficients remain virtually identical to the case in which we use source occupation instead. This suggests that the aggregate mobility-duration profile does not seem to be a result of selection, whereby those occupations with high gross occupational flows are also associated with long unemployment durations.

Panel D further investigates whether the slopes of the mobility-duration profiles are different across source occupations. It reports the results of testing whether the implied slopes of the mobility-duration profiles across source occupations are equal. Using an F-test, we cannot reject the hypothesis that all slopes are equal, with high p-values in many cases.[8] Although not shown here, we also tested whether the semi-elasticity of the *relative* increase in occupational mobility associated with a one-month higher duration is equal across occupations. Once again we find that we cannot reject the hypothesis that they are equal across occupations and this result holds for all classifications and samples used in Table 5.

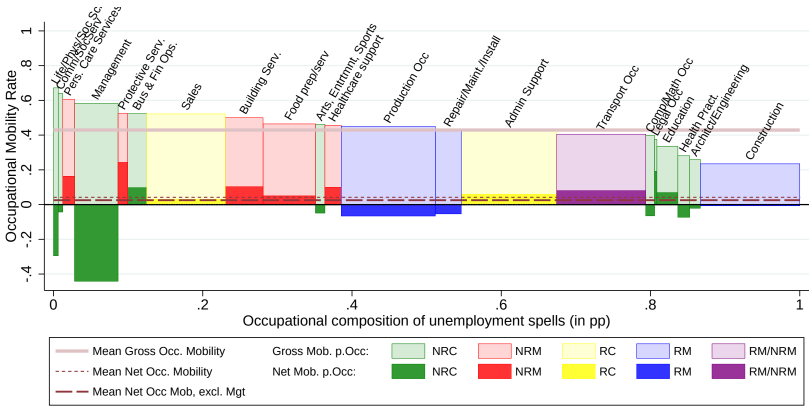
2 Excess and net occupational mobility

In this section we show that excess occupational mobility accounts for the vast majority of the gross mobility documented in Section 1 and is the main driver of the mobility-duration profile. We also show that although the extent of net mobility is small compared to the extent of gross mobility or the overall amount of unemployment spells, it exhibits a well defined pattern. Consistent with the job polarization literature we observe that during the 1983-2013 period routine manual occupations have experienced net outflows, while non-routine manual occupations have experienced net inflows. At the same time we find that routine cognitive occupations have experienced net inflows, while non-routine cognitive occupations have experienced net outflows. We document the importance of "management" occupations in driving the net mobility patterns within the set of cognitive occupations.

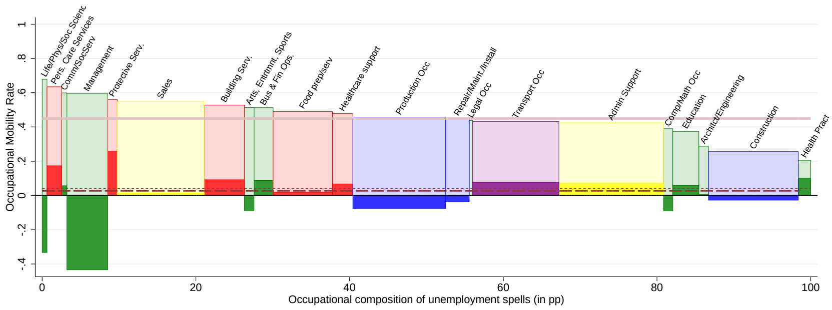
2.1 Net and gross flows per occupation

Figure 7 depicts the Γ-corrected gross and net occupational mobility per individual major occupation and industry. The width of each bar corresponds to the proportion of workers' unemployment spells that originate from a given occupation (industry) among all workers' unemployment spells in our sample. The height of each *light* colored bar corresponds to the proportion of workers' unemployment spells that originate from a given occupation and that end with an occupational change. That is, the height of each light colored bar measures the occupation-specific gross mobility rate. On the other hand, the height of each *dark* colored bar corresponds to the proportion of the workers' unemployment spells that originate from a given occupation that cover the total net flows from that occupation. A positive value for the height of a dark colored bar refers to inflows, while a negative value refers to outflows. The area of each light (dark) colored bar then gives the occupation-specific gross (net) flows as a proportion of all workers unemployment spells. It is important to note that a net flow appears twice on the graph, once as an outflow and then as an inflow. It is also important to note that because the SIPP has a longitudinal dimension a workers may have more than one unemployment spell in which he ends up changing occupation. This is the reason why we describe our measures of mobility based workers' unemployment spells. Total net flows are then obtained as the absolute value of the sum of all occupation-specific outflows, or the sum of all occupation-specific inflows, or the absolute value of the sum of both divided

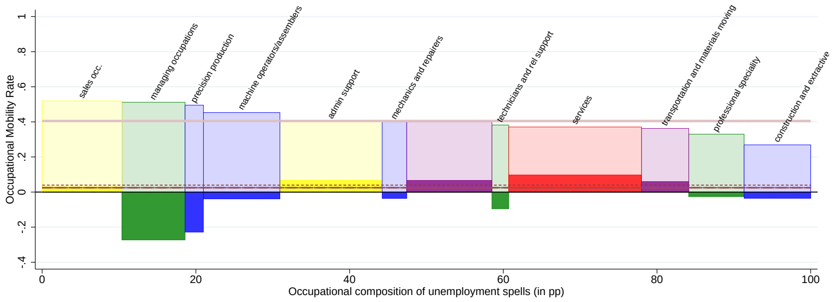
[8]The somewhat lower p-value for the 'NUN' measure (0.25) is driven by women in the education/library occupational category. Excluding this occupation yields a p-value for equality of slopes in all remaining occupations of 0.66.



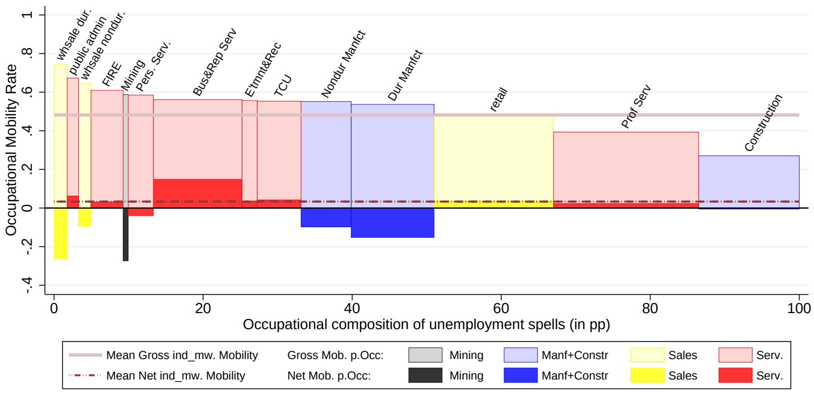
(a) Major Occupational Groups (2000 SOC) - Unemployed



(b) Major Occupational Groups (2000 SOC) - 'NUN'



(c) Major Occupational Groups (1990 SOC) - Unemployed



(d) Major Industry Groups - Unemployed

Figure 7: Net and Gross Mobility per Occupation (Industry)

by two. Total gross flows are obtained as the sum of all occupation-specific gross flows. The dashed lines depict total net flows as a proportion of all unemployment spells. The light colored line depicts the average gross occupational mobility rate.

It is evident that total gross flows are much larger than total net flows. Using the 2000 SOC, for example, the proportion of all workers unemployment spells in our sample that cover total net flows is just 4.2%, while the proportion of all workers' unemployment spells in our sample that cover total gross flows is 44.4% (see Table 1). The proportion of all gross occupational flows that are necessary to generate the observe net flows between major occupations is then 9.5%. When considering "NUN" spells the proportion of all workers' unemployment spells that cover total net flows is 4.1%, while the proportion of total gross flows is 9.1%. Using the 1990 SOC and considering unemployment spells we find that these proportions hardly change: 4% and 9.9%, respectively. We find that when considering industry mobility these proportions are even smaller: 3.4% and 7%, respectively. Taken together this evidence implies that about 95% of workers' unemployment spells and about 90% of all gross occupational flows are driven by excess mobility.[9]

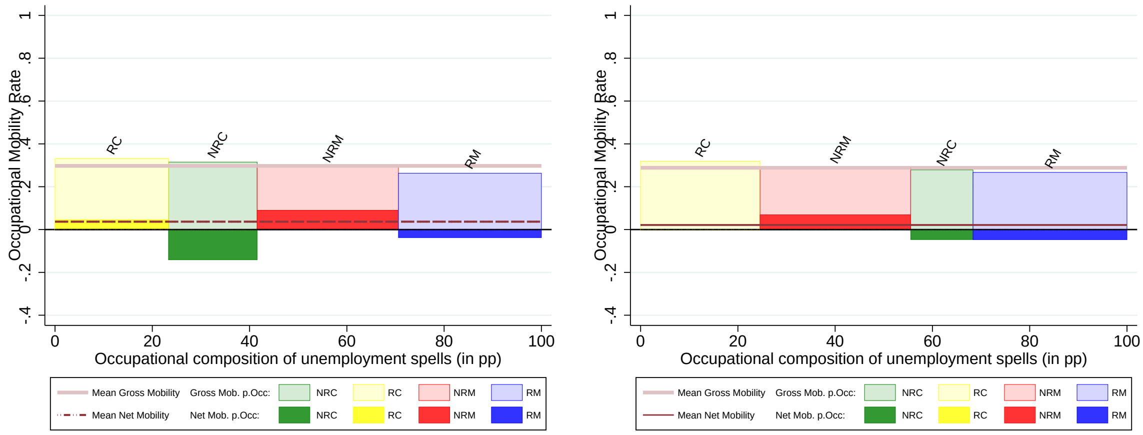
It is also evident that the importance of excess relative to net mobility occurs across nearly all major occupations (industries). The main exception to this pattern is "management". This is clearest when using the 2000 SOC. Figures 28a and 28b show that the proportion of workers' unemployment spells that originate from "management" that cover the total net flows of that occupation is around 40%. The latter reflects two underlying forces. (i) A high outflow rate: around 62% of workers who lose their jobs as managers change occupation after their unemployment (non-employment) spell, where the majority of the "management" outflows end up in "sales and related occupations" (22.1%), "office and admin support" (19.9%), "business and financial operators" (13%) and "food preparation/serving" (12.7%). (ii) A very small inflow rate: very few unemployed workers from other major occupations obtain jobs as managers at re-employment. We find that less than 1% of all unemployment spells end up in non-managers becoming managers. Excluding all flows involving "management" (7% of all workers' unemployment spells) implies that now 2.6% (instead of 4.2%) of all unemployment spells and 6.1% (instead of 9.5%) of all gross occupational flows are needed to generate the observed net flows among the remainder occupations.[10]

Figure 8 presents the same information as Figure 7, but when aggregating the major occupational groups into task-based categories. The left panel includes "management", while the right panel excludes it. Once again we find an overwhelming importance of excess mobility relative to net mobility. When including "management" net mobility can be covered by 3.7% of all unemployment spells and 12.4% of all gross flows across the four task-based occupational groups. When excluding workers with employment in "management" before or after unemployment, net mobility can be covered by 2.1% of all remaining unemployment spells, which is 7.4% of all grows flows in this set.

Even though net mobility is small, we find clear patterns among the net flows across these task-based categories. In particular, Figure 8 shows that during the 1983-2013 period more workers left jobs in routine manual occupations than took up jobs in these occupations. It also shows that more workers took up jobs in non-routine manual occupations than left these occupations. There is also a clear pattern in the net flows of non-routine cognitive and routine cognitive occupations. Figure 8a shows that the non-routine cognitive occupations

[9]The overwhelming importance of excess relative to net mobility we document is consistent with the results of Murphy and Topel (1987), Jovanovic and Moffitt (1990) and Kambourov and Manovskii (2008), who obtained large differences between excess and net mobility on pooled samples of employer movers and stayers.

[10]Using the 1990 SOC we obtain a lower net mobility rate because in this categorisation "management" includes the 2000 SOC "management" and "business and financial operators" occupations. Also note that in the 1990 SOC both "transportation" and "helpers/laborers" are in purple, reflecting that the average routine intensity score of "helpers/laborers" is also low (see Section A.1).



(a) RM/NRM/RC/NRC incl. Management

(b) RM/NRM/RC/NRC excl. Management

Figure 8: Net and Gross Mobility per Occupation Task-based Categories

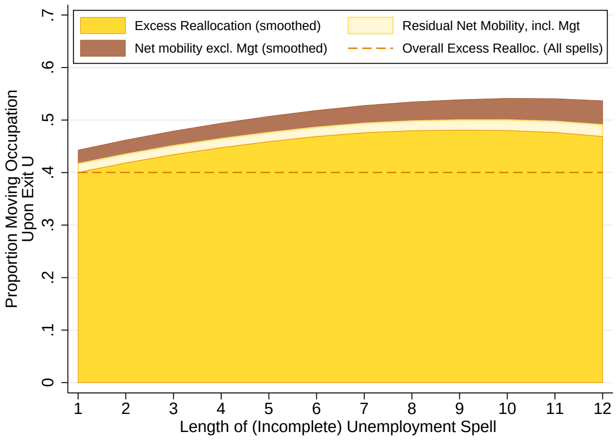
experienced net outflows. It is immediate from comparing Figures 8a and 8b that the vast majority of the net outflows from the non-routine cognitive occupations come from “management”. At the same time, Figure 8a shows that the routine cognitive occupations experience net inflows. As suggested by Figure 8b by far the main contributor to these net inflows is “management”. We observe that by excluding the “management” flows the net inflow into the routine cognitive category basically disappears.

Taken together this evidence suggests that the net mobility that occurs through unemployment or non-employment spells across task-based categories is best understood through the manual versus cognitive dimensions. Within the manual set of occupations there is clear evidence of job polarization: routine jobs are disappearing while non-routine jobs are on the rise. Within the cognitive set of occupations job polarization is not so evident. Instead we observe that much of the net flows that arise between non-routine cognitive and routine cognitive occupations take the form of managers losing their jobs and then re-gaining employment as sales or office/administrative support workers. This type of mobility does not seem much related to structural change, but suggests a picture in which workers in higher skilled jobs move down their career ladder to perform less skilled jobs after experiencing job loss.

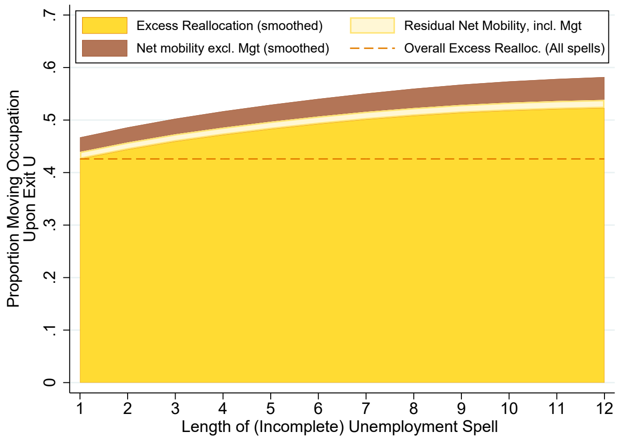
2.2 Mobility - duration profile

We now turn to show that excess mobility is also the main driver of the mobility-duration profile. Figure 9a depicts the Γ-corrected mobility-duration profile based on the major occupational groups of the 2000 SOC (as in Figure 1a in Section A) and subdivides the area below it into the contribution of net and excess mobility. Recall that for a given unemployment duration x, the profile shows the gross occupational mobility rate as the fraction of workers who had at least x months in unemployment and changed occupation at re-employment among those workers who had at least x months in unemployment before regaining employment. To compute the net and excess mobility rate for a given unemployment duration, we only use those employment-unemployment-employment spells that had at least x months in unemployment. In the main text we provide the formula for deriving these measures.

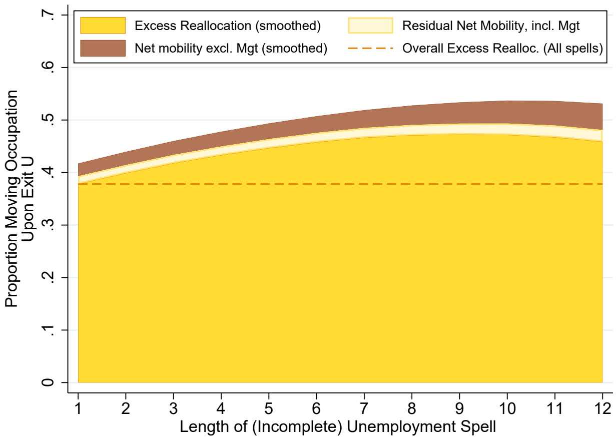
The area immediately below the profile show the contribution of total net mobility at each unemployment duration. This area is further subdivided into the contribution that corresponds to the “management” flows and to the contribution that corresponds to the flows of the remainder occupations. The area below net mobility



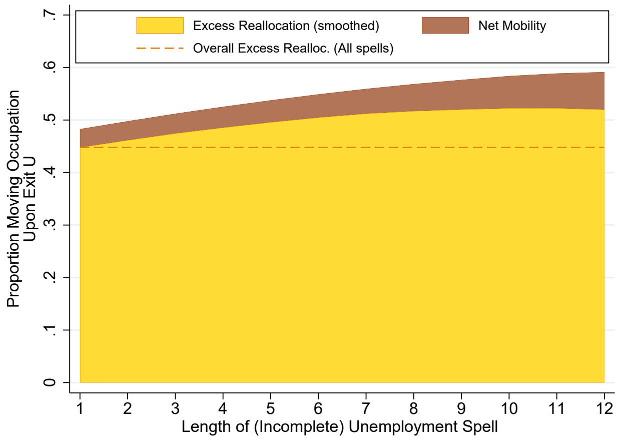
(a) Major Occupational Groups (2000 SOC) - Unemployed



(b) Major Occupational Groups (2000 SOC) - 'NUN'



(c) Major Occupational Groups (1990 SOC) - Unemployed

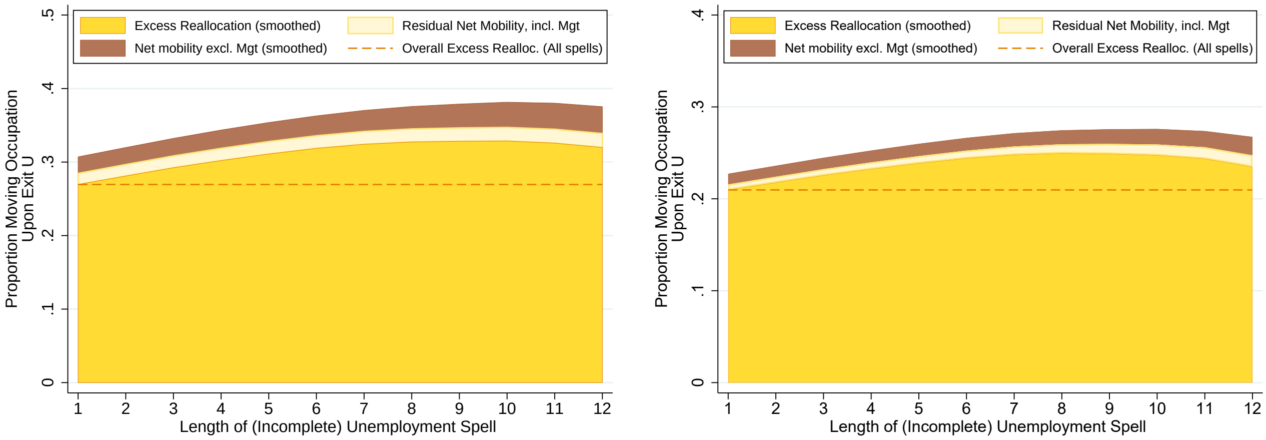


(d) Major Industry Groups - Unemployed

Figure 9: The importance of excess and net mobility

show the contribution of excess mobility at each unemployment duration. The horizontal dashed line crossing this area shows the average excess occupational mobility rate. The rest of the graphs in Figure 9 depicts the same information, but instead consider occupational mobility through non-employment spells with at least one period of unemployment ('NUN' spells), occupational mobility using the 1990 SOC and industry mobility. It is immediate from these graphs that excess mobility is the largest component of gross mobility at all unemployment (non-employment) durations. Further, the importance of excess mobility increases with unemployment (non-employment) duration. At the same time we observe that the importance of net mobility also increases with unemployment (non-employment) duration, particularly the net mobility flows that corresponds to the non-"management" occupations.

Figure 10a present the same information as above but now aggregating occupations using a task-based classification. Figure 10b presents a very similar pattern as in Figure 10a, but now aggregating non-routine cognitive and routine cognitive into one category to subsume the "management" flows into one (larger) cognitive category. Once again we observe the importance of excess mobility in shaping the mobility-duration profile.



(a) RM/NRM/RC/NRC

(b) RM/NRM/C

Figure 10: The importance of excess and net mobility - Task based categorisation

3 Cyclical patterns of occupational mobility

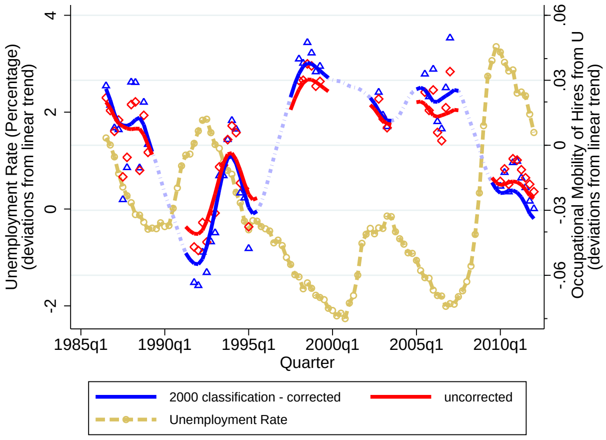
In Section 2 of the paper we document the cyclical patterns of occupational mobility for those workers who changed employers through intervening unemployment (non-employment) spells. Here we investigate in more detail these cyclical patterns. Below we return to these patterns using the CPS and PSID.

3.1 Cyclical responsiveness of gross occupational mobility

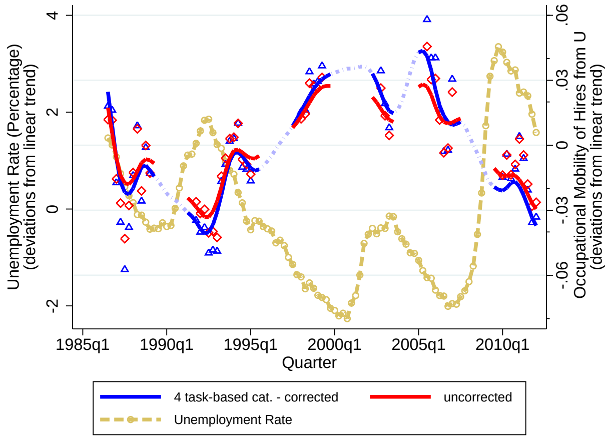
Figure 11 displays the time series of the Γ-corrected and uncorrected occupational (industry) mobility rates of unemployed workers, together with that of the aggregate unemployment rate, in level deviations from their respective linear trends to first investigate the cyclical behaviour of the series with any formal filtering method. Figure 11a displays these patterns using the major occupational groups of the 2000 SOC, while Figure 11b displays these patterns using the 4 task-based categories: Non-routine cognitive, routine cognitive, non-routine manual and routine manual. The markers in the graphs depict the 5-quarter centered moving averages of the time series, while the curves around these markers smooth the averages locally. The key message from both graphs is that gross occupational mobility among unemployed workers is *procyclical*. When comparing the linearly de-trended time series of the centered 5-quarter moving average of the (log) occupation mobility rate with that of the (log) unemployment rate, we find correlations of -0.62 and -0.47 for the 2000 SOC and the 4 task-based categories classification, respectively.[11] Figure 11c shows that the procyclicality of occupational mobility among the unemployed is also present when using the 1990 SOC. Differences in the cyclical patterns

[11]Observations at the end of de-trended time series are estimated more imprecisely than those in the middle. For this reason, bandpass filtering typically excludes those observations. If we restrict our attention to the time series window for which we would have bandpass de-trended observations, 1988q3 - 2010q1, the aforementioned correlations rise to (in absolute value) -0.82 for the case of the 2000 SOC and -0.80 for the 4 task-based categories. Restricting the sample to this window does not change any of our conclusions. In particular, all empirical mobility elasticities from the linearly de-trended series stay significant at the 1%. For the HP filtered series, conclusions also carry over, with the restriction sharpening the pro-cyclicality of occupational mobility across the 4 task-based groups, while blunting somewhat the cyclicality of industry mobility (see below). An exercise in which we directly use each individual quarterly observation, which are much noisier (for example, there are quarters in the data in which relatively few unemployed workers are hired), also yields broadly similar results in these restricted window. While in this case correlations drop to around (-0.50,-0.30) when linearly de-trended and around (-0.30,-0.10) when HP-filtered, all linear de-trended series discussed in this section stay statistically significantly procyclical (with respect to unemployment) at the 1%. Further, the elasticities of the HP-filtered procyclical series of occupational mobility with respect to HP-filtered unemployment show procyclicality and still reach significance at the 5% level (1990 and 2000 SOC), and 10% (4 task-based categories), within the 1988q3-2010q1 window.

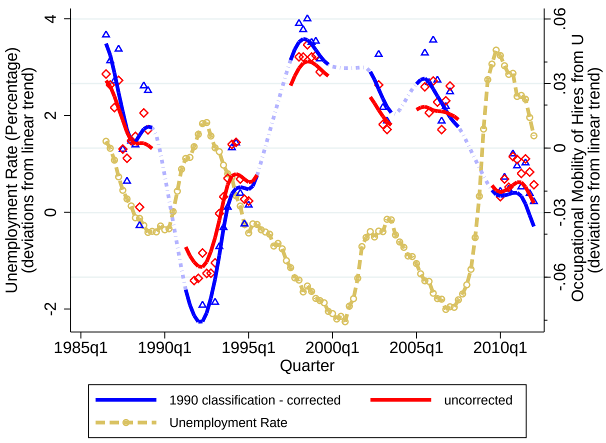
between the 2000 SOC and 1990 SOC appear to be of second order. If anything, occupational mobility seems somewhat more cyclically responsive when using the 1990 SOC. Figure 11d further shows the cyclical patterns of industry mobility. It shows that the gross industry mobility rate among the unemployed is also procyclical, exhibiting a correlation of -0.56 between the linear de-trended industry mobility and unemployment rates.



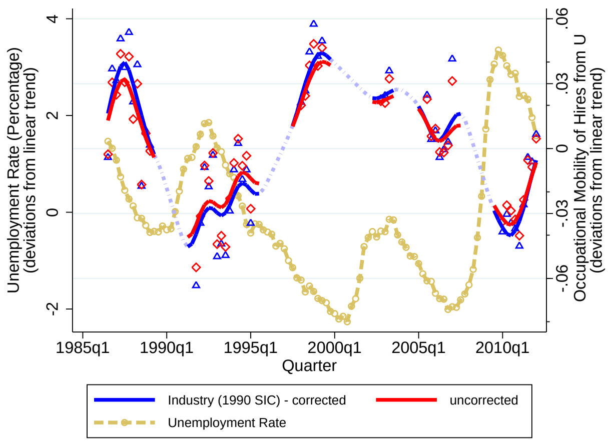
(a) 2000 SOC



(b) 4 task-based categories



(c) 1990 SOC



(d) Industry (1990 SIC)

Figure 11: Occupational Mobility of the Unemployed

Panel A of Table 6 reports the OLS elasticities and correlation coefficients of the 5-quarter centered moving average of the (log) occupational mobility rate relative to the 5-quarter centered moving average of the (log) unemployment rate. Panel B present the same statistics using instead (log) productivity. In both cases we perform the analysis using either the corresponding linearly de-trended or HP-filtered series for the 1985q3-2013q1 period. Given the gaps in the SIPP before implementing the HP-filter we interpolate the data, but then drop the interpolated observations from the resulting series to estimate the regressions.[12] In the main text we have also shown evidence suggesting that the gaps in the SIPP series no do meaningfully affect the

[12]While we do not use any interpolated quarters for the calculation of correlations and estimation of elasticities, the HP-trend can only be obtained using interpolated time series. This likely introduces some further noise for those quarters adjacent to interpolated quarters. On the other hand, including interpolated quarters in the HP-filtered time series allows some further information that is contained in the linearly de-trended time series to weigh in the HP-filtered series as well. Indeed, including interpolated quarters in our calculation appears to strengthen the statistical significance of our coefficients. To conservatively minimize the impact of interpolation, we focus on the statistics excluding any interpolated quarters. In contrast, the linearly de-trended series are derived without restoring to interpolation.

Table 6: Cyclicality Occupational Mobility Using Unemployment Spells

	5Q MA Γ-CORRECTED				5Q MA UNCORRECTED			
	linear de-trend		HP 1600		linear de-trend		HP 1600	
Category	elasticity	ρ	elasticity	ρ	elasticity	ρ	elasticity	ρ
Panel A. Mobility wrt Unemployment								
2000 SOC	-0.19***	-0.62	-0.17***	-0.38	-0.12***	-0.63	-0.10***	-0.36
	(0.03)		(0.06)		(0.02)		(0.03)	
1990 SOC	-0.24***	-0.51	-0.19***	-0.34	-0.15***	-0.58	-0.12***	-0.40
	(0.06)		(0.07)		(0.03)		(0.04)	
4 task-based categories	-0.20***	-0.47	-0.08	-0.11	-0.14***	-0.49	-0.05	-0.12
	(0.05)		(0.09)		(0.03)		(0.06)	
4 task-based cat. (Excl. Manag.)	-0.23***	-0.50	-0.21**	-0.29	-0.16***	-0.52	-0.13**	-0.29
	(0.05)		(0.09)		(0.03)		(0.06)	
Industries (1990 SIC)	-0.16***	-0.56	-0.15**	-0.33	-0.13***	-0.58	-0.12**	-0.32
	(0.03)		(0.06)		(0.02)		(0.05)	
Panel B. Mobility wrt Productivity								
2000 SOC	3.08***	0.73	2.20**	0.28	1.86***	0.72	1.20*	0.25
	(0.38)		(1.01)		(0.24)		(0.63)	
1990 SOC	4.81***	0.73	1.45	0.15	2.64***	0.75	0.89	0.17
	(0.60)		(1.27)		(0.32)		(0.68)	
4 task-based categories	4.06***	0.68	3.85**	0.33	2.55***	0.67	2.25**	0.29
	(0.58)		(1.48)		(0.38)		(0.98)	
4 task-based cat. (Excl. Manag.)	4.37***	0.68	4.38***	0.35	2.85***	0.69	2.66**	0.33
	(0.63)		(1.58)		(0.40)		(1.00)	
Industries (1990 SIC)	1.73***	0.46	-0.31	-0.04	1.36***	0.46	-0.27	-0.04
	(0.45)		(1.08)		(0.35)		(0.84)	
Panel C. Unemployment wrt Productivity								
Unemployment	-8.72***	-0.64	-4.44*	-0.25	-8.72***	-0.64	-4.44*	-0.25
	(1.41)		(2.25)		(1.41)		(2.25)	
N(quarters)	58		58		58		58	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

degree of procyclicality. This is done using the CPS (see Section 5, below) as an alternative data source and comparing the SIPP and CPS uncorrected series and estimated elasticities with respect to unemployment. The first four columns report the results for the Γ-corrected mobility series and the last four columns for the uncorrected series. The results in panel A confirm the conclusion obtained from Figure 11: gross occupational mobility of the unemployed is procyclical. For all linearly de-trended series, the correlations are substantially negative and the elasticities are statistically significantly negative at a 1% level. HP-filtering leads to lower correlations because unemployment and productivity are less aligned (see panel C of the table) and the relative impact of noise is higher after HP-filtering. Nevertheless, using the HP-filtered series yields elasticities with respect to the unemployment rate that are significant at the 5% level, with the exception of the 4 task-based categories. The latter appears to be driven in part by the mobility patterns of those workers in managerial occupations. As we highlighted before, management occupations behave differently throughout the entire sample period, with consistently large relative net outflow. Excluding those unemployment spells that are related to managerial occupations results once again in a statistically significant procyclical series when using the 4 task-based categories.

Panel B shows that gross occupational mobility through unemployment is also procyclical when using (log) productivity instead of (log) unemployment rate. For the linearly de-trended series, the correlations are again high (around 0.70) and the empirical elasticities are positive and significant at a 1% level. Although the HP-filtered series are more noisy, they still yield statistically significantly positive elasticities at a 5% level for the 2000 SOC and 4 task-based categories series; and at a 1% level when considering the 4 task-based categories series without managerial occupations. In the case of mobility across industries, we also find positive and statistically significant elasticities with respect to labor productivity. In terms of the correlation coefficients we find that these are positive with respect to the linearly de-trended productivity, but is nearly zero in the HP-filtered series.[13]

Note that across panels A and B all elasticities are higher for the Γ-corrected series than for the uncorrected series, illustrating that miscoding reduces the cyclical response of gross occupational mobility.[14]

Table 7: Cyclicality Occupational Mobility Using NUN Spells

	5Q MA Γ-CORRECTED				5Q MA UNCORRECTED			
	linearly de-trend		HP 1600		linearly de-trend		HP 1600	
Category	elasticity	ρ	elasticity	ρ	elasticity	ρ	elasticity	ρ
Mobility across NUN-spells, wrt Unemployment Rate								
2000 SOC	-0.14***	-0.73	-0.13***	-0.43	-0.09***	-0.73	-0.08***	-0.42
	(0.02)		(0.04)		(0.01)		(0.02)	
1990 SOC	-0.17***	-0.60	-0.16***	-0.35	-0.11***	-0.67	-0.11***	-0.42
	(0.03)		(0.06)		(0.02)		(0.03)	
4 task-based categories	-0.11***	-0.38	-0.00	-0.01	-0.08***	-0.43	-0.02	-0.07
	(0.04)		(0.07)		(0.02)		(0.04)	
4 task-based cat. (Excl. Manag.)	-0.14***	-0.48	-0.08	-0.21	-0.10***	-0.53	-0.06*	-0.23
	(0.03)		(0.05)		(0.02)		(0.04)	
Industries (1990 SIC)	-0.16***	-0.72	-0.21***	-0.55	-0.13***	-0.72	-0.16***	-0.53
	(0.02)		(0.04)		(0.02)		(0.03)	
N(quarters)	58		58		58		58	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Cyclical responsiveness using non-employment spells To complement the above analysis, Table 7 considers the cyclical behavior of occupational mobility among those workers who mixed periods of unemployment with periods of out-of-labor-force during their non-employment spells (NUN-spells). In this case we also find that occupational and industry mobility are procyclical. Point estimates of the elasticities of occupational mobility with respect to unemployment are somewhat lower when using NUN spells rather than pure unemployment spells, but generally these differences are not statistically significant. Point estimates of the procyclical responsiveness of industrial mobility are instead higher. The linearly de-trended data once again yield statistically significant procyclicality at the 1% level across all mobility measures. The HP-filtered series also yields similar results when considering mobility across major occupational groups (both 1990 and 2000 classification) and

[13]One reason is that the HP-filtered productivity series peaks around 2005, at which time industry mobility of the unemployed is high compared to the average level, but at the same time somewhat lower than in the earlier 2000s. The HP-filtered series weighs the latter more heavily. Further, while industry mobility subsequently meaningfully dropped in the Great Recession, it recovered at a rate mirroring the recovery of unemployment. In contrast, HP-filtered productivity dropped sharply at the beginning of the Great Recession, but also recovered relatively sharply before the beginning of 2010. This behavior is partly behind the relatively low correlation between productivity and unemployment as well. Interestingly, the correlations between mobility and unemployment, and between mobility and output typically are at the same level, and at times even stronger, than the correlation between output and unemployment for the main occupational mobility series.

[14]A further exercise, in which we reduced the impact of noise (and very high frequency movements), by isolating (using TRAMO/SEATS) the trend-cycle component, yields similar results. As a consequence of the reduction in noise, standard errors are much smaller, and more of the elasticities are significant at the 1% level.

Table 8: Cyclicality of Mobility at Different Moments of the Unemployment Spell

	2000 SOC (1)	1990 SOC (2)	2000 SOC-NUN (3)	OCC*IND (4)	IND (5)	NR/R-M/C (6)	C/NRM/RM (7)
Panel 1. Regression of Individual Mobility on Linearly De-trended Unemployment Rate							
1(a) unemployment in quarter of hiring							
U hiring	-0.0788***	-0.0890***	-0.0583***	-0.0606***	-0.0952***	-0.0575***	-0.0589***
(s.e.)	(0.0180)	(0.0211)	(0.0153)	(0.0192)	(0.0219)	(0.0192)	(0.0191)
1(b) unemployment in quarter of separation							
U sep	-0.0628***	-0.0691***	-0.0536**	-0.0420*	-0.0586**	-0.0700***	-0.0659***
(s.e.)	(0.0211)	(0.0239)	(0.0206)	(0.0249)	(0.0256)	(0.0211)	(0.0202)
1(c) unemployment at hiring and at separation averaged							
U ave	-0.0868***	-0.0969***	-0.0704***	-0.0630***	-0.0946***	-0.0776***	-0.0758***
(s.e.)	(0.0218)	(0.0259)	(0.0204)	(0.0239)	(0.0247)	(0.0231)	(0.0222)
1(d) unemployment at moment of hiring & separation							
U. hiring	-0.0676***	-0.0782***	-0.0429**	-0.0583**	-0.0996***	-0.0241	-0.0306
(s.e.)	(0.0236)	(0.0253)	(0.0204)	(0.0265)	(0.0316)	(0.0242)	(0.0256)
U sep.	-0.0182	-0.0175	-0.0271	-0.0037	0.0071	-0.0540**	-0.0456*
(s.e.)	(0.0277)	(0.0293)	(0.0268)	(0.0334)	(0.0352)	(0.0261)	(0.0267)
Panel 2. Regression of Individual Mobility on HP-filtered Unemployment Rate							
2(a) unemployment in quarter of hiring							
U hiring	-0.1594***	-0.1768***	-0.1182***	-0.1198**	-0.2092***	-0.0840**	-0.0959**
(s.e.)	(0.0420)	(0.0449)	(0.0366)	(0.0458)	(0.0543)	(0.0408)	(0.0419)
2(b) unemployment in quarter of separation							
U sep	-0.0916*	-0.0943*	-0.1017**	-0.0628	-0.1015	-0.1292***	-0.1238***
(s.e.)	(0.0479)	(0.0505)	(0.0455)	(0.0535)	(0.0633)	(0.0402)	(0.0406)
2(c) unemployment at hiring and at separation averaged							
U ave	-0.2187***	-0.2358***	-0.2078***	-0.1588**	-0.2697***	-0.1895***	-0.1938***
(s.e.)	(0.0590)	(0.0677)	(0.0601)	(0.0635)	(0.0685)	(0.0563)	(0.0547)
2(d) unemployment at moment of hiring & separation							
U. hiring	-0.1492***	-0.1666***	-0.1127***	-0.1130**	-0.1985***	-0.0671	-0.0794*
(s.e.)	(0.0437)	(0.0460)	(0.0387)	(0.0483)	(0.0579)	(0.0439)	(0.0451)
U sep.	-0.0723	-0.0727	-0.0960**	-0.0482	-0.0756	-0.1205***	-0.1132***
(s.e.)	(0.0467)	(0.0503)	(0.0458)	(0.0521)	(0.0575)	(0.0400)	(0.0406)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

industry mobility. However, the pattern is statistically weaker for mobility across the 4 task-based categories, but still marginally significant (at the 10% level) in the uncorrected data when managers are excluded.

Cyclical responsiveness at different moments of the unemployment spell The preceding analysis documents the procyclicality of occupational (industry) mobility, measuring the state of the economy at the end of the unemployment spell; i.e. at the time of job finding. Table 8 investigates whether this result survives when instead we measure the unemployment rate at the beginning of the worker's unemployment spell (at the time of job separation) or use the average of the unemployment rates at job separation or job finding. The first panel considers the case in which we use the linearly de-trended (log) unemployment rate as our cyclical measure and reports estimates of a regression incorporating a linear time trend and a dummy variable for the change of occupational classification at the 2004 panel. The main message from the first two rows is that measuring the unemployment rate at the moment of job separation or job finding does not affect our conclusions. In both cases we find that the occupational (industry) mobility of unemployed workers is procyclical. Note that the point estimates obtained in the first five columns decrease when measuring the unemployment rate at the moment of job separation. However this decrease is not meaningful and the point estimates remain statistically significant. Taking the average of the unemployment rates at job separation and job finding yields the highest empirical responsiveness in the point estimates, with significance at the 1% across all columns. Further, including both the unemployment rate at job separation and at job finding, the point estimates reveal an additional negative impact on mobility when unemployment rates are high both at the time of job separation and job finding (and, in practice, in between), but this impact is not statistically significant.

In the second panel of Table 8 we relate occupational (industry) mobility to the HP-filtered (log) unemployment rate, measured again at the time of job separation or of job finding. Here we also observe that occupational (industry) mobility remains procyclical. However, we observe a meaningful drop in the responsiveness of occupational mobility with respect to the unemployment rate when using the 2000 SOC and 1990 SOC and in the case of industry mobility. As in the previous case, the clearest response is obtained when we use the average HP-filtered unemployment at the begin and end of the spell, with statistically significant coefficients at the 1% level. When including both HP-filtered unemployment rates, although measured imprecisely, the impact of higher unemployment rate at the end of the spell, ceteris paribus, is additionally negative (and not economically insignificant) for mobility. For mobility across the 4 task-based categories, this impact is at least marginally significant at the 10% level, while for those NUN spells it is significant at the 5% level.

The above results then suggest that our benchmark analysis is conservative in that we have not selected the timing of unemployment to maximize the cyclical responsiveness of the occupational mobility rate among unemployed workers.

Cyclical responsiveness when controlling for demographic characteristics and occupational identities Next we investigate whether the cyclical behavior of occupational mobility among the unemployed is affected by demographic characteristics and/or the possible effects of source or destination occupations. Panels A and B of Table 9 consider regressions of the form of the form

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_1 \text{Cyclical Variable} + \text{Controls} + \varepsilon, \tag{R1}$$

where as the cyclical variable we use either the linearly de-trended (log) unemployment rate and on the HP-filtered (log) unemployment rate. Each panel is divided into a number of sub-panels that present different set of controls. In the first sub-panel we consider a regression relating the uncorrected mobility to the relevant cyclical variable, a linear time trend, and a dummy for 2000 SOC (implemented in the 2004 and 2008 panels).[15] In the second sub-panel we add demographic controls to the previous regression, while in the third sub-panel we further add source occupation dummy variables. In the fourth sub-panel we further control for destination occupation dummy variables instead of controlling for source occupation. Column (i) considers the 2000 SOC, column (ii) the 1990 SOC, while column (iv) considers simultaneous occupation and industry mobility and column (v) considers industries based on the 1990 Census classification. We analyse the 4 task-based categories including managerial occupations in column (vi) and excluding managerial occupations in column (vii). In addition, in column (iii) we consider NUN spells instead of just pure unemployment spells. Note that all of these regression extend the corresponding regressions reported in Section 1 of this appendix by including the relevant cyclical variable. Standard errors are derived by clustering at the quarter level.

The main message from this table is that including demographic controls, or occupation (industry) fixed effects do not seem to meaningful change the measured responsiveness of mobility with respect to the business cycle. Our evidence therefore strongly suggests that the procyclicality of occupational/industry mobility among

[15] We further have investigated the cyclical patterns during 1985-2003 period in isolation. This analysis gives very similar results, although they produce less precise estimates.

Table 9: Cyclicality of Mobility Controlling for Demographics and Occupation Identities

	2000 SOC (1)	1990 SOC (2)	2000 SOC-NUN (3)	OCC*IND (4)	IND (5)	NR/R-M/C (6)	C/NRM/RM (7)
Panel A. Regression of Individual Mobility on Linearly De-trended Unemployment Rate							
A1: uncorrected, time controls, no demog, no occ/ind controls							
U.rate	-0.0788***	-0.0890***	-0.0583***	-0.0606***	-0.0952***	-0.0575***	-0.0589***
(s.e.)	(0.0180)	(0.0211)	(0.0153)	(0.0192)	(0.0219)	(0.0192)	(0.0191)
A2: uncorrected, time and demog. controls, no occ/ind controls							
U.rate	-0.0763***	-0.0910***	-0.0552***	-0.0579***	-0.0904***	-0.0542***	-0.0547***
(s.e.)	(0.0176)	(0.0213)	(0.0151)	(0.0199)	(0.0217)	(0.0198)	(0.0198)
A3: uncorrected, time, demog. & source occ. Controls							
U.rate	-0.0707***	-0.0810***	-0.0521***	-0.0546***	-0.0783***	-0.0560***	-0.0578***
(s.e.)	(0.0176)	(0.0217)	(0.0148)	(0.0200)	(0.0217)	(0.0193)	(0.0192)
A4: uncorrected, time, demog. Controls and dest. Occ controls							
U.rate	-0.0766***	-0.0831***	-0.0564***	-0.0568***	-0.0817***	-0.0545***	-0.0568***
(s.e.)	(0.0176)	(0.0214)	(0.0146)	(0.0197)	(0.0218)	(0.0197)	(0.0197)
Panel B. Regression of Individual Mobility on HP-filtered Unemployment Rate							
B1: uncorrected, time controls, no demog, no occ/ind controls							
HP U.rate	-0.1594***	-0.1768***	-0.1182***	-0.1198**	-0.2092***	-0.0840**	-0.0959**
(s.e.)	(0.0420)	(0.0449)	(0.0366)	(0.0458)	(0.0543)	(0.0408)	(0.0419)
B2: uncorrected, time and demog. controls, no occ/ind controls							
HP U.rate	-0.1520***	-0.1782***	-0.1088***	-0.1137**	-0.2012***	-0.0751*	-0.0829*
(s.e.)	(0.0418)	(0.0457)	(0.0367)	(0.0472)	(0.0536)	(0.0421)	(0.0438)
B3: uncorrected, time, demog. & source occ. Controls							
HP U.rate	-0.1409***	-0.1623***	-0.1045***	-0.1090**	-0.1825***	-0.0782*	-0.0884**
(s.e.)	(0.0396)	(0.0451)	(0.0347)	(0.0472)	(0.0542)	(0.0413)	(0.0427)
B4: uncorrected, time, demog. Controls and dest. Occ controls							
HP U.rate	-0.1476***	-0.1577***	-0.1172***	-0.1115**	-0.1697***	-0.0770	-0.0906*
(s.e.)	(0.0427)	(0.0495)	(0.0364)	(0.0479)	(0.0542)	(0.0466)	(0.0474)
obs	12639	12591	16574	12260	12309	12639	11506

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

the unemployed is not driven by compositional shifts, whereby in expansions (recessions) we observe more (less) workers who are linked to occupation/industries or demographic characteristics that are associated with higher mobility.

Cyclical responsiveness when controlling for unemployment duration We now investigate the role of unemployment (non-employment) duration in the cyclicality of gross occupational mobility. To do so, we estimate regressions of the form

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_1 \text{Cyclical Variable} + \beta_2 \text{ (u. duration)} + \text{Controls} + \varepsilon. \tag{R-dur}$$

Panel A show the estimated coefficients of the HP-filtered (log) unemployment rate together and spell duration when using the uncorrected mobility data (see the main text for the Γ-corrected estimates. Panel B presents these estimates using the uncorrected data by further adding a time trend and controlling for classification changes. Panels C, D and E progressively add demographic controls (gender, education, race, age), source occupation fixed effects or destination occupation fixed effects, respectively. Panel F considers the estimated duration coefficient with added controls over the same uncorrected data, but without a cyclical regressor. Note that because of we use only those quarters with an uncensored duration distribution in the cyclical analysis (and in panel F), these data is a subset of the one used to estimate the overall duration profile in the main text and the previous sections of this appendix.

Table 10: Cyclicality of Mobility Controlling for Unemployment Duration

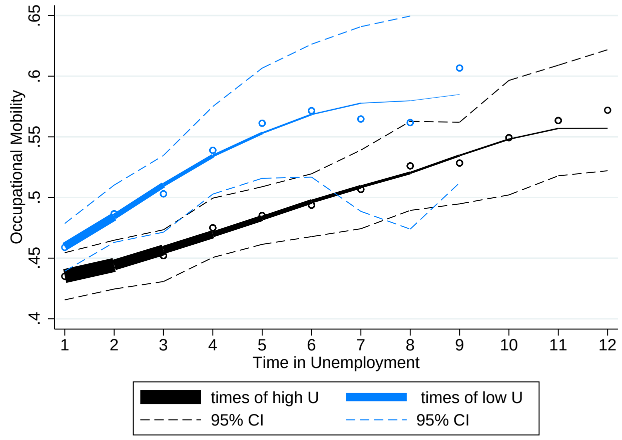
	2000 SOC	1990 SOC	2000 SOC-NUN	OCC*IND	IND	NR/R-M/C	C/NRM/RM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: uncorrected, no demog, no time, no occ/ind controls							
HP U.rate	-0.1655***	-0.1831***	-0.1126***	-0.1251***	-0.2068***	-0.0834*	-0.0974**
(s.e.)	(0.0475)	(0.0518)	(0.0385)	(0.047)	(0.0554)	(0.0449)	(0.0444)
Duration	0.0139***	0.0148***	0.0139***	0.0110***	0.0115***	0.0093***	0.0093***
(s.e.)	(0.0019)	(0.0017)	(0.0017)	(0.0019)	(0.0018)	(0.0015)	(0.0016)
Panel B: uncorrected, with time and classification controls							
HP U.rate	-0.2037***	-0.2237***	-0.1494***	-0.1549***	-0.2458***	-0.1137***	-0.1240***
(s.e.)	(0.0421)	(0.0453)	(0.0360)	(0.0459)	(0.0540)	(0.0418)	(0.0422)
Duration	0.0142***	0.0151***	0.0141***	0.0112***	0.0117***	0.0095***	0.0095***
(s.e.)	(0.0019)	(0.0017)	(0.0017)	(0.0019)	(0.0018)	(0.0015)	(0.0016)
Panel C: uncorrected, with demog, time controls, no occ/ind controls							
HP U.rate	-0.2019***	-0.2297***	-0.1419***	-0.1527***	-0.2418***	-0.1085**	-0.1138**
(s.e.)	(0.0417)	(0.0461)	(0.0361)	(0.0471)	(0.0530)	(0.0432)	(0.0444)
Duration	0.0160***	0.0166***	0.0143***	0.0125***	0.0130***	0.0107***	0.0106***
(s.e.)	(0.0019)	(0.0018)	(0.0016)	(0.0018)	(0.0017)	(0.0015)	(0.0016)
Panel D: uncorrected, source occupation controls, time and demographic controls							
HP U.rate	-0.1863***	-0.2106***	-0.1357***	-0.1436***	-0.2178***	-0.1123***	-0.1206***
(s.e.)	(0.0397)	(0.0457)	(0.0340)	(0.0471)	(0.0534)	(0.0423)	(0.0432)
Duration	0.0148***	0.0155***	0.0134***	0.0112***	0.0112***	0.0109***	0.0109***
(s.e.)	(0.0019)	(0.0017)	(0.0016)	(0.0019)	(0.0018)	(0.0015)	(0.0016)
Panel E: uncorrected, destination occupation controls, time and demographic controls							
HP U.rate	-0.2036***	-0.2085***	-0.1462***	-0.1545***	-0.2259***	-0.1081**	-0.1188***
(s.e.)	(0.0397)	(0.0457)	(0.0332)	(0.0466)	(0.0521)	(0.0426)	(0.0433)
Duration	0.0152***	0.0156***	0.0133***	0.0117***	0.0113***	0.0109***	0.0109***
(s.e.)	(0.0019)	(0.0017)	(0.0016)	(0.0019)	(0.0018)	(0.0015)	(0.0016)
Panel F: comparison (duration profile, no cycle, with time + demog controls)							
Duration	0.0149***	0.0153***	0.0136***	0.0117***	0.0119***	0.0102***	0.0101***
(s.e.)	(0.0019)	(0.0018)	(0.0016)	(0.0018)	(0.0018)	(0.0015)	(0.0016)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

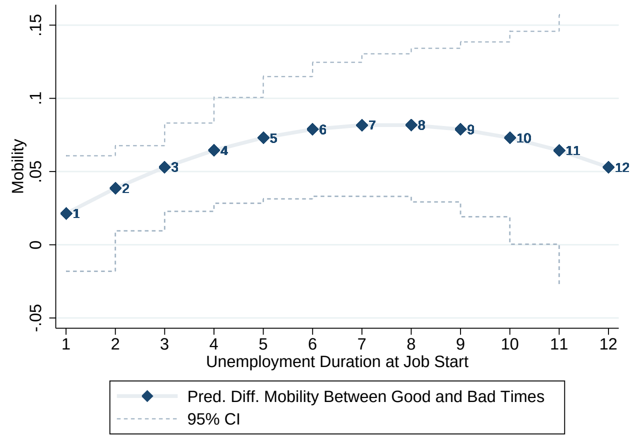
Relative to the results in Table 9 (panel B), we observe that controlling for the duration of the unemployment (non-employment) spell increases the cyclical responsiveness of occupational mobility. This arises as the estimated unemployment coefficient conditional on duration captures the vertical shift of the mobility-duration profile. Without controlling for duration, the unemployment coefficient captures both the vertical shift of the profile and the rightward shift of the unemployment duration distribution that one observes in recessions. The inclusion of further controls does not meaningfully change either the slope of the profile or the cyclical responsiveness of occupational mobility. This suggests that the scope to link compositional shifts across source occupations (or demographics) to the observed cyclicality of mobility *conditional on completed unemployment duration* is limited. Further, it also runs counter to a role of occupational or demographical shifts in our finding that recessions also exhibit a moderately increasing mobility-duration profile for the unemployed .

3.2 Cyclical responsiveness of the mobility-duration profile

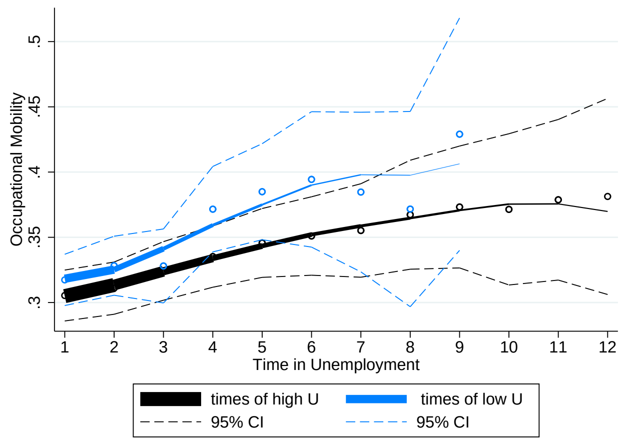
We now turn to investigate the cyclicality of the mobility-duration profile. Figures 12a, c and e depict the mobility-duration profile in periods of high and low unemployment, using the major occupations of the 2000



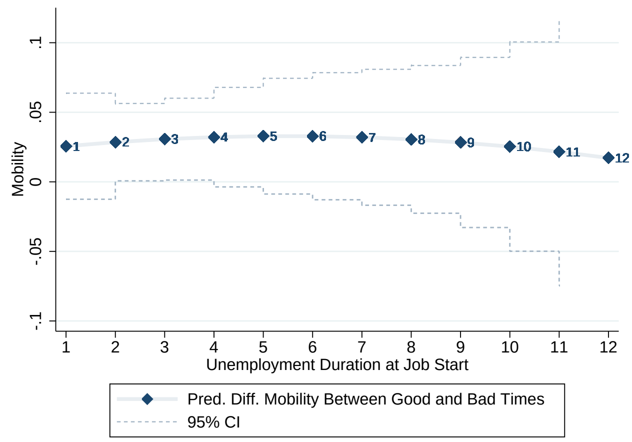
(a) 2000 SOC - Aggregate mobility-duration profile



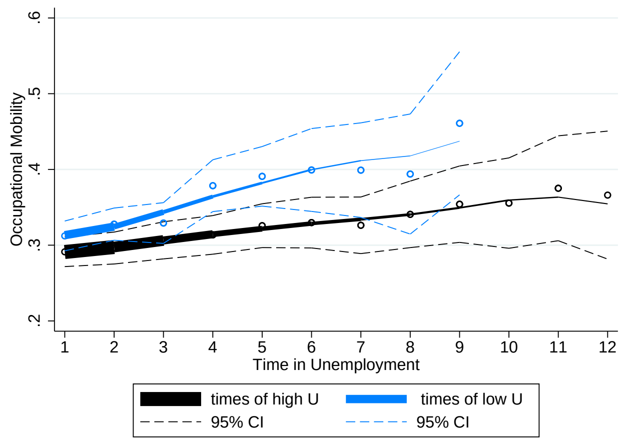
(b) 2000 SOC - Marginal mobility-duration profile



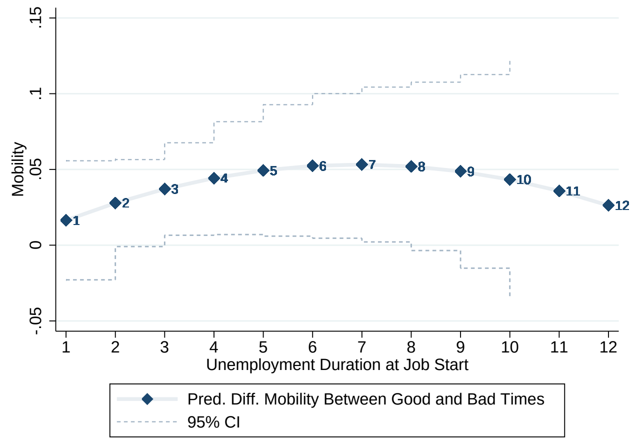
(c) 4RTMC - Aggregate mobility-duration profile



(d) 4RTMC - Marginal mobility-duration profile



(e) 4RTMC, excl. Mgt - Aggregate mobility-duration profile



(f) 4RTMC, excl. Mgt - Marginal mobility-duration profile

Figure 12: Cyclical responsiveness of the mobility-duration profile

SOC and the 4 task-based categories. Periods of high unemployment are defined as those in which the HP-filtered (log) unemployment rate lies within the top third of the distribution of HP-filtered (log) unemployment rates; while periods of low unemployment are defined as those in which the HP-filtered (log) unemployment rate lies within the bottom third of the distribution. The thickness of each profile reflects the number of unemployed workers with an unemployment spell of at least x months of duration. It is readily seen that in periods of high unemployment there are both more unemployed workers and longer unemployment spells. The main conclusion from these graphs is that occupational mobility is higher in periods of low unemployment than in periods of high unemployment *at all unemployment durations*. Figure 12a shows that when considering major occupations the two mobility-duration profiles are statistically different from each other for those unemployment durations of up to 6 months. Beyond this point, the mobility-duration profile associated with periods of low unemployment becomes thinner and its confidence bands become wider.[16] Figure 12e shows that when considering the 4 task-based occupations without the managerial occupations, the two mobility-duration profiles are also statistically different from each at shorter unemployment durations. Including the managerial occupations decreases the precision of the estimates, generating wider confidence intervals.

As a complementary way to investigate the shift of the mobility-duration profile between periods of high and low unemployment, Figures 12b, d and f depict the *marginal* mobility-duration profile. The latter measures the change in occupational mobility at the same *completed* unemployment duration between periods of high and low unemployment. This is in contrast to the mobility-duration profiles considered in Figures 12a, c and e where, for example, a substantial part of those in unemployment at 4 months will still be in unemployment at 5 months, and thus contributing to the average occupational mobility at 4 and 5 months. Since the construction of the marginal mobility-duration profile relies on a much lower number of observations at each duration, we make a functional form assumption on the shift of this profile over the cycle. Specifically, we estimate the probability that a worker changed occupation (industry) at a given unemployment duration as

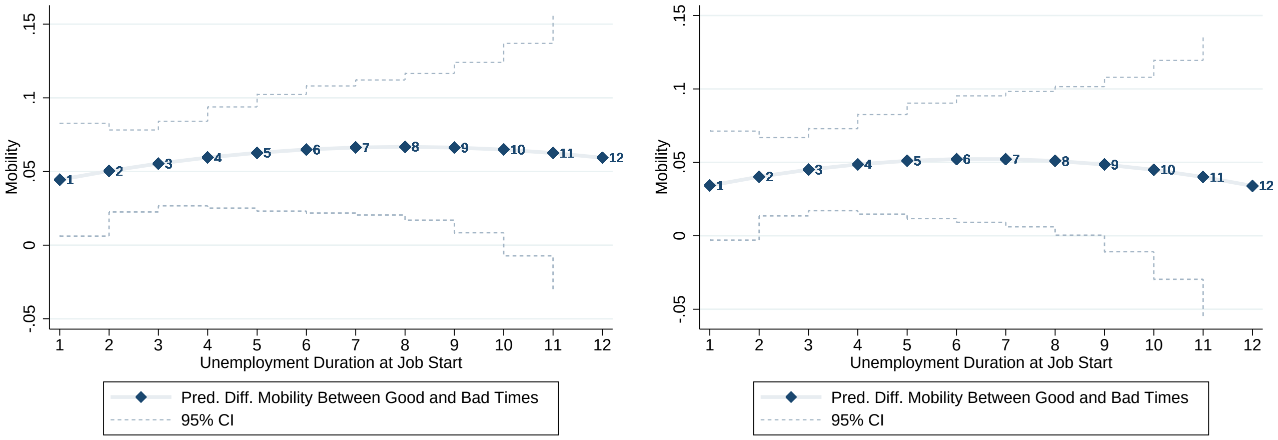
$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_1 \mathbf{1}_{\text{Cycl}} + \sum_{n=1}^{12} \beta_{2n} \text{ (u. duration dummy)}+$$
$$+ \beta_3 \left(\mathbf{1}_{\text{Cycl}} \times \text{u. duration}\right) + \beta_4 \left(\mathbf{1}_{\text{Cycl}} \times (\text{u. duration})^2\right) + Controls + \varepsilon, \qquad \text{(R-X)}$$

where $\mathbf{1}_{\text{Cycl}}$ is the cyclical indicator (0 for periods of high unemployment and 1 for periods of low unemployment), and unemployment duration refers to completed spell duration. We estimate this equation on the uncorrected (from miscoding) SIPP data, controlling for a linear time trend and classification changes. Note that equation R-X allows us to shift the marginal mobility-duration profile differently at different durations following a quadratic relationship.[17] Figures 12b, d and f show that in times of high unemployment, workers who end their unemployment spells at any duration have a lower probability of changing occupation. The differences in probability of an occupational change is statistically significant for durations between 2 and 10 months when using the 2000 SOC and between 2 and 7 months when using the 4 task-based categories, excluding managerial occupations.

Figure 13 shows the marginal mobility-duration profile by estimating regression R-X using instead the linearly de-trended unemployment rate as the cyclical indicator. In this case we observe an even stronger difference in the occupational mobility rates of unemployed workers at any completed duration during periods of high and low unemployment rates. In particular, for the 4 task-based categories, including managers, we now see that in periods of high unemployment the entire profile shifts down, and statistically significantly so between 2 and 8 months.

[16]We do not plot the duration profile when the associated confidence interval becomes wider than 0.2.

[17]We have also experimented with a cubic and quartic relationship. These alternatives at times make the response stronger for durations between 6-10 months, while declining beyond 10 months. However, beyond 10 months, the confidence intervals in all cases become rather wide. Using an alternative specification, where instead of duration dummies for the profile, we use a linear baseline relation between mobility and duration does not change the presented relationship meaningfully. Using a cubic or quartic formulation does not meaningfully change the direction of the shifts or its statistical significance, throughout this section.



(a) Major Occupation Groups (1990 SOC)

(b) NRMC

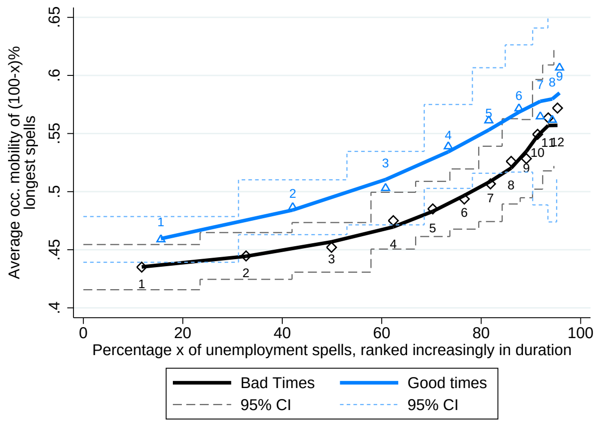
Figure 13: Cyclical Occupational Mobility Shift of the Unemployed

Occupational Mobility and Rank in the Duration Distribution over the Business Cycle To investigate to what extend the rightward shift in the mobility-duration profile observed in Figures 12a, c and e is due to a rightward shift in the unemployment duration distribution, we derive workers' occupational mobility as a function of the rank of their unemployment spell in the duration distribution. We do this both in times of high and low unemployment, as defined above. Figures 14a and c, depict the relation between the average occupational mobility rate of the 100-x% of longest unemployment spells with the rank of these unemployment spells in the unemployment duration distribution. For both the major occupational groups of the 2000 SOC and the 4 task-based categories we observe that at *any* given rank, occupational mobility is lower in periods of high unemployment and this difference appears statistically significant for a wide interval of ranks around the median. This implies that the downward shift of the mobility-duration profile in times of high unemployment goes beyond the rightward shift of the duration distribution associated with recessions. In particular, we do not observe that the business cycle shifts mobility at lower quantiles of the duration distribution in a different direction than it does at the higher quantiles. Therefore, it is not the case that *relatively* shorter unemployment spells display more occupational attachment in a recession, while simultaneously the relatively longer spells display less occupational attachment.

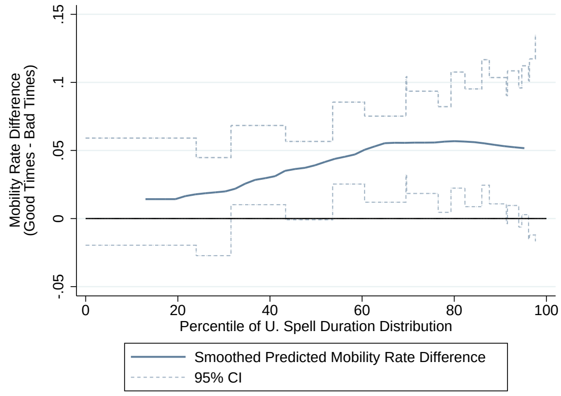
Figures 14b and d, investigate this issue further and depict the estimated change in occupational mobility between period of high and low unemployment on individual panel (uncorrected) data, controlling for a time-trend and classification effects. We analyse occupational mobility *at* a given percentile of the (completed) duration distribution, rather than the average occupational mobility of the subset of all spells including *and above* that percentile, as in Figures 14a and c. Once again since this exercise involves a lower number of observations we make a functional form assumption on the relationship between unemployment duration and occupational mobility. In particular, we estimate a variant of R-X as

$$\mathbf{1}_{\text{occmob}} = \beta_0 + \beta_1 \mathbf{1}_{\text{Cycl}} + \beta_{2,1}\,(\text{u. duration}) + \beta_{2,2}\,(\text{u. duration})^2 + \beta_3\left(\mathbf{1}_{\text{Cycl}} \times \text{u. duration}\right) + \beta_4\left(\mathbf{1}_{\text{Cycl}} \times (\text{u. duration})^2\right) + \text{Controls} + \varepsilon, \qquad \text{(R-XX)}$$

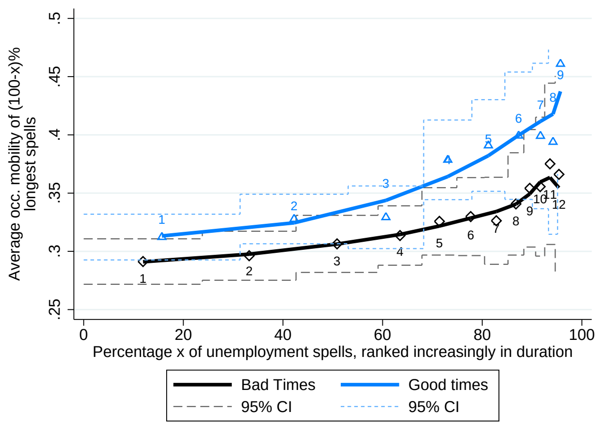
where $\mathbf{1}_{\text{Cycl}}$ is the cyclical indicator (0 for periods of high unemployment and 1 for periods of low unemployment) and instead of unemployment duration dummies we have a smooth quadratic duration profile in



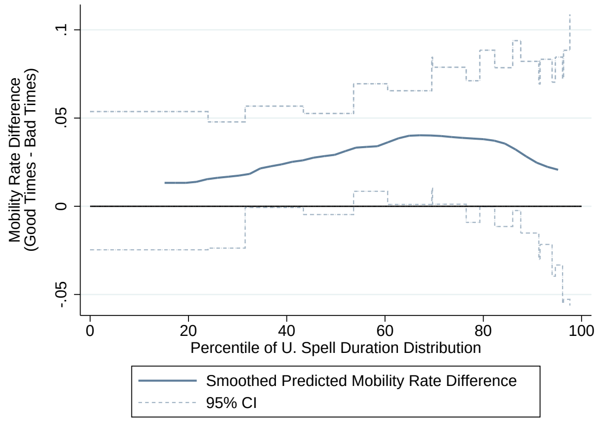
(a) 2000 SOC - Corrected Mobility in Surviving Spells



(b) 2000 SOC - Cyclical Shift of Mobility across Percentiles of Completed Spell Distribution



(c) NRMC excl. Mgt, Code-Error Corr in Surviving Spells



(d) NRMC excl. Mgt, Cyclical Shift of Mobility across Percentiles of Completed Spell Distribution

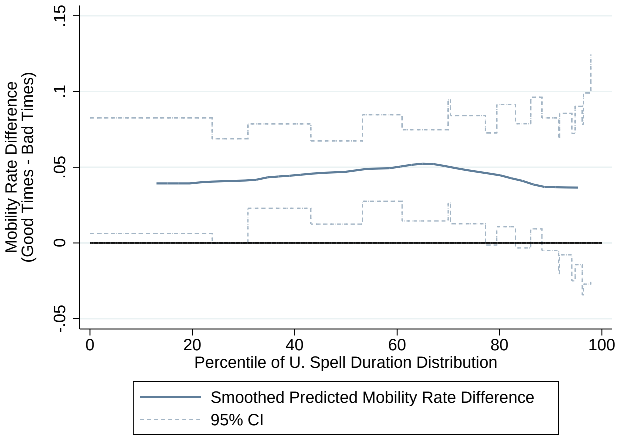
Figure 14: Cyclical change in Mobility, and Rank in Unemployment Duration Distribution

recessions, and a (potentially) different quadratic duration profile in booms.[18]

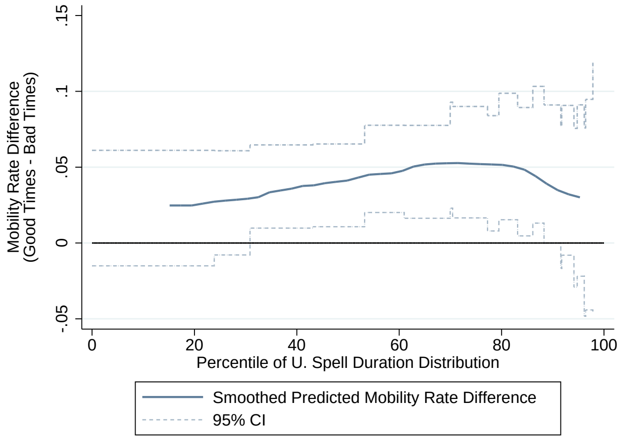
For mobility across major occupational groups we observe that at any given percentile of the completed unemployment duration distribution, mobility is higher in periods of low unemployment relative to periods of high unemployment. This difference is statistically significant for the vast majority of spells between the 35th and 90th percentile. This pattern is very similar for mobility across the 4 task-based categories, albeit statistically weaker. Thus recessions appear to reduce occupational mobility *across* a wide range of the percentiles of the unemployment spell distribution. Figure 15 shows the estimates for the same exercises as before, but using the linearly de-trended unemployment rates as a cyclical indicator. Here we also observe a cyclical shift in mobility across the whole distribution of unemployment spells. In this case, the difference between periods of high and low unemployment is statistically significant at almost all quantiles of the distribution up to the 80-90th percentile (2000 SOC) and between the 35th and 95th percentile (4 task-based caterories).

Conclusion In recessions, unemployment spells are longer and unemployed workers are less mobile. This pattern is shared across many subsets of the population, when dividing by gender, education, age, occupations

[18] We also have experimented with linear, cubic and quartic specifications of the duration profile, which do not lead to different conclusions for the first-order patterns discussed here, unless stated.

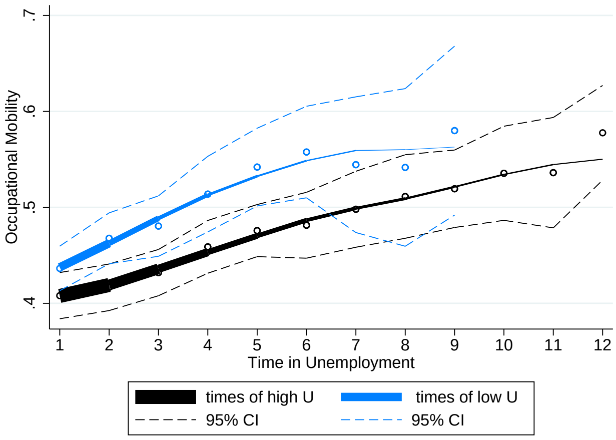


(a) 21 MOG (2000) Mobility in Outflow from U

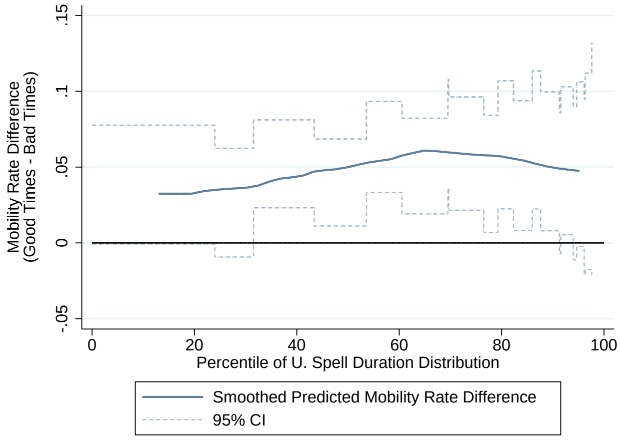


(b) 4 NRMC excl. Mgt Mobility in Outflow from U

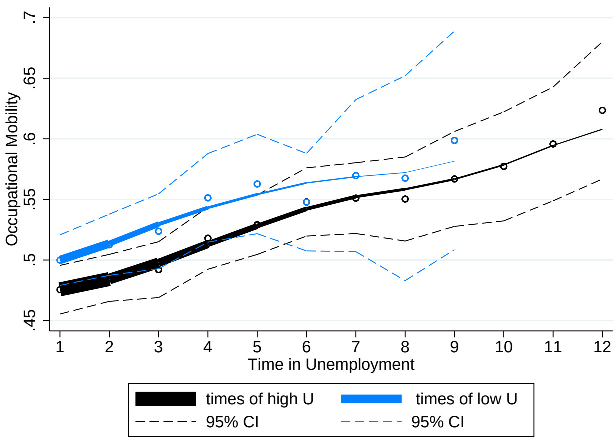
Figure 15: Good and Bad Times according to Linearly-Detrended Unemployment Series



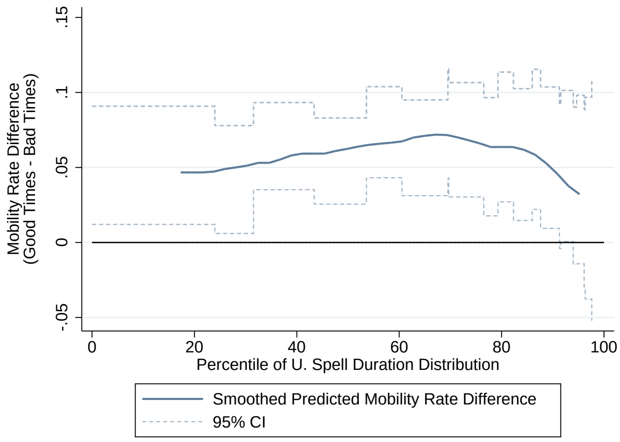
(a) Major Occ. Groups (1990 SOC)



(b) Major Occ. Groups (1990 SOC)



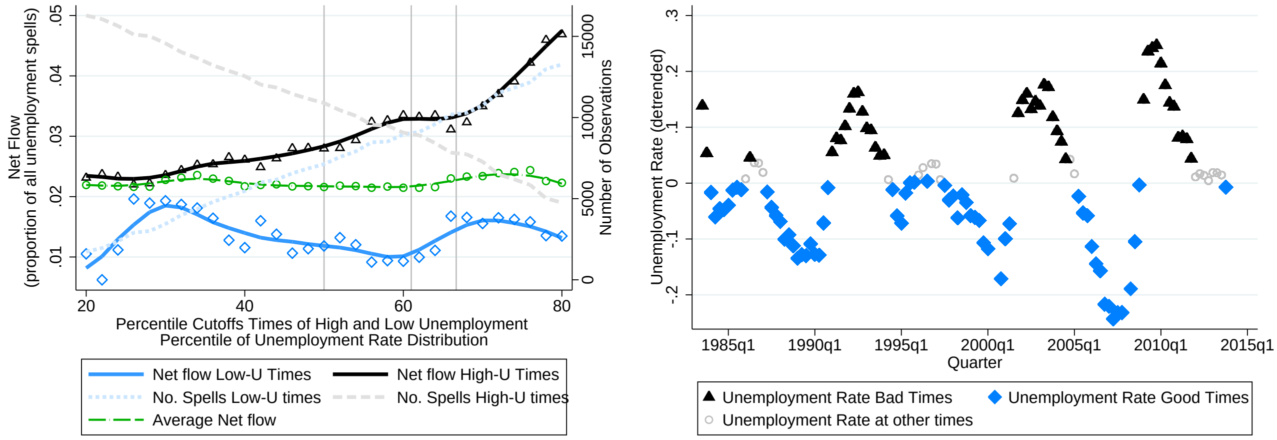
(c) Major Industry Groups (1990 Census Ind. Cl.)



(d) Major Industry Groups (1990 Census Ind. Cl.)

Figure 16: Occupation and Industry Mobility of the Unemployed (1990 Census Classifications)

and industries. Within a recession as within an expansion, longer-unemployed workers are relatively more mobile. We show that the mobility-duration profile appears to shift down in recessions. However, the cyclical



(a) Net Mobility (and no. observations)

(b) High-U times (above 67th pctile), Low-U (below 50th pctile)

Figure 17: Net Mobility and Definition of High-U and Low-U times

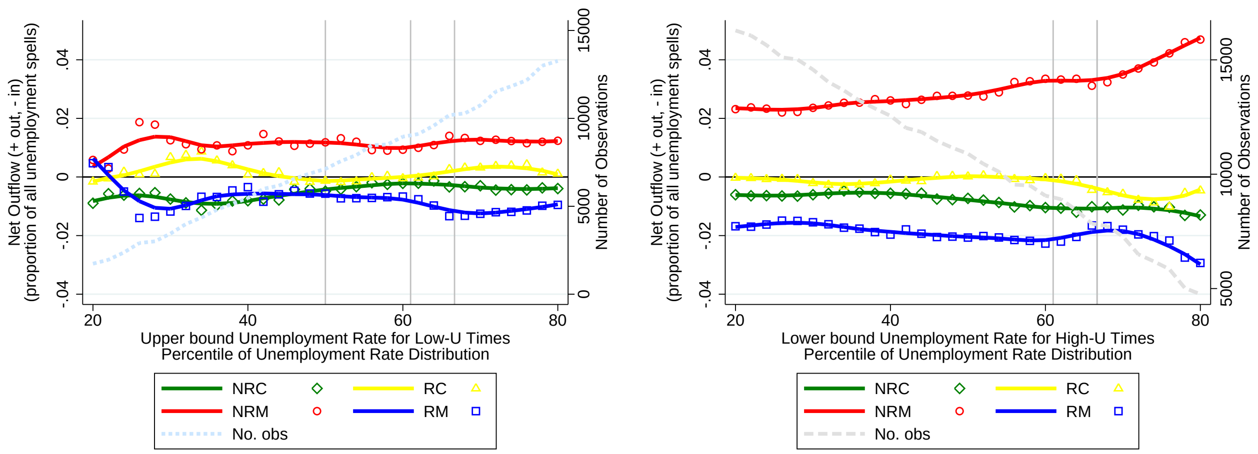
shift down of the duration profile in recession goes beyond a slowdown in the job finding rate. Throughout the quantiles of the unemployment spell distribution, occupational mobility goes down in recessions (statistically so for a substantial part of the distribution). This pattern appears a general feature of occupational and industrial mobility of the unemployed, and is likewise present for the 1990 SOC and for 1990 Industry Census Classification, in Figure 16.

3.3 The cyclical behaviour of net occupational mobility

To study the cyclical behavior of net mobility we split the sample of unemployment spells into two groups. The first group is composed by those spells that ended in quarters with the *highest* $(100 - \underline{x}_b)\%$ of HP filtered (log) unemployment rates. We label these quarters as "downturns". The second group is composed by those unemployment spells that ended in quarters with the *lowest* $\overline{x}_g\%$ of HP filtered (log) unemployment rates. We label these quarters as "expansions". To proceed we need to choose values for $\overline{x}_g$ and $\underline{x}_b$. The choice of these percentile cutoffs, however, presents the following trade-off. On the one hand, a low $\overline{x}_g$ (and/or a high $\underline{x}_b$) implies a relatively small sample of unemployment spells. This could be problematic, as the law of large numbers is not necessarily strong enough in small samples to mitigate randomness in the direction of observed occupational flows.[19] On the other hand, it could be the case that for structural reasons the response of net mobility is larger when we restrict to more extreme cyclical periods. The latter will imply that a low $\overline{x}_g$ (and/or a high $\underline{x}_b$) by itself might go hand-in-hand with more net mobility, because it concentrates on the most responsive periods.

To investigate whether this trade-off is important for the cyclicality of net mobility, Figure 17 shows the net flows across the 4 task-based categories as a function of $\underline{x}_b, \overline{x}_g \in [0.2, 0.8]$. As described in the main paper these flows are normalised by the number of employment-unemployment-employment spells observed during either expansion and recessions as defined above. The blue curve depicts net flows in expansions and the black curve depicts net flows in downturns. To compare net mobility between expansions and recessions, defined for example as periods with the lowest and highest 33% of HP filtered (log) unemployment rates, one

[19]Consider for example a set of gross flows obtained from an underlying distribution of flows were net mobility is zero. If this set contains only one observation of occupational mobility, this observation will be categories as a net flow and one would need 100% of gross flows to cover the net flow.



(a) Times of High U

(b) Times of Low U

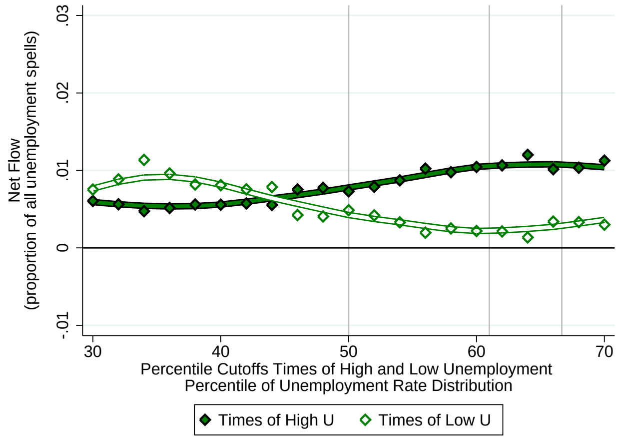
Figure 18: Net Mobility per (NRMC) Occupation and Definition of High-U and Low-U times

needs to compare the value of the blue curve at the x-coordinate 0.33 with the value of the black curve at the x-coordinate 0.67. The green dashed line (with circles) denotes the *average* net mobility obtained from calculating net mobility in expansions and in downturns and then averaging over these, weighting them by the number of underlying unemployment spells. In this case, the percentile on the x-axis represents the upper bound of unemployment rates to define expansions, and simultaneously the lower bound to define downturns. In all these cases the net flows are calculated from the implied occupational transition matrix of all unemployment spells that ended in an expansion or a downturn. We then applied the Γ-correction to this matrix.

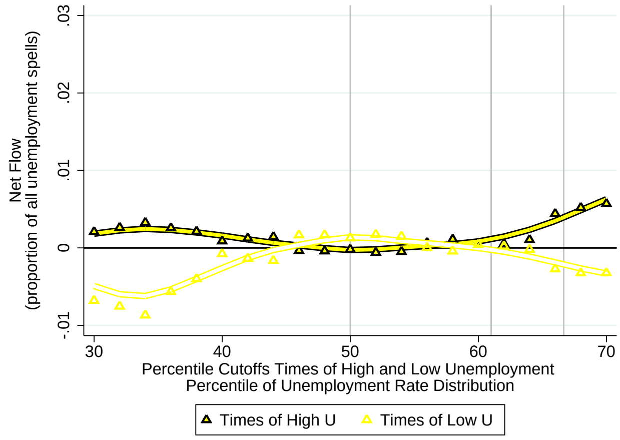
The main message that comes out of Figure 17 is that overall net mobility across task-based categories is *countercyclical* for any $\underline{x}_b, \overline{x}_g \in [0.2, 0.8]$. Thus, the variations in the size of our samples do not seem to affect our finding that net mobility is countercyclical. Figure 18 presents the same exercise but focusing on individual task-based categories. Figure 18a shows net mobility in expansions as a function of $\overline{x}_g$; while Figure 18b shows net mobility in downturns as a function of $\underline{x}_b$. Here we observe that the net flows of the routine manual and non-routine manual categories are larger in downturns than in expansions, implying that the net flows of these categories are countercyclical for any $\underline{x}_b, \overline{x}_g \in [0.2, 0.8]$. Further, both in expansions and downturns the non-routine manual category exhibits *net inflows* while the routine manual category exhibits *net outflows*, consistent with the job polarization literature. The patterns for the cognitive categories, however, are not as clear. For example, we find that the net flows of the non-routine cognitive category are only higher in downturns when considering $\underline{x}_b, \overline{x}_g \in [0.45, 0.8]$. Figure 19 shows all these net mobility flows in more detail, depicting the pairwise expansion and downturn comparison of net flows for each category separately.

In light of the above, when analysing net mobility flows we will take expansions to represent quarters with below median HP filtered (log) unemployment rates and downturns to represent quarters with the 33% highest HP filtered (log) unemployment rates. The benefit of defining the business cycle in this way is that the aforementioned small sample issue seems to be less important in this definition of an expansion, where unemployment spells are less frequently observed. Indeed, the blue curve in Figure 17a appears well behaved around the median.[20] Figure 17b also shows that the standard NBER recessions and their immediate aftermath closely correspond to this definition of downturns, while the second half of the 1990s, late 1980s, and mid-

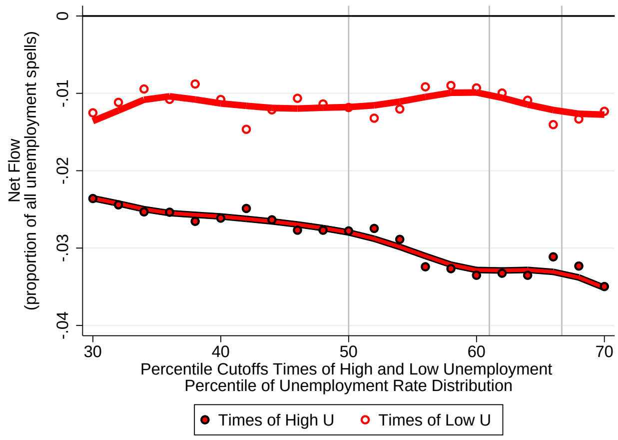
[20] Also note the there is relatively little variation in the average net mobility between the 40th and 65th percentile. As we restrict sample sizes when moving across these different cutoffs, noisier observations of net flows in the smaller set can drive up the average net mobility rate. This does not seem to be the case for our measures.



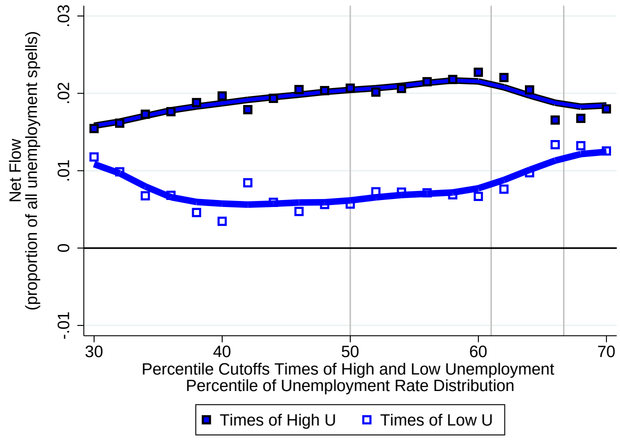
(a) NRC



(b) RC



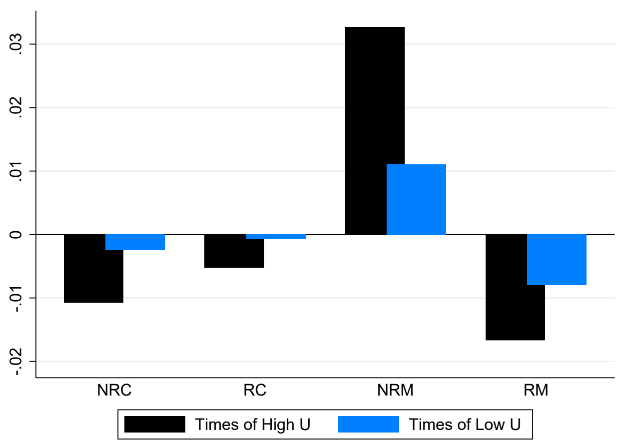
(c) NRM



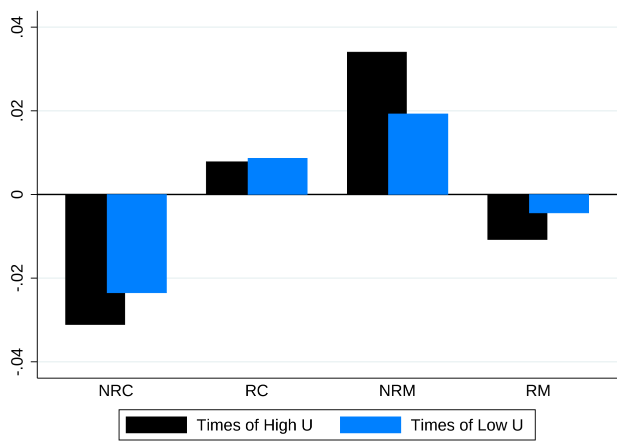
(d) RM

Figure 19: Net Mobility Outflows (Inflows) per Occupations, and definition of High-U and Low-U times

2000s till the beginning of the Great Recession closely correspond to this definition of expansions.



(a) Cyclical Net Mobility (NRMC excl. Management)

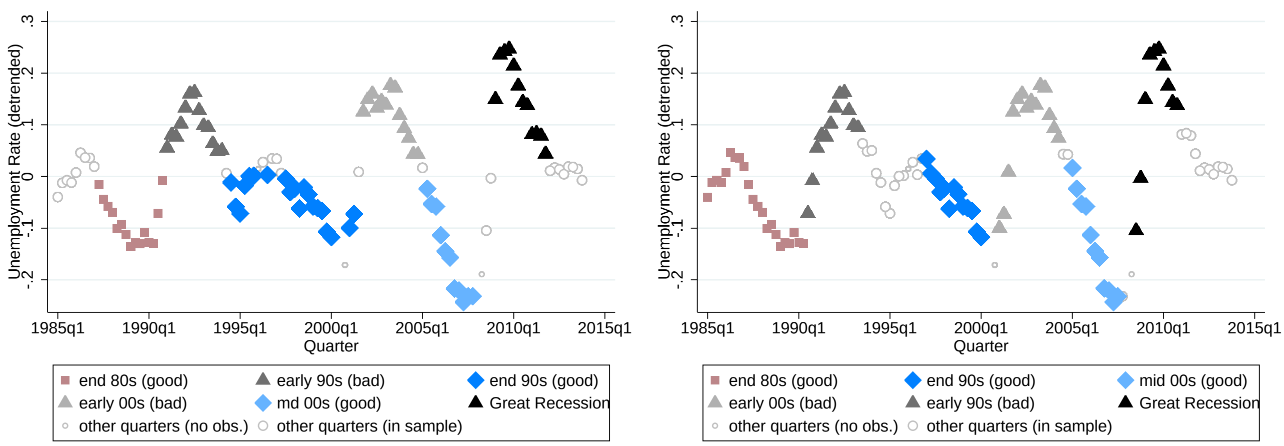


(b) Cyclical Net Mobility (NRMC incl. Management)

Figure 20: Net Mobility by Task-based categories

Analysing the business cycles in such a way implies that overall net mobility accounts for 1.1% of workers unemployment spells in expansions, while it accounts for 3.2% of workers unemployment spells in downturns. Figure 17 depicts these values as the intersection between the left-most vertical line with the blue curve and the intersection between the right-most vertical line with the black curve, respectively.[21] Figure 20a displays the net mobility patterns for each of the 4 task-based categories also using this business cycle definition. As suggested by Figures 18 and 19, the non-routine manual category exhibits a countercyclical increase in net inflows: in downturns 3.2% of workers' unemployment spells cover the net mobility of workers into non-routine manual occupations, while only 1.1% of spells in expansions. In contrast, the routine manual category exhibits a countercyclical increase in net outflows: in downturns 1.7% of workers' unemployment spells are needed to cover the net mobility of workers out of routine manual occupations, while only 0.7% of spells in expansions.

Figure 20b display the net mobility across the four task-based categories, but now including managerial occupations in the non-routine cognitive category. In this case net flows of over 2% of all unemployment spells now originate from the non-routine cognitive category, while the routine cognitive category now experiences a net inflow as a result of former managers taking up administrative or sales jobs. Further, the inflow from management mutes somewhat the outflow from the routine manual category. Nevertheless, the same cyclical patterns regarding non-routine and routine manual categories emerge. Net inflows into the former and net outflows from the latter are larger in absolute value during downturns.



(a) Baseline episodes

(b) Alternative (NBER) episodes

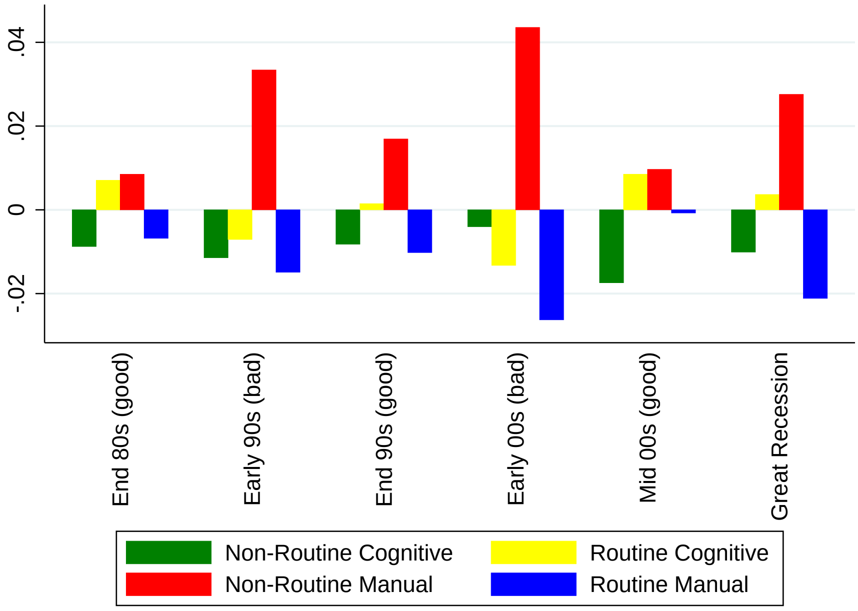
Figure 21: Expansion and downturn episodes: 1986-2013

We now investigate whether the above net mobility patterns appear common across the various expansion and downturn episodes we observe during our sample period. Using the above definition of the business cycle, Figure 21a distinguishes three expansion and three downturn episodes, where the quarters of our sample are divided into largely connected (continuous) episodes.[22] To check the robustness of our results, Figure 21b considers an alternative definition of the business cycle that is closer to the NBER one. In this case we label as downturns the set of quarters that starting with an NBER recession go until one year after peak unemployment

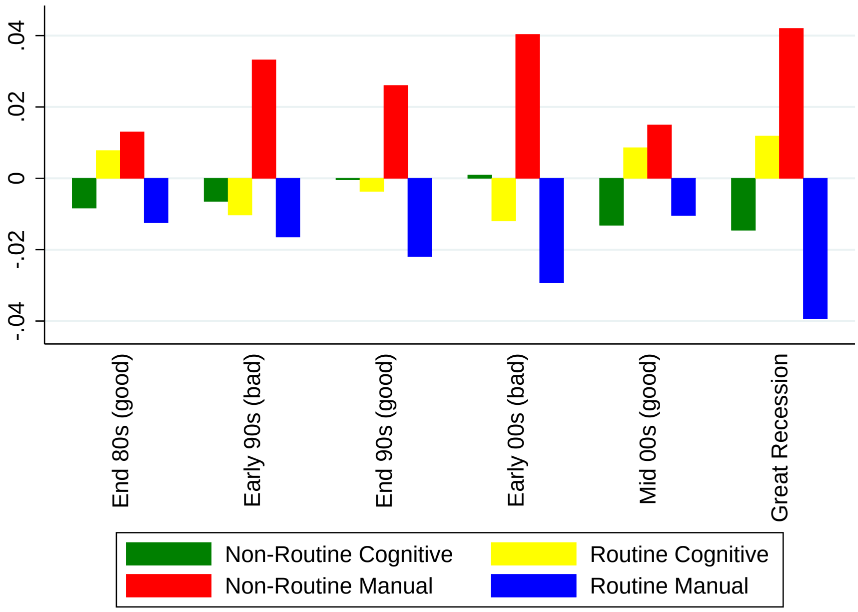
[21] As an alternative to the above benchmark we also split the sample into two parts with an equal number of observations. In this case expansions correspond to the lowest 61% of HP filtered (log) unemployment rates, and recessions correspond to the highest 39% of HP filtered (log) unemployment rates. This alternative generates a similar cyclical change in net mobility, whereby net mobility accounts for 1.0% of unemployment spells in expansions and accounts for 3.3% of unemployment spells in recessions.

[22] We take those quarters with below-median unemployment rates in the second part of the 90s as one period, and exclude the 2008 quarters in the Great Recession that still have below-median unemployment rates from the expansion.

is reached. Expansions are the set of quarters preceding these downturns, going backwards until a previous downturn is reached (with a two quarter gap) or until the sample sizes are about balanced. This alternative definition differs from the baseline one by including early NBER recession quarters in which HP-filtered (log) unemployment rates were low but rising fast, and by limiting the 1990s expansion to the 1997-2000 period. Given that the overall number of net mobility flows is small (see Section 2 of this appendix), note that the main caveat of these exercises is that each episode ends up containing an even smaller number of net flows. As discussed earlier this can generate nosier and potentially (upward) biased estimates.



(a) Cyclical Net Mobility (Baseline episodes)



(b) Cyclical Net Mobility (Alternative (NBER) episodes)

Figure 22: Net mobility at different expansions and downturns

The resulting net mobility patterns are displaying in Figures 22a and 22b. We observe that the overall patterns described in Figure 20a seem to be common across all expansions and downturns. In particular, we observe that across all episodes the non-routine manual category exhibit net inflows, while the routine manual category exhibits net outflows. The non-routine cognitive category also exhibits net outflows in most episodes across the two business cycle definitions. The routine cognitive net flows, however, are close to zero but change direction across episodes. This means that the overall low net mobility rate over the entire sample period does not mask meaningful reversals of direction or more substantial net mobility over time and this seems to be consistent across different definitions of the business cycle.

We also observe that each expansion episode is associated with less net mobility than in the downturn episodes. Moreover, across both business cycle definitions the net inflows into the non-routine manual category are larger in downturns than in expansions. A difference, however, is that the net inflows during the Great Recession are more pronounced using the business cycle definition that is close to the NBER one. This appears to reflect that in our data net mobility into the non-routine manual category is noticeably higher during the NBER recession quarters of the Great Recession, and less so in the aftermath. Since Figure 22b includes more of the aforementioned NBER recession quarters, it naturally observe a stronger responds. Note also the cyclical pattern in the net outflows from the routine manual category. These net outflows appear typically larger in downturns than in expansions. This pattern is strongest when using our baseline definition of the business cycle, but when using the definition closer to the NBER one we observe an increase in the net outflows during the late 1990s expansion episode.

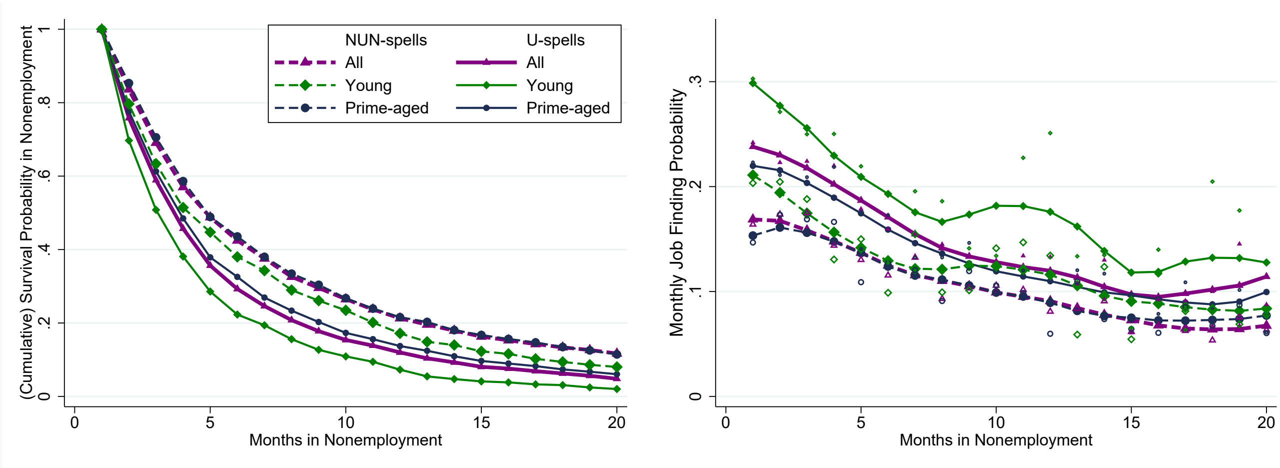
4 Job Finding Hazards and Spell Duration with Occupational Mobility

In this section we first investigate the re-employment hazard functions of those workers who changed employers through spells of non-employment, differentiating between these workers' degrees of labor market attachments. This connects to our calibration targets. We then analyse the differences in unemployment durations between those workers who changed occupations and those who did not, and how these durations respond over the cycle. This further connects to the model and calibration, including the calibration outcomes. In particular, we document that in cyclical downturns, it is the unemployment duration of movers that lengthens more. We show that this result is robust even when controlling for destination and/or source destinations.

4.1 Job Finding Hazard

The right-hand panel of Figure 23 shows the probability that a worker is still without a job as a function of the number of months that have passed since losing his previous job. The solid lines capture the survival functions for the set of workers who have experienced *un*employed for all months since losing their jobs, while the dashed lines refer to male workers who have been unemployed for at least one month since losing their job, but not necessarily all months, i.e. have a non-employment spell that mixes out of the labour force with unemployment (labelled a "NUN-spell"). We restrict our attention to males here because females have interestingly different patterns (with higher survival in non-employment at longer duration), which nevertheless might be driven by different motives than the conditions in their labour market alone. Males which have been unemployed for every month since losing their job are not displayed separately, because the associated graph stays very close to the depicted "U-spell" category for both males and females.

Within these categories, we can separately investigate the subset of young workers (between 20-30 years old) and prime-aged (between 35-55 years old), drawn in green (with diamond-shaped markers) and dark-blue (with circle markers) respectively. We observe that survival in non-employment is indeed higher for those workers who are not searching for a job in every month, but the general shape and age differences seem preserved across both groups.



(a) Survival in Nonemployment with Duration

(b) Job Finding Rate with Duration

Figure 23: Job finding out of non-employment

The left-hand panel of Figure 23 depicts the implied monthly job finding probabilities, with Epanechnikov-kernel weighted local polynomial smoothing (bandwidth 2.5). First note the extent of duration dependence in job finding in the first 10 months, with a job finding rate that falls about 1 percentage point per month for all unemployed workers. This "moderate" duration dependence is in part because we focus on those workers who have become more strongly detached from employment. By construction, the workers we consider are without work for at least a whole month (hence, the job finding rate in the first month refers to the probability of finding a job within the next month, after having been unemployed for a month). We also exclude workers in temporary layoff, who have a higher job finding rate.

As a result of these restrictions, our hazard functions do not exhibit the steep drop typically observed during the first month in unemployment (which can be seen e.g. in Farber and Valletta, 2015, Figure 3, based on the CPS). As argued in the main text, our restrictions are motivated by the finding in the literature that entrants into unemployment can be separated roughly into two different groups: a set of workers who has high job finding rates and behaves differently over the cycle, with most of the cyclical movement in the unemployment rate due to those who are in the second, slower job-finding group. We want to focus on the latter group. Fujita and Moscarini (2017) highlight the roll of recalls for the first group and, importantly also for our paper, highlight the different job finding expectations of the first group. This motivates our exclusion from unemployment/non-employment of those who are classified in the SIPP as "with a firm, on layoff". Ahn and Hamilton (2019) similarly argue that two different sets of workers enter unemployment, with cyclical movements largely driven by the group which exhibits in comparison less propensity to return to employment.

Figure 24 depicts the hazard function of those workers who reported *conventional* unemployment the month before the interview (to 'mimic' the CPS), after dropping the aforementioned restrictions on entering unemployment and non-employment. In this case we indeed observe a much stronger duration dependence, where there is a large drop in the hazard function during the first month (see Fujita and Moscarini, 2017, for a similar result also using the SIPP). Thus, the negative duration dependence among the unemployed (non-employed) we consider in this paper is indeed relatively weaker than when considering the full set of conventionally-unemployed workers in the same data. Aside from this, the *seam effect* on the job finding rate is an additional

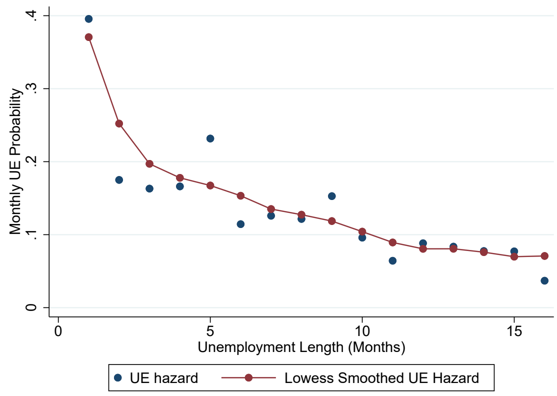


Figure 24: Aggregate Job Hazard - unconstrained unemployment definition

issue that is clearly visible in Figure 24, at four month intervals. Although with our restrictions the seam effect is weaker in Figure 23, we will attempt to minimize its impact in the calibration by using survival rates at four month intervals (in addition to the first-month job finding rate).

Note that the extent of negative duration dependence exhibited by each group-specific hazard function depicted in Figure 23b is not too dissimilar from each other. Workers in the 'U' group exhibit the higher absolute change in the job finding rate with duration and workers in the 'NUN' group exhibit the lower absolute change, but with similar relative changes of the job finding rate with duration. The main difference between these hazard functions seem to be more in levels, where workers in the 'U' group exhibit the highest hazard rates and workers in the 'NUN' groups exhibit the lowest hazard rates across all durations. The relative reduction in job finding of prime-aged workers in "pure" unemployment spells (when compared to younger workers) seems to be similarly present in the "mixed" spells of non-employment with some unemployment. Interesting, although not further emphasized in our paper is the non-monotonicity in the job finding rate with duration of the young around 12 months, which is suggestive of a sensitivity to benefit exhaustion that is particularly strong for this group. We abstract from this feature in the paper, but it is worth noting that our calibration targets, which consider survival probabilities in four months intervals, smooth this non-monotonicity out.

4.2 Job finding differences among occupational movers and stayers

4.2.1 Long-run patterns

The positive slope of the mobility-duration profile implies that occupational movers take longer to find jobs than occupational stayers. We now investigate whether this difference is still present after controlling for demographic characteristics and occupational identities. To do this we report several estimates of the difference between the unemployment *durations* of occupational stayers and movers based on the uncorrected data. These estimates are obtained from regressions of the form

$$\text{Duration of U} = \beta_0 + \beta_{\text{occmob}}\mathbf{1}_{\text{occmob}} + \beta_{\text{dm}}\,\text{demog.ctrls} + \beta_{\text{occ}}\text{occ.dum} + \varepsilon, \tag{R4}$$

where "Duration of U spell" is the individual's *completed* unemployment spell, $\mathbf{1}_{\text{occmob}}$ is a binary indicator that takes the value of one (zero) if a worker changed (did not change) occupation at the end of his/her unemployment (non-employment) spell, the demographic controls include dummies for gender, education, marital status, race and age, "occ.dum" denotes occupation identity dummies and ε is the error term. Table 11 present the results of these regressions by progressively adding demographic and occupation identity controls. Columns (2) and (3) use the sample of completed durations among all unemployed workers, while Columns (4)-(8) restricts the sample to the completed durations of young and prime-aged unemployed workers.

Column (2) shows the results from estimating (R4) without any controls other than the occupational mobility dummy. It shows that occupational movers take on average an additional 0.5 months to find a job. This difference arises as the average unemployment duration of occupational stayers is 3.6 months, while the average unemployment duration of occupational movers is 4.1 months. This difference is also economically significant: it represents nearly half of the differences between the average unemployment spell duration in times of low unemployment (expansions) and times of high unemployment (recessions).[23]

The rest of the columns show that the estimated difference between the average unemployment durations of occupational movers and stayers does not seem to be driven by composition effects. Column (3) reports the results from estimating (R4) when adding worker demographic characteristics. It shows that the estimated coefficient of the occupational mobility dummy hardly changes. Column (4) shows that the estimated coefficient of the occupational mobility dummy also hardly changes when restricting the sample to young and prime-aged workers and adding demographic characteristics. In columns (5)-(7) we further add source and destination occupational identity dummies. Here we observe a drop of up to 5 percentage points in the difference between average unemployment durations of occupational movers and stayer. However, note that a difference of 0.45 months still remains economically significant. This suggests that the difference in the average duration of the unemployment spell between occupation movers and stayers is not a result of workers moving out of (or into) occupations in which typically all workers take longer to find jobs. The increased unemployment duration of occupational movers thus seems to be associated with the act of moving itself. Therefore this evidence does not seem to support theories that are based on workers moving into a particular subset of occupations in which newcomers need to spend relatively more time to find jobs because of, for example, re-training.

Table 11, however, does show important differences across age groups. Column (8) reports that prime-aged workers take 0.33 months longer to find a job when they changed occupations than young occupational movers. In this case the role of other demographic characteristics factors appears more limited, once we control for age and occupational identities. The bottom panel of Table 11 present several F-tests evaluating the equality of the occupational mobility dummies specific to demographic characteristics and occupational identities. These F-test highlight two important results. There is a statistically significant interaction between age and the additional unemployment duration of occupational movers. There is not a statistically significant interaction between the rest of the demographic or occupational identity dummies and the additional unemployment duration of occupational movers.

4.2.2 Business cycle patterns

Table 12 extends the previous analysis and considers the cyclicality of the difference between the completed unemployment durations of occupational movers and stayers. In Section 3.2 we documented that the mobility-duration profile is procyclical: at any duration the occupational mobility rate is higher in expansions than in recessions. We now show that ties in with a countercyclical distance between the unemployment durations of movers versus stayers. In particular, we estimate

$$\text{Duration of U} = \beta_0 + \beta_{\text{occmob}}\mathbf{1}_{\text{occmob}} + \beta_{\text{occ.un}}\mathbf{1}_{\text{occmob}} \times urate + \beta_{\text{dm}}\,\text{demog.ctrls} + \beta_{\text{occ}}\text{occ.dum} + \varepsilon, \quad \text{(R5)}$$

[23] We consider times of high (low) unemployment as those quarters in which the HP de-trended (log) unemployment rate lies within the 33% highest (lowest) HP de-trended unemployment rates. The average unemployment length in those quarters with high unemployment is 4.4 months, whereas the average unemployment spell lasts 3.3 months in the quarters with the low unemployment.

Table 11: Unemployment Duration and Occupational Mobility

	(1) all U	(2) all U	(3) all U	(4) U yng+prm	(5) U yng+prm	(6) U yng+prm	(7) U yng+prm	(8) U yng+prm
Average Unemp. Duration								
All	3.91							
	(.033)							
Occ. Stayers		3.646	3.646	3.627	3.627	3.627	3.627	3.627
		(.048)	(.047)	(.052)	(.051)	(.052)	(.051)	(.056)
Occ. Movers		4.146	4.146	4.063	4.063	4.063	4.063	4.063
		(.045)	(.045)	(.048)	(.048)	(.048)	(.048)	(.055)
Regression Coefficients								
Coeff. Occ. Mob Dummy		0.500	.507	.499	.462	.472	.451	.262
		(.065)	(.065)	(.071)	(.072)	(.072)	(.073)	(.114)
Occ. Mob x Prime-Age Dum.								.336
								(.157)
Worker's Characteristics			X	X	X	X	X	X
Age (prime-age dummy)				X	X	X	X	X
Source Occupation Dummies					X		X	X
Dest. Occupation Dummies						X	X	X
F-test Interactions (p-value)								
Age x Occ Mob				0.008	0.012			0.024
Worker Char. x Occ Mob.			0.029	0.118	0.194	0.616	0.630	0.607
Occupation x Occ Mob.					0.806	0.463	0.931	0.927
Num. of Observations	10886	10886	10886	8887	8887	8887	8887	8887

where the new explanatory variable is relative to equation (R4) is the interaction between occupational mobility and the unemployment rate. The latter appears as "diff resp. (responsiveness between) movers vs stayers" in Table 12.

Panel A of Table 12 considers as the measure of the business cycle the log of the aggregate unemployment rate, controlling for a linear time trend. The results presented in the first set of four columns use as the dependent variable spells in which the worker was classified unemployed since loosing his/her job until finding a new one (U-spells). The second set of four columns use as the dependent variable spells in which the worker was classified at least one month as unemployed and the rest as out of the labour force since loosing his/her job until finding a new one (NUN-spells). In each case, the first three columns consider all workers, while the last column restricts the sample to young and prime-aged workers.

For both types of non-employment spells, we observe that when the aggregate unemployment rate increases the differences between the completed spell duration of occupational movers and stayers increases. That is, during recession (times when unemployment is high) occupational movers experience even stronger increases in unemployment duration than occupational stayers do. As shown across the columns, this result also holds (with rather stable coefficients for U-spells) when controlling for demographic characteristics (including a quadratic in age) and dummies for the occupation of origin and destination.[24] Our results also show that the responsiveness of the difference in unemployment durations to the unemployment rate is stronger when considering NUN-spells.

Panel B of Table 12 instead considers as the measure of the business cycle the cyclical component of the log

[24] Kroft et al. (2016) find that compositional shifts matter little for the increase in long-term unemployment in recessions; our results are related in the sense that we find that compositional shifts matter little for the increase in the duration difference between occupational movers and stayers in recessions. This increase is proportionally stronger than the drop in occupational mobility of the unemployed that is broadly shared across occupations. Hence the lengthening of spells of occupational movers contributes to the lengthening of unemployment and, in particular, long-term unemployment across occupations in recessions.

Table 12: Unemployment Duration and Occupational Mobility over the Business Cycle

Panel A: Semi-Elasticity Un-/Nonemployment Duration with Log linearly detrended Unemployment rate								
	Unemployment Duration				NUN-spell duration			
Coefficient	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Occupation Stayers x U. rate	1.65***	1.64***	1.63***	1.64***	1.07***	1.15***	1.13***	1.14***
(s.e)	(.18)	(.18)	(.18)	(.18)	(.25)	(.25)	(.25)	(.25)
Occupation Movers x U. rate	2.04***	2.03***	2.04***	2.03***	1.72***	1.81***	1.81***	1.81***
(s.e)	(.17)	(.17)	(.17)	(.17)	(.23)	(.23)	(.23)	(.23)
difference resp. mover-stayer	0.40**	0.40**	0.41**	0.40**	0.65**	0.66**	0.68**	0.67**
(s.e)	(.18)	(.18)	(.18)	(.18)	(.31)	(.29)	(.30)	(.29)
Worker's Characteristics		X	X	X		X	X	X
Source Occupation		X		X		X		X
Destination Occupation			X	X			X	X
Panel B: Semi-Elasticity Un-/Nonemployment Duration with HP-Filtered Log Unemployment rate								
	Unemployment Duration				NUN-spell duration			
Coefficient	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Occupation Stayers x U. rate	2.47***	2.47***	2.49***	2.48***	1.345***	1.591***	1.608***	1.616***
(s.e)	(.46)	(.43)	(.43)	(.43)	(.62)	(.60)	(.60)	(.60)
Occupation Movers x U. rate	3.20***	3.14***	3.21***	3.16***	3.516***	3.67***	3.705***	3.691***
(s.e)	(0.56)	(.54)	(.54)	(.54)	(.60)	(.60)	(.60)	(.59)
difference resp. mover-stayer	0.73*	0.67*	0.72*	0.68*	2.17***	2.08***	2.098***	2.074***
(s.e)	(.42)	(.40)	(.39)	(.40)	(.76)	(.71)	(.72)	(.72)
Worker's Characteristics		X	X	X		X	X	X
Source Occupation		X		X		X		X
Destination Occupation			X	X			X	X
Number of observations	9840	9840	9840	9840	15506	15506	15506	15506

Notes: Standard errors in parenthesis. *** significant at a 1% level; ** significant at a 5% level; * significant at a 10% level. Controls: gender, age, age squared, number of years of education, family status.

of aggregate unemployment rate, where the cyclical component is obtained through an HP filter. It is immediate from the table that the conclusions obtained from using this measure are the same as the ones obtained when using the linearly de-trended logged unemployment rate.

4.2.3 Summary

In Section 1 we have documented that at any unemployment duration, occupational movers largely move across all occupations. Here we have shown that conditional on a given occupation, an occupational mover takes longer to find a job than an occupational stayer and that this difference increases in recessions. It is important to highlight that this does not mean that different occupations exhibit the same average unemployment duration. Indeed, we do find differences in the estimated coefficients of the source and destination occupation dummies (see Section 1.5), suggesting that some occupations do lead *all workers* (occupational movers and stayers) to find jobs fasters than workers in other occupations (in line with Wiczer, 2015). What our results suggest is that even though a worker might have experienced job loss in an occupation that exhibits short or long overall unemployment durations, this worker will take on average longer to find a job if he/she is to change occupations at re-employment and even longer if he/she changes in a recession.

5 Occupational mobility in the PSID and the CPS

We now turn to investigate some of our main findings using alternative data sources: the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID). Analysing occupational mobility through the CPS is helpful even though these data is not corrected for measurement error. In particular, the CPS has the advantage of providing the longest, uninterrupted series of occupational mobility, even spanning into 2021. This allows us to evaluate whether the breaks in the SIPP time series have a meaningful effect on the extent and cyclicality of gross occupational mobility. For this purpose and because the individual-worker panel dimension of the CPS is much shorter relative to the SIPP, we only use these data to investigate the average gross mobility rate. In Section 2 of the main paper we conclude that the CPS and the (uncorrected) SIPP gross mobility series have very similar degrees of procyclicality. Another advantage of using the CPS is that it is easily accessible. We use the CPS data available via IPUMS.[25]

The PSID is also useful for several reasons: (i) It provides a longer panel dimension than the SIPP. (ii) We can compare our main results with the analysis of Kambourov and Manovskii (2008), who use this data set to provide a highly influential analysis of the occupational mobility patterns found in the US labor market. Therefore, in constructing our sample we closely follow Kambourov and Manovskii (2008, 2009). The details of this sample are described in the "Data Construction" section of this appendix. (iii) It allows us to evaluate the extend of coding error using retrospective coding as an alternative method. In particular, we use the PSID retrospective occupation-industry supplementary data files, which contain the re-coding the PSID staff performed on the occupational mobility records obtained during the 1968-1980 period. Since the 1981-1997 records were not re-coded and collected under independent interviewing, the earlier period can be used to construct "clean" occupational mobility rates and to analyse the effect of measurement error at the coding stage.

5.1 Occupational mobility in the CPS

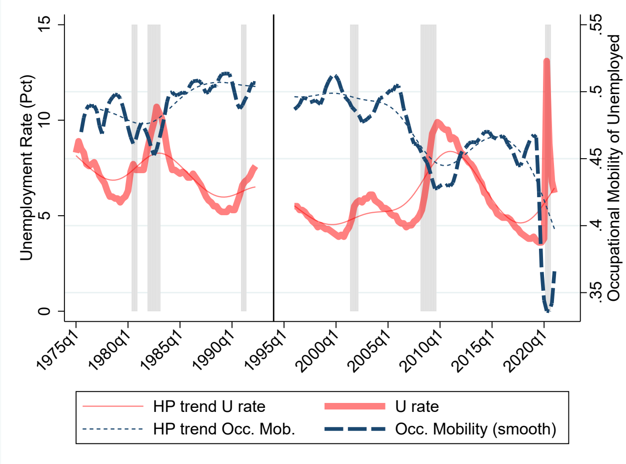
5.1.1 Extent of occupational mobility

To derive the average gross occupational mobility rate among the unemployed in the CPS we compare the occupation coded immediately before the worker became unemployed with the occupational code at re-employment. From this set of workers, the gross mobility rate is then computed as the proportion of occupational movers among all those who went through unemployment and subsequently found a job. We focus on the 22 major occupational groups of the 2010 SOC, which are provided homogenized for the entire 1976-2021 period by IPUMS. Using the full extent of our sample, we obtain an average occupational mobility rate of 47.5%. One concern could be that since in 1994 the CPS underwent a significant re-design, the occupational mobility rate should be affected. However, computing this rate for the period 1994-2021 yields 46.6%, hardly changing the extent of mobility.

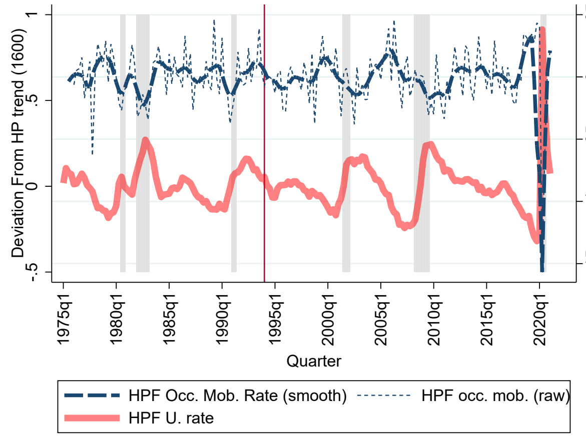
A perhaps more important concern is that in this sample we are including workers in temporary layoffs, who are very likely to return to their previous occupations and employers (see Fujita and Moscarini, 2017). This would bias downward the occupational mobility rate. To leave out temporary layoffs, we drop those unemployed classified as "job loser/on layoff" in the reported reasons for unemployment. This category corresponds to individuals who are on *temporary layoff*, with the expectation to be recalled with a specific date or within 6 months. Note that in this case we only use data from 1994 onwards as after the 1994 redesign we have available a homogenous series for "reasons for unemployment", without discrete jumps associated with shifting

[25] Our STATA do-file is available upon request, while the underlying data can be download from IPUMS, at `https://cps.ipums.org/cps/`

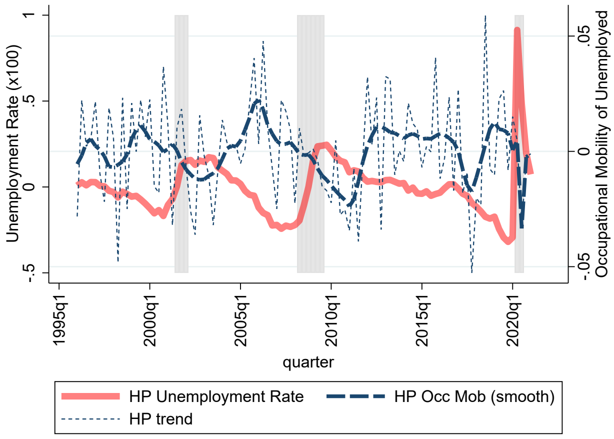
definitions/survey questions. Once we drop these temporary layoff workers, the average occupational mobility rate indeed increases to 56.9%. This value is very similar to the 55.0% we obtained from the uncorrected SIPP when using the 21 major occupational groups of the 2000 SOC and dropping the temporary layoffs (See Table 1 in Section 1 of this Appendix).



(a) Occup. mobility - smoothed series



(b) Occup. mobility - deviations from HP trend



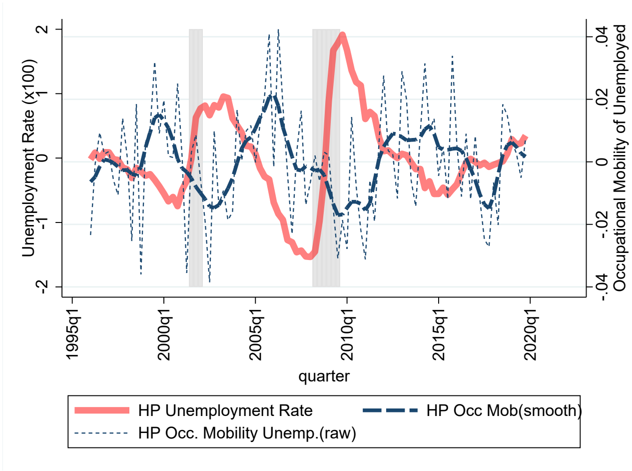
(c) Occup. mobility - no temp layoffs

Figure 25: Occupational mobility of the unemployed - CPS

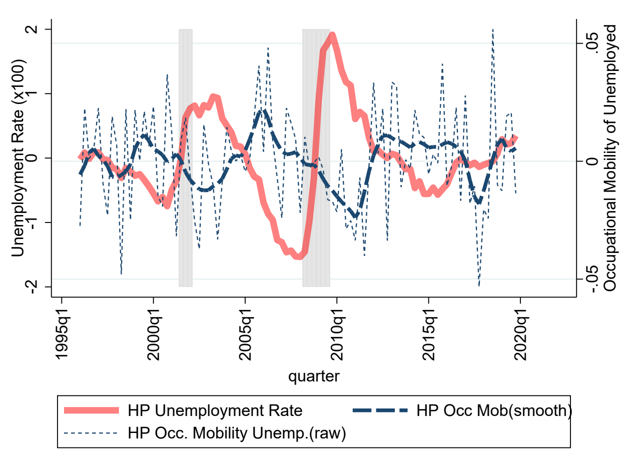
5.1.2 Cyclicality of occupational mobility

Figure 25a plots the time series of the average gross occupational mobility rate of workers hired from unemployment. To smooth out some of the noise in the quarterly observations, we present a lowess smoothed version in such a way that business cycle patterns remain visible. We also depict this series HP trend (filtered with parameter 1600). The redesign of the CPS in the mid-1990s means that the pre-1994 series might not be fully comparable to the post-1994 series. Following a conservative approach, we have HP filtered the entire 1976-2021 series but then removed observations for the period 1992-1995 to stay clear of the 1994 design break. To capture business cycle conditions, Figure 25a depicts the unemployment rate (and its HP trend with parameter 1600).

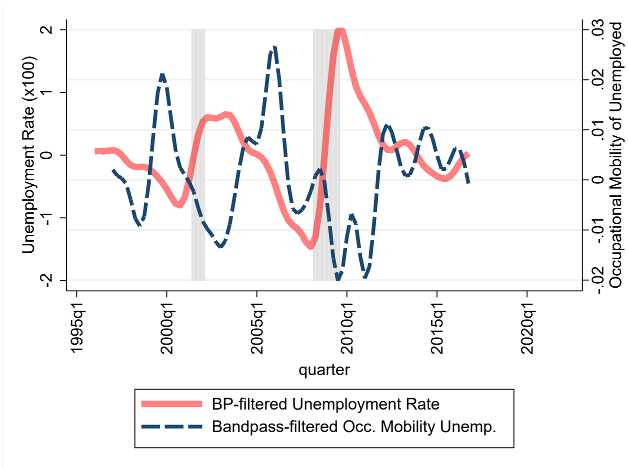
A comparison of these series reveals a procyclical pattern in occupational mobility. When the occupational mobility rate is above its trend, unemployment is typically below its trend. This is clearly visible around the last three recessions (including the Covid recession), but also in the double-dip recession in early 1980s. Figure 25b shows a similar conclusion using the HP-filtered unemployment and occupational mobility rates for the full sample. A reasonable concern is that the observed occupational mobility in the previous graphs is affected by an increased importance of temporary layoffs in recessions. Figure 25c considers the series without temporary layoffs and once again shows a procyclical occupational mobility rate.



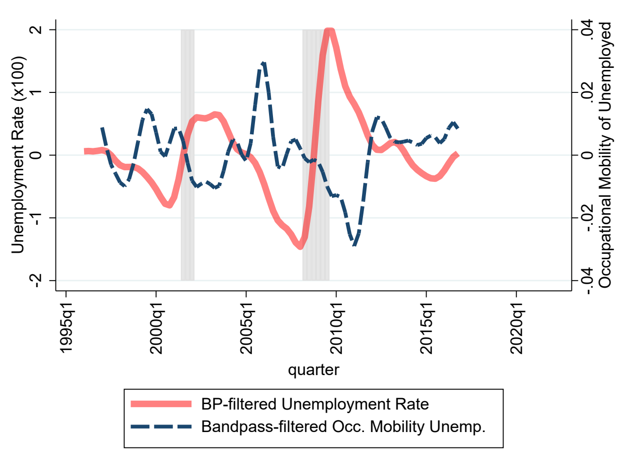
(a) HP-filter: Occup. mobility - up to 2019q4



(b) HP-filter: Occup. mobility - up to 2019q4, no temp layoffs



(c) Bandpass filter: Occup. mobility - up to 2019q4



(d) Bandpass filter: Occup. mobility - up to 2019q4, no temp layoffs

Figure 26: Occupational Mobility under Alternative Filtering

To further investigates the robustness of our findings, in Figures 26a and 26b we only consider the time series from 1994 up to the fourth quarter of 2019. In this way we focus on the period after the 1994 re-design and drop the large decrease in occupational mobility observed during the Covid recession. While this somewhat changes the de-trended behavior in the last five years of the series, it does not seem to meaningfully affect its procyclicality. In Figures 26c and 26d we re-do this exercise but now using bandpass filtering instead of the HP-filter to better deal with the noise in the raw data. If anything, the bandpass filtered series depicts even stronger procyclicality in the occupational mobility series, with clearly visible drops in occupational mobility during and in the aftermath of the 2001 and 2008 recessions.

Finally, Table 13 investigates the cyclicality of HP and bandpass filtered observations without additional smoothing. In particular, we regress the quarterly observations of the *de-trended log gross occupational mobility rate* on a constant and the de-trended log unemployment rate. We report the coefficient and standard error

Table 13: OLS regression - Cycalility of occupational mobility

Level and Responsiveness of Mobility to the Unemployment Rate					
	Level	Cyclical responsiveness			
	Ave.	HP Filtered (1600)		Band-Pass Filtered	
	Mob.	up to ’21	up to ‘19	up to ’21	up to ’19
Quarterly Occupational Mobility Rate, Hires from U (2010 MOG)					
All unemployed, 1976-	0.475	-0.223***	-0.105**	-0.105 ***	-0.104***
		(0.030)	(0.039)	(0.016)	(0.017)
All unemployed, 1994-	0.464	-0.254***	-0.103**	-0.096***	-0.104***
		(0.036)	(0.050)	(0.018)	(0.019)
Unemployed, not on temporary layoffs, 1994-	0.569	-0.044◇	-0.091*	-0.063**	-0.085***
		(0.024)	(0.037)	(0.019)	(0.017)

*** p-value<0.001; ** p-value<0.01; * p-value<0.05; ◇ p-value<0.1.

associated with the latter. We observe that, after taking out the HP-trend (with parameter 1600), occupational mobility decreases in times of higher unemployment. This relationship is statistically significant when using all the sample period or after the 1994 CPS re-design (with and without temporary layoffs). Using the bandpass filtered series confirms these results.

5.2 Occupational mobility in the PSID

5.2.1 Extent and cyclicality

Using these data, Supplementary Appendix A.3 documents that when conditioning the sample only on those who changed employers through non-employment (ENE), the gross occupational mobility rates are high across different levels of aggregation. In particular, the raw data shows that the average occupational mobility rates among the non-employed are 39.6%, 44.7% and 56.2% at a one-, two- and three-digit levels, respectively, for the period 1970-1980. The average occupational mobility rates for these workers for the period 1981-1997 are 41.1%, 47.4% and 60.1% at a one-, two- and three-digit levels, respectively.

To compare these mobility rates with the occupational mobility rate among all workers (employer movers and stayers pooled together), we divide the numerator of the ENE rate by the total number of employed workers at year t (the denominator of our overall rate). In this case we find that the occupational mobility rates through non-employment are 2.5%, 2.8% and 3.5% for the period 1970-1980 and 3.2%, 3.7% and 4.7% for the period 1981-1997, at a one-, two- and three-digit levels, respectively. These rates are consistent with the results of Kambourov and Manovskii (2008), who show that unemployed workers contribute 2.5% to the year-to-year occupational mobility rate of a pooled sample of employer movers and stayers based on a two-digit level. It is important to note, however, that the information presented in Kambourov and Manovskii (2008) *does not* allow us to infer that their 2.5% estimate is consistent with mobility rates among the non-employed of over 40%. To arrive to this conclusion one has to re-do Kambourov and Manovskii’s (2008) analysis as done here.

Table 6 in Supplementary Appendix A.3 shows the marginal effects obtained from probit regressions to further investigate the cyclicality of gross occupational mobility.[26] In these regressions the dependent variable

[26]These estimates are obtained using the personal weights provided by each survey, but similar results are obtained when using the unweighted data. We also obtained very similar results when using the linear probability model on weighted and unweighted data and when using robust standard errors and clustering standard errors at a yearly level.

takes the value of one if the worker changed occupation and zero otherwise. We control for age, education, full or part-time work, occupation of origin, region of residence, aggregate and regional unemployment rates, a quadratic time trend, number of children and the impact of retrospective coding.[27] Our results show that gross occupational mobility of the non-employed is also procyclical.

These results corroborate the ones obtained using the SIPP. Hence, we find that across data sets the probability of an occupational transition among the unemployed (or non-employed) is high and increases in expansions and decreases in recessions. The procyclicality of gross occupational mobility among the unemployed complements the result found by Kambourov and Manovskii (2008), who show that the year-to-year occupational mobility rate of a pooled sample of employer movers and stayers is procyclical. In principle there is no reason to expect that the procyclical pattern these authors find in the overall occupational mobility rate would translate to the occupational mobility rate for the unemployed. Indeed, as discussed above, the latter contributes a small proportion to the overall rate.

5.2.2 Repeat mobility

In the SIPP analysis we found that a large proportion of workers who experienced an occupational change in their previous non-employment spell also experienced an occupational change at the end of their current non-employment spell. Similarly, we found that a large proportion of workers who did not change occupation in their previous non-employment spell experienced an occupational change at the end of their current non-employment spell.

A potential concern with the SIPP structure is that it does not follow workers for a long enough period. This might generate a bias in the repeat occupational mobility statistics as it will disproportionally capture: (i) those workers with shorter non-employment spells, even though we leave enough time towards the end of the SIPP panel to try to capture longer non-employment spells; and (ii) those workers with short employment durations between consecutive non-employment spells. To analyse the extent of this bias we re-compute the repeat mobility statistics using the PSID based on the sample used to construct the ENE occupational mobility rate depicted in Figure 3.b in Supplementary Appendix A.3. Since these data sets allow us to follow the same workers for a longer period of time, we expect (i) and (ii) to have a much smaller impact.

Table 14 shows the repeat mobility statistics at a one-, two- and three-digit level of aggregation, using the 1970 SOC. The proportions are based on weighted data, but similar proportions are obtained using unweighted data. For each level of aggregation we divide the sample by whether a worker was an occupational stayer or an occupational mover after the first non-employment spell. We then compute the proportion of stayers (movers) who, after a subsequent non-employment spell, did not change occupation and the proportion who changed occupation. For each level of aggregation, the first two rows show the proportions for stayer- stayer and stayer-mover. These proportions add up to one. Similarly, the second two rows show the proportions for mover-stayer and mover-mover. Further, the columns labelled "Occ. Mobility" consider workers who only changed occupations. Since these statistics are based on raw (uncorrected) data, the propensity to change occupations would be biased upward. As a way to deal with the latter, we consider simultaneous occupation and industry mobility and re-compute the repeat mobility statistics. These are presented in the columns labelled "Occ. + Ind. Mobility". As discussed in Section 1 of this appendix, conditioning on simultaneous occupation and industry mobility provides an alternative way to correct for coding errors. In particular, we consider a worker to be an

[27] As in Kambourov and Manovskii (2008), the education indicator variable takes the value of one when the worker has more than 12 years of education and zero otherwise. This is to avoid small sample problems if we were to divide educational attainment in more categories. The regional unemployment rates are computed using US states unemployment rates.

Table 14: Repeat Mobility - PSID 1968-1997

	All workers		Male workers	
	Occ. Mobility	Occ.+Ind. Mobility	Occ. Mobility	Occ.+Ind. Mobility
1-digit				
Stayer - Stayer	67.3	77.2	67.4	77.0
Stayer - Mover	32.7	22.8	32.6	23.0
Mover - Stayer	46.9	58.8	45.8	57.8
Mover - Mover	53.1	41.2	54.2	42.2
2-digits				
Stayer - Stayer	61.9	69.9	62.8	71.0
Stayer - Mover	38.1	30.1	37.2	29.0
Mover - Stayer	40.6	49.7	40.5	48.8
Mover - Mover	59.4	50.2	59.5	51.2
3-digits				
Stayer - Stayer	54.3	61.2	57.8	64.1
Stayer - Mover	45.7	38.8	42.2	35.9
Mover - Stayer	25.9	33.2	27.5	34.8
Mover - Mover	74.1	66.8	72.5	65.2

Note: Total number of observations among all workers (male) = 3,261 (2,467).

occupational mover if and only if he/she reported a change in occupation and a simultaneous change in industry at the same level of aggregation, where industry changes are based on the 1970 census industries codes.[28]

The PSID shows a very similar picture to the one obtained from the SIPP. There is a high proportion of workers who changed occupation after a non-employment spell and once again changed occupations after a subsequent non-employment spell. Out of all those workers who were occupational movers after a non-employment spell in the raw data, between 53% (at a one-digit level) and 74% (at a three-digit level) moved occupations once again after a subsequent non-employment spell. There is also an important proportion of workers who did not change occupation after a non-employment spell, but did change occupations after a subsequent non-employment spell. Out of all those workers who were stayers after a non-employment spell, between 33% (at a one-digit level) to 48% (at a three-digit level) moved occupations after the subsequent non-employment spell.

Conditioning simultaneous occupation and industry changes does not drastically change these results. In this case, out of all those workers who were occupational movers after a non-employment spell, between 41% (at a one-digit level) and 67% (at a three-digit level) moved occupations once again after a subsequent non-employment spell. Out of all those workers who were stayers after a non-employment spell, between 23% (at a one-digit level) to 33% (at a three-digit level) moved occupations after the subsequent non-employment spell. That is, conditioning on simultaneous occupation and industry changes, decreases by about 10 percentage points the occupational mobility rates, but still shows a high propensity for repeat mobility among the non-employed.

[28]These repeat mobility statistics are calculated based on up to five consecutive non-employment cycles, where a cycle is constructed as non-employment, employment, non-employment, employment sequence. The number of observations in our repeat mobility sample is then the product of the number of cycles per individual. The majority of workers, however, experience only one cycle, which make up for 80% of the total number of observations. We find that our results do not change if we were to compute these same statistics based only on workers' first cycle.

6 Self-reported retrospective occupational mobility

In this section we propose an alternative way to analyse the occupational mobility patterns of the non-employed that is not subject to coding errors. In particular, we use information on workers' self-reported employer and occupational tenure obtained from the SIPP core panels and topical modules. For the majority of SIPP panels the first topical module asks "for how many [months/years] has [the worker] done the kind of work [he] does in this [current] job", or a variation of it.[29] In addition, it records the start date with the *current* employer *and* the start and end dates of the most recently finished employer spell previous to the panel.[30]

Using this information we restrict attention to those workers whose completed non-employment spells lasted between one and twelve months. This restriction helps us capture a group of workers who have not lost their attachment to the labour market even though they might be categorised as non-participants at some point during the spell[31] Below, we also focus on subsets of this group that e.g. are observed with periods of unemployment. To determine whether or not one of these workers changed occupations, we compare the employer tenure with the occupational tenure information. In particular, out of all those workers who found their current job out of non-employment, we label a worker as an occupational mover when his/her occupational tenure equals (or is very close to) his/her employer tenure and as an occupational stayer when his/her occupational tenure is (sufficiently) greater than his/her employer tenure.[32] We then compute the occupational mobility rate by dividing the number of non-employed workers who re-gained employment and changed occupation over the number of non-employed workers who re-gained employment.

6.1 The extent of self-reported occupational mobility

Table 15 shows the extent of occupational mobility of the non-employed using four different samples. The first column (overall) considers all employed workers who (i) went through a spell of non-employment before starting with the current employer, provided that the non-employment spell occurred during the last ten years; (ii) have spent more than two years in the labor force, (iii) have finished their previous job at least one year after entering the labor market and (iv) have held their previous job for at least twelve months.[33] These restrictions are made to focus on those who have had meaningful employment before any spell of non-employment, so we are considering changes of occupation, rather than a start within an occupation at the beginning of working life. These restrictions also help with inferring occupational mobility from occupational tenure.

The second column (attached workers) restricts the "overall" sample to those spells in which the worker en-

[29]This question is asked in topical module in the 1984, 1987, 1990, 1991, 1992 and 1993 panels. In the 1996, 2001, 2004 and 2008, the question is in the core waves and makes explicit reference to the entire working life, while invoking 'occupation'/'line of work' rather than 'kind of work': "Considering entire working life, how many years has [the worker] been in this occupation or line of work?".

[30]The question referring to the current employer is "when did [the worker] start working for [explicit employer name]". The wording means that employer recalls are not (or, at least, should not be) recorded as starts of employment. In the 1996-2008 panels, the question also refer to "... the month/year when [worker's name] began employment with [employer name]".

[31]For most of the panels we obtain the duration of the non-employment spell by subtracting the date in which the job with the previous employer ended from the day the re-employment job started with the current employer. In the 1984 panel the duration of the non-employment spell is asked directly. In the 2004 and 2008 panels we can only observe a lower bound of the non-employment spell as we only have information on the year the job with the previous employer ended. For this reason some of our analysis (see below) will not use the 2004 and 2008 panels. Note that the mobility reported in the 1984 panel lies

[32]When occupational tenure does not exactly match the employer tenure due to, potentially, recall errors, we consider several plausible adjustments to identify occupational movers and stayers. We discuss these in the next section.

[33]We have excluded workers who have imputed start and dates of the previous job in the data, or an imputed start date of the current job. In case ambiguity remains about occupational changing, we have excluded these workers as well. If we take a strict approach to assignment of mobility within this subset of workers, mobility is closer to 50% than in the unambiguous group. Hence, we consider the exclusion of ambiguous observations to yield conservative levels of self-reported occupational mobility.

tered non-employment because they were laid off, discharged, a temporary job ended, indicated dissatisfaction with the previous job, or because of a non-family/non-personal ("other") reason.[34] We consider these workers to be attached to the labor market as they did not leave their jobs for reasons that indicate leaving the labor force.[35] Given that the above restrictions could not be applied across all panels, these two samples only rely on the topical modules of the 1984, 1987-88 and 1990-1993 SIPP panels.

Table 15: Self-reported occupational mobility rates

	(a) Overall 1984-1993	(b) Attached workers 1984-1993	(c) Recent hires 1984-2001	(d) Hires after U 1984-2001
All workers	0.446	0.434	0.372	0.397
	(0.007)	(0.008)	(0.013)	(0.019)
Males	0.467	0.437	0.393	0.439
	(0.010)	(0.012)	(0.018)	(0.026)
Females	0.429	0.433	0.352	0.343
	(0.010)	(0.012)	(0.017)	(0.026)
HS dropouts	0.476	0.476	0.409	0.507
	(0.021)	(0.025)	(0.032)	(0.046)
HS grads	0.478	0.486	0.405	0.405
	(0.013)	(0.015)	(0.021)	(0.031)
Some college	0.437	0.413	0.342	0.347
	(0.014)	(0.017)	(0.024)	(0.037)
College grads	0.412	0.380	0.330	0.350
	(0.013)	(0.015)	(0.026)	(0.042)
20-30 years old	0.555	0.548	0.441	0.476
	(0.015)	(0.018)	(0.025)	(0.039)
35-55 years old	0.387	0.385	0.323	0.347
	(0.010)	(0.012)	(0.018)	(0.027)

Standard Errors in parentheses. Sample weights: using person weights of SIPP panels within panel, normalized such that average weight of observations across all panels is one, while cross-sectionally weights make the sample representative).

The third column (recent hires) considers those workers whose re-employment job started within six months prior to the time of interview and had a job tenure of at least 12 months before transiting into non-employment. The last restriction enable us to more confidently distinguish the current employer's tenure from the sum of the current and previous employer's tenure, which reduces ambiguous cases when inferring occupational mobility from self-reported occupational tenure. The cost, obviously, is a smaller sample of workers, as logically we can include only workers with a low job tenure at the moment that the retrospective occupational questions are asked. Note also that this sample is selected differently, columns (c) naturally samples more those in the

[34]Including "Other" (but excl.: "other, family reasons") does not change our conclusions.

[35]For the "overall" and "attached" samples, we only count an occupational move at the end of the non-employment spell when the current job started within six months of the start of the occupation and the previous job lasted for at least one year. For a worker to be considered an occupational mover in these samples, the current job starting date must be within a six months interval around the implied start of the occupation and the previous job must have lasted at least a year. Further, given that occupational tenures above twelve months are reported in full years it was difficult to assess an occupational change when a relatively long tenure in the current job is preceded by a short tenure in the previous job. We take a conservative approach and categorise the latter cases as a employer move without an occupational change.

population who are more likely to experience non-employment spells. The fourth column ("Hires after U") uses an even more restricted sample of "recent hires" for whom the employment status is observed within the core waves and who were unemployed for at least one month prior to re-gaining employment. Since the retrospective question is asked in the early waves of a panel, this leaves relatively little room to observe the unemployment status of those workers in the core wave dataset (which is a requirement to be included in this group). For these samples we use the 1984 up to 2001 panels.[36]

For a worker to be considered as an occupational mover, the current job starting date must be within a one month interval around the implied start of the occupation, or before.[37] Across all these sample we once again find that non-employed workers' self-reported occupational mobility is high. Combining retrospective employer and occupational tenure information implies that roughly about 40% of non-employed workers accept jobs in a new line of work. Average mobility of recently hired workers in columns (c) and (d), which uses recall of more recent non-employment spells, and allows us to distinguish tenures more clearly, is broadly in line with columns (a) and (b), where the former have a reported mobility in 35-42% range, versus 42-46% for all workers in columns (a) and (b). Retrospective measures of occupational mobility do subtly differ from the ones derived by comparing occupational codes, first because they reflect the workers' own assessment of 'line of work'/occupations, rather than the Census', but also because the occupational tenure in question can reasonably refer to jobs even before the previous job. Nevertheless, we find that the extent of occupational mobility obtained from individuals reporting a "different kind/line of work" aligns very well with the adjusted rate of occupational mobility for the non-employed obtained by comparing the major occupations of the 2000 SOC or the 1990 SOC described in Section 1.1 of this appendix. This confirms that, after a gap in their employment history, about two out of five workers ends up in a different line of work than they had before.[38]

Table 15 shows that the retrospective occupational mobility rate is also high across several demographic groups. In particular, both male and female workers have mobility rates around 40%, with an average mobility rate across the four samples that is higher for males. Interestingly, in some measures (for example in column (d)) this gap appears meaningful, but on the other hand is smaller when considering women who were classified as "attached" (in column (b)). Occupational mobility upon re-employment is substantial for workers from all education groups, though again we can discern an education gradient, with college workers more often taking re-employment in a line of work they held before. Finally, we find that the perhaps clearest differences in the occupational mobility rates by demographic characteristics is across age groups, where the mobility rate decreases significantly as workers get older. Nevertheless, the mobility rate of prime-aged workers also remains high, between 32.5 and 39%.[39]

It is important to note some differences across panels. For example, how the duration of non-employment was solicited: directly as a duration or implied by the starting and end dates of a job. In the 1984 panel

[36] For the most recent two panels, 2004 and 2008, we can find a lower bound and an upper bound on the non-employment spell, but typically not a precise monthly duration. When restricting the 1996 and 2001 panels to provide the same amount of information as the 2004 and 2008 panels (by ignoring start and end months of the previous jobs), we find that the loss of information appears to be small.

[37] Here we use a one month 'margin' to reflect one month of rounding error. The impact of including an additional margin of one month is small, ranging from 0 to 3 percentage points change in the occupational mobility rate at most. Below we use an alternative measure to check the robustness of our measure.

[38] The retrospective question, is consistent with the interpretation of occupational mobility in the main paper, where an occupational change is a start of a new career. In the calibration, this occurs in 44% of unemployment spells, according to the retrospective question, workers start something they have not done before in about 40% of the cases.

[39] The relative drop across age groups is somewhat stronger in our retrospective measure than in the occupational mobility based on comparing codes, falling between 12 to 16 percentage points from young to prime-aged workers. A potential explanation is the difference between comparing occupational codes after an unemployment spell with the occupational code just before, rather than asking whether, at some point in their entire working life, workers have had a line of work similar to the current one. The relevance of this difference, intuitively, seems larger for older workers.

individuals are asked explicitly for the duration of the non-employment spell and the tenure on the job, rather than reporting start and end months of employment, as done in more recent panels. Another difference is that the labor market topical module is asked in the interview of wave 2 between 1987 and 1991 panels, but from the 1992 panel onwards in the interview of wave 1. The SIPP was redesigned in 1996 panel and carried over to 2001 panel. Generally, a large part the new design of 1996 is carried forward till the 2008 panel. However, in the labor market topical module there are changes that lead the 2004 and 2008 panels to differ from the 1996 and 2001 panels and make it much harder to determine the combination of non-employment duration and occupational mobility. For this reason these former panels are omitted from the analysis. The setup of the labor market history questionnaire is perhaps the most distinct in the 1984 panel; however, it also contains the most direct question on the employment gap. Implied occupational mobility in this panel is somewhat higher than in other panels, while its sample size is relatively large relative to the other panels in the 1980s. Excluding it from the analysis means that the average implied occupational mobility across the remaining panels is lower, typically, by 1-4 percentage points. For example, mobility of all workers (pooled) in the first column, drops to 42.9%. Nevertheless, even excluding this panel, mobility is high, and broadly shared across many demographic groups.

6.2 Self-reported occupational mobility and non-employment spell duration

We now turn to analyse the mobility-duration profile that arises from the retrospective measure of occupational mobility. Table 16 reports the results of linear probability models based on the implied occupational mobility rates obtained from self-reported occupational tenure as a function of the time in non-employment between jobs and a set of controls. These include an indicator variable for gender, a quadratic in age and categorical variables for the completed duration of the non-employment spell (where we take 1-4 months as the baseline category) and for workers' educational levels (where we take high school graduate as the baseline category). We also add controls for previous and current occupational tenure and occupation of origin and destination, include a linear time trend and grouped-panel fixed effects to control for differences between SIPP panel setups.

In panel A we consider the retrospective information on the (most recent) spell of non-employment of all workers, if they have gone through non-employment after entering the labor force. We observe that self-reported occupational mobility increases with non-employment duration, roughly at a rate of one percentage point per month. These results are well in line with the results presented in the main text, for occupational mobility according to changes in the occupational code.

In the first column we relate the probability of self-reported change in occupation to the reported time between employment. We only allow for a linear time trend in occupational mobility. In the second column, we add controls for gender, race, a quartic in age and marital status, and grouped panel fixed effects. This hardly affects the slope of the mobility-duration profile. In the third column, we include the occupational code on the job previous to the non-employment spell. Interestingly, the earlier panels of the SIPP, up to 1993, include both a question on occupational tenure and the occupation code of this previous job. Controlling for the 'source' occupation reduces slightly the point estimate of the mobility - duration profile, but not in a significant way. In the fourth and fifth columns we repeat these regressions for the smaller subset of workers who do not separate for "personal reasons", i.e. our "attached" sample discussed above. Again, we see that a broadly similar picture appearing, again without much difference when controlling for demographics, grouped panel fixed effects and source occupations.

In panel B, we concentrate on recent hires, i.e. those who started a job, after non-employment, within 6 months of the interview on their labor market history. We apply the same sample selection criteria as discussed

Table 16: Self-reported Occupational Mobility and Non-employment Duration

Panel A. Retrospective Occ. Mobility of All Workers (1984-1993 panels)					
	(i) Overall	(ii) Overall	(iii) Overall	(iv) Attached	(v) Attached
no obs.	5219	5219	5170	3656	3622
NE duration	0.0109***	0.0112***	0.0096***	0.0095***	0.0094***
(s.e.)	(0.0024)	(0.0024)	(0.0023)	(0.0028)	(0.0028)
linear time trend	X	X	X	X	X
panel FEs		X	X		X
demogr. controls		X	X		X
source occup.			X		X

Panel B. Retrospective Occ. Mobility of Recent Hires (1984-2001 panels)					
	(vi) All Hires	(vii) All Hires	(viii) Hires after U	(ix) Hires After U	(x) Hires After U*
no. obs	1549	1549	692	692	679
NE duration	0.0062	0.0068*	0.0110*	0.0107*	0.0114*
(s.e.)	(0.0039)	(0.0039)	(0.0062)	(0.0061)	(0.0063)
linear time trend	X	X	X	X	X
panel FEs		X		X	
demogr. controls		X		X	

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Observation weighted by person weights within panel, by number of total observations per panel across panels. "Recent Hires" means hired within 6 months of interview. "Hires After U*" refers to an alternative measure of occupational mobility, where everyone with occupational tenure weakly less than current job tenure (allowing for one month of ambiguity) is a mover, while everyone with an occupational tenure larger than current job tenure + 4 months is a stayer.

above. The smaller sample size means that the gradients of mobility with duration are more imprecisely estimated. Nevertheless, a similar broad (but less precise) conclusion can be drawn. There is a positive slope of mobility with duration that is not too steep, with point estimates well in line with panel A and the occupational code-driven mobility in the main text. Although care has to be taken, given the size of the standard errors, we observe that the point estimates of the slope of the mobility-duration profile of all workers hired after non-employment is somewhat lower, while for those who have been unemployed the point estimates of the slope is rather close to panel A of Table 16, and the main text. Although not shown here, the coefficients on education, age, gender paint a similar relative picture as Table 15.

The above results show that occupational mobility is high at any non-employment duration and exhibits a moderate increase with the duration of the non-employment spell, where between 50% and 60% of workers with at least 9 months of non-employment duration return to previous occupations at re-employment. These are very similar characteristics as the ones found in our main analysis based on the comparison of occupational codes. Once again we find a prominent decline in the probability of an occupational change with age. We also find small differences in the probability of an occupational change between males and females and across education levels, with the exception of the group of recently hired from unemployment (as in Table 15). Note that including indicator variables for the occupations of origin and destination (as done in 1b) does not alter greatly the outcomes for non-employment spell durations and other coefficients, with the exception of the point estimates for the education coefficients. This suggests that specific occupational identities are not the main drivers of both non-employment duration and occupational mobility of workers. This is once again in line with the conclusions of Section 1.5 in this appendix.

6.3 The cyclicality of self-reported occupational mobility for the non-employed

We now turn to investigate the cyclicality of our occupational mobility measure. When comparing the occupational mobility of workers recently hired from non-employment across different panels, Figure 27 suggests a procyclical pattern. This figure depicts, for each panel, the occupational mobility implied by the answer to the occupational tenure question of those who were recently hired after a period of unemployment. Note that the retrospective work history questions are only asked at the beginning of a panel, so if we were to focus on recent hires we would not have a complete quarterly time series. Rather, we measure this mobility at various points over the business cycle. In the graph, we show the observations in the quarter in which the “recent hiring" typically took place for each panel. One can observe that, with the switch from overlapping panels to sequential panels in 1996, the length between the points for which we have observations widens significantly over time.

We focus on those panels which share their survey design with at least one other panel, so that we can also compare within survey design. In particular, the 1987-1993 panels share the same retrospective questioning, but we separate the 1990-1993 panels because we can use the re-coded firm identities to reduce measurement error in these panels. However, this has only a very minor impact on the recent hires, as firm identifiers do not play a large role in extracting the implied occupational mobility from self-reported occupational tenure. Potentially more important is that the timing of the retrospective question changes from wave 2 to wave 1 between the 1990-91 panels and the 1992-93 panels. This means that we observe less of the non-employment spell inside the core waves (and consequently have less monthly observations in which we could distinguish unemployment), which may have relevance for our “hires from unemployment” measure. As noted, from the 1996 panel onwards, the SIPP was redesigned such that we can only use the occupational tenure question to gauge occupational mobility of those who are recently hired.[40]

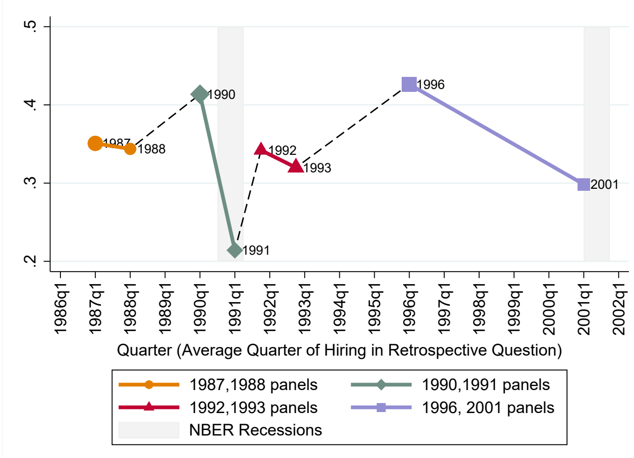


Figure 27: Retrospective self-reported occupational mobility of recent hires (after u), by panel

The first observation from Figure 27 is the procyclicality of occupational mobility over the entire time series. In times of low unemployment such as 1996 but also late 1989 to early 1990, self-reported occupational mobility is high, while in times of recession (high, or at least rather rapidly increasing unemployment) as in late 1990 to early 1991 and 2001, mobility is lower than in preceding “good times”. Second, to assuage concerns about changes in survey design, we observe that the aforementioned observation occurs precisely across panels that share the same survey design, i.e. the 1990-1991 panels, and the 1996-2001 panels.

[40]The 1984 has a different design that is not shared with any other panel, and is omitted from the picture but is included in the regressions below.

Table 17: The cyclicality of the probability of an occupational change

Panel A: Recent Hires from Nonemployment (1984-2001)								
	(i) occ.move	(ii) occ.move	(iii) occ.move	(iv) occ.move	(v) occ.move	(vi) occ.move*	(vii) occ.move*	(viii) occ.move*
no obs.	1546	1546	1546	1546	1546	1507	1507	1507
HP-filt.log(U)	-0.288***	-0.315***	-0.291**	-0.323***	-0.587***	-0.310***	-0.383***	-0.648**
(s.e.)	(0.103)	(0.085)	(0.112)	(0.098)	(0.209)	(0.108)	(0.101)	(0.215)
panel FE v1		X		X			X	
panel FE v2					X			X
demog. ctrls			X	X	X		X	X

Panel B: Recent Hires after *Unemployment* (1984-2001)								
	(ix) occ.move	(x) occ.move	(xi) occ.move	(xii) occ.move	(xiii) occ.move	(xiv) occ.move*	(xv) occ.move*	(xvi) occ.move*
no obs.	689	689	689	689	689	676	676	676
HP-filt.log(U)	-0.360*	-0.270	-0.342*	-0.246	-0.765***	-0.418**	-0.325	-0.828***
(s.e.)	(0.184)	(0.164)	(0.189)	(0.183)	(0.176)	(0.184)	(0.196)	(0.188)
panel FE v1		X		X			X	
panel FE v2					X			X
demog. ctrls			X	X	X		X	X

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable occ.move* is our alternative mobility indicator that excludes cases where occupational between 1-4 months longer than current job tenure, while previous job tenure is larger than 12 months. All regressions include a linear time trend. Demographic controls are a quartic in age, a gender dummy, race and education dummies. *panel FE v1* has dummies for the following groups of panels, {1984}, {1987, 1988}, {1990, 1991, 1992, 1993 }, {1996, 2001}; *panel FE v2* for {1984}, {1987, 1988}, {1990, 1991}, {1992, 1993 }, {1996, 2001} Observation weighted by person weights within panel, by number of total observations per panel across panels. Standard errors clustered by quarter.

We confirm the procyclicality of occupational mobility using regression analysis. Table 17 shows the estimates of a linear probability model, were the dependent variable again takes the value of one if the worker reported a new line of work and zero otherwise. Our baseline is again occupational mobility as inferred from the occupational tenure question, where all those who have an occupational tenure higher than the current job tenure (allowing for a month of ambiguity) are considered stayers. In our alternative measure (denoted with $\star$, in columns (vi-viii) and (xiv-xvi)), we drop those observations who were coded as stayers but reported an occupational tenure within four months of the current job tenure.

When only controlling for a linear time trend, in columns (i) and (ix), we observe that times of high unemployment, as captured by positive deviations from HP-filtered log unemployment trend, are times of lower self-reported occupational mobility. This is also observed for the alternative measure of self-reported occupational mobility, in columns (vi) and (xiv). In panel A, we take all recent hires, while in panel B we consider all recent hires for whom we observed a period of unemployment. Naturally, the number of observations in panel B is lower, which makes our inference harder. Nevertheless, we also observe a procyclical response of self-reported occupational mobility, statistically significant at the 10%, having clustered standard errors at the quarter level. Restricting stayers to have an occupational tenure more than four months longer than current job tenure leads to a slightly stronger observed procyclical responsiveness.

As noted above, the SIPP's survey design changed over time, which may affect our results. To address this issue, we consider two variants of dummies for sets of panels that share the same survey design. As noted above, the 1990 to 1993 panel share the same survey design apart from a change of the timing of the retrospective question, from wave 2 to wave 1. This can be relevant for observing unemployment during the preceding non-employment spell. Therefore, in the first version (v1), we add four dummies for grouped panels, one for the 1984 panel, one for both 1987 and 1988 panel, one for the 1990-1993 panels, and one for the 1996-2001 panels. In the second version (v2), we add two separate dummies for the 1990-1991 panels and the 1992-1993 panels.

We observe that the responsiveness to the unemployment is much stronger in (v2). This responsiveness is driven by the variation within pairs of two panels, which puts a lot of weight on the behavior of the 1990 vs 1991 panel (and also on the 1996 vs 2001) panel, and less on the lower-frequency (but still business-cycle) behavior of the time series of observations in the subsequent recovery of the 1991 recession *as measured relative* to the pre-recession 1990 panel and full-recession 1991 panel. While these responses are statistically significant in both panels, we find it conservative to prefer *v1* and consider results in these two panels on a similar base to those in 1992 and 1993 panels, and estimate the responsiveness of mobility also taking into account that response to unemployment in the recovery of the 1991 recession.

Overall, controlling for grouped panel effects (v1) does not change the estimated empirical responses much relative to e.g. columns (i) and (ix), while grouped panel effect (v1) leads to stronger procyclical responses. Comparing the estimates in panel B to panel A we do not observe meaningful differences in the point estimates, even though the underlying samples are smaller, with this naturally affecting the precision of our inference. Controlling for demographic characteristics does not change the empirical responsiveness to cyclical unemployment, fully in line with the results of the occupational code-based analysis. Taken together, it appears clear that occupational mobility of recent hires from non-employment, inferred from retrospective questions on occupational tenure and job history, is procyclical. For those hired after unemployment, the evidence points in the same direction, though tends to be statistically weaker as a result of a low numbers.

Cyclical Shift of the Mobility-duration profile Finally, we investigate whether the self-reported occupational mobility profile with non-employment duration shifts down with recessions and whether on average exhibits a similar slope as in the pooled cross-sectional sample. Table 18 shows that this is indeed the case. We observe that the modest positive slope on the non-employment duration is preserved when including the HP-filtered log of the unemployment rate. Controlling for non-employment duration largely leaves the empirical cyclical responsiveness unaffected. This result again mimics the result for the code-based mobility measures as they change with duration and the cycle.

6.4 Retrospective Self-reported Occupational Mobility – Conclusion

In this section, we have investigate occupational mobility after non-employment spells using very different data than in the main text. None of the occupational information used in the occupational code-based measures of the main text has been used in the measures in this section. Further, in the code-based measures of the main text, census coders are the judge of occupational change, while in the retrospective occupational tenure, this judgement is made by the interview subject. It is then comforting to observe that both measures line up well. First, according to workers, they are starting in a new line of work after nonemployment in about 40% cases. Second, with a longer nonemployment duration comes an increased tendency to change one's line of work. However, this tendency is modest, around 6 p.p. higher after 6 months of unemployment, fully consistent with the occupational-code results in the main text and in Section 1 of this appendix. Third, when cyclical unemployment is high, self-reported occupational mobility tends to be cyclically low. Fourth, controlling for the business cycle, we still observe a modest increase of self-reported mobility with nonemployment duration, again keeping with the pattern of code-based occupational mobility documented in the main text.

Table 18: The cyclicality of the probability of an occupational change

Panel A: Recent Hires from Nonemployment (1984-2001)								
	(i) occ.move	(ii) occ.move	(iii) occ.move	(iv) occ.move	(v) occ.move	(vi) occ.move*	(vii) occ.move*	(viii) occ.move*
no obs.	1546	1546	1546	1546	1546	1507	1507	1507
HP-filt.log(U)	-0.270**	-0.304***	-0.271**	-0.311***	-0.583***	-0.291**	-0.370***	-0.660***
(s.e.)	(0.104)	(0.082)	(0.113)	(0.095)	(0.201)	(0.108)	(0.100)	(0.215)
NE duration	0.006**	0.006**	0.007**	0.007**	0.007**	0.006**	0.007**	0.007**
(s.e.)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
panel FE v1		X		X			X	
panel FE v2					X			X
demog. ctrls			X	X	X		X	X

Panel B: Recent Hires after *Unemployment* (1984-2001)								
	(ix) occ.move	(x) occ.move	(xi) occ.move	(xii) occ.move	(xiii) occ.move	(xiv) occ.move*	(xv) occ.move*	(xvi) occ.move*
no obs.	689	689	689	689	689	676	676	676
HP-filt.log(U)	-0.349*	-0.271	-0.333*	-0.250	-0.877***	-0.405**	-0.327	-0.890***
(s.e.)	(0.187)	(0.175)	(0.189)	(0.192)	(0.175)	(0.188)	(0.206)	(0.188)
NE duration	0.013**	0.013**	0.014**	0.013**	0.015**	0.014**	0.013**	0.014**
(s.e.)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
panel FE v1		X		X			X	
panel FE v2					X			X
demog. ctrls			X	X	X		X	X

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable occ.move* is our alternative mobility indicator that excludes cases where occupational between 1-4 months longer than current job tenure, while previous job tenure is larger than 12 months. All regressions include a linear time trend. Demographic controls are a quartic in age, a gender dummy, race and education dummies. *panel FE v1* has dummies for the following groups of panels, {1984}, {1987, 1988}, {1990, 1991, 1992, 1993 }, {1996, 2001}; *panel FE v2* for {1984}, {1987, 1988}, {1990, 1991}, {1992, 1993 }, {1996, 2001} Observation weighted by person weights within panel, by number of total observations per panel across panels. Standard errors clustered by quarter.

Once again our estimates show that the probability of an occupational change for the non-employed is procyclical. This holds true for both samples and with or without controlling for the duration of the non-employment spell. In particular, for the sample of recent hires that were unemployed for at least one month before re-employment, we still observe the moderate increase in the probability of an occupational mobility with the duration of non-employment. Likewise, controlling for destination occupations, we also find strong procyclicality in the probability of an occupational change. This suggests that the procyclicality is not driven by shifts in the occupational destinations over the business cycle. This is once again inline with the results of Section 4 of this appendix.

7 Data Construction

7.1 Survey of Income and Program Participation

The Survey of Income and Programme Participation (SIPP) is a longitudinal data set based on a representative sample of the US civilian non-institutionalized population. It is divided into multi-year panels. Each panel comprise a new sample of individuals and is subdivided into four rotation groups. Individuals in a given rotation group are interviewed every four months such that information for each rotation group is collected for each month. At each interview individuals are asked, among other things, about their employment status as well as their occupations and industrial sectors during employment in the last four months.[41]

The SIPP offers a high frequency interview schedule and aims explicitly at collecting information on worker turnover. Further, its panel dimension allows us to follow workers over time and construct uninterrupted spells of unemployment (or non-employment) that started with an employment to unemployment transitions and ended in a transition to employment. Its panel dimension also allows us to analyse these workers' occupational mobility patterns conditional on unemployment (or non-employment) duration and their post occupational mobility outcomes as outlined in Section 2 in the main text.

Survey design and use of data. We consider the period 1983 - 2013. To cover this period we use 13 panels in total: the 1984-1988, 1990-1993, 1996, 2001, 2004 and 2008 panels. For the 1984-1988 and 1990-1993 panels we have used the Full Panel files as the basic data sets, but appended the monthly weights obtained from the individual waves (sometimes referred to as core wave data). Until the 1993 panel we use the occupational information from the core waves. We do this for two reasons: (i) the full panel files do not always have an imputation flag for occupations; and (ii) between the 1990 and 1993 panels firm identities were retrospectively recoded, based on core wave firm identifiers. For our study it is important to be clear to which firm the occupation belongs. We exclude the 1989 SIPP panel because the US Census Bureau does not provide the Full Panel file for the 1989 data set and this panel was discontinued after only three waves (12 months). Since we want to be conservative regarding censoring, we opted for not using this data set. This is at a minor cost as the 1988 panel covers up to September 1989 and the 1990 panel collects data as from October 1989. For the 1996, 2001, 2004 and 2008 panels there is no longer a Full Panel file nor a need for one. One can simply append the individual wave information using the individual identifier "lgtkey" and merge in the person weights of those workers for whom we have information from the entire panel (or an entire year). In this case, the job identifier information is also clearly specified. Two important differences between the post and pre-1996 panels are worth noting. The pre-1996 panels have an overlapping structure and a smaller sample size. Starting with the 1996 panel the sample size of each panel doubled in size and the overlapping structure was dropped. We have constructed our pre-1996 indicators by obtaining the average value of the indicators obtained from each of the overlapping panels.

The SIPP's sample design implies that in *all* panels the first and last three months have less than four rotation groups and hence a smaller sample size. For this reason, in our time series analysis, we only consider months that have information for all four rotation groups. For statistics for which the distribution of unemployment duration matters we require that workers have at least 14 months of labor market history at the moment of re-employment in their corresponding SIPP panel. If necessary (and discussed in detail below), we impose further restrictions to deal with censored spells in order to generate a representative distribution of unemployment spells for at least up to one year. This restriction addresses that e.g. short completed unemployment spells typically have lower mobility, while in the first waves of a panel spells started and completed within the panel are necessarily of short duration. This is even more important when constructing the job finding rates, especially when we want to focus on the job finding rates in completed spells for which we know the occupational mobility outcomes. For the cumulative survival profile in unemployment, we consider all spells that at their start have at least 32 months of subsequent continuous presence in the sample and restrict these observations to be in the first 4 waves of the panel. For job finding rates in the time series, which are based on incomplete spells, we require that all workers whose job finding rate is measured at duration x remain continuously in the sample for at least 19-x more months.

[41] See http://www.census.gov/sipp/ for a detailed description of the data set.

The data also shows the presence of seams effects between waves, where transitions are more likely to occur at a seam (i.e. between waves, and therefore at 4,8, 12... months) than based on other characteristics, e.g. duration. When we consider time series and given the above restrictions, there is always one rotation at the seam in every month we consider which effectively smoothes out the clustering at the seam. In the case of the duration statistics for which the seam effect matters, we either consider observations in 4 months bins (e.g. survival at 4, 8, 12, 16 months of unemployment) or use the standard methods to reducing the seam bias by smoothing out the survival rates or considering "cumulative" mobility rates with duration (see e.g. for the mobility-duration profile reported in Section 2.2 of the main text).

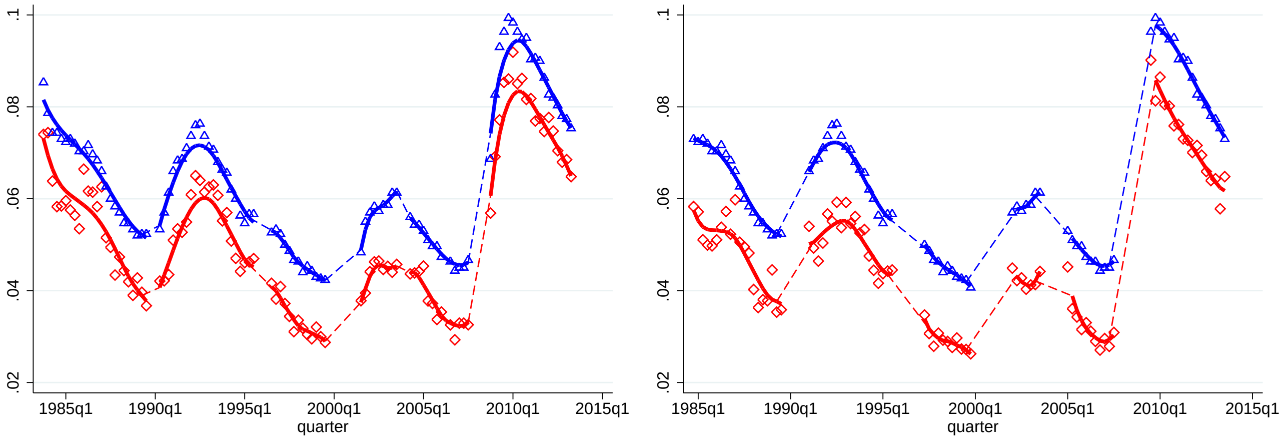
We use the person weights per wave ("wpfinwgt", and equivalent), but normalize these such that the average weight within a panel is equal to one. This is done because the size of panels is not constant, and we do not want to weigh panels with less observations more heavily as within a wave of a panel "wpfinwgt" adds up to population totals and thus is higher on average when sample size is smaller. We think of our normalization as a reasonably agnostic approach that keeps the relative weights within a panel intact, but also takes into account the number of available observations.

Sample selection and labor market status. For the 1984-2008 panels, we consider all workers between 18 and 65 years of age who are not in self-employment or in the armed forces nor in the agricultural occupations.[42] We measure an individual's monthly labor force status in the SIPP using two sources of information. The first one relies on the labor force status reported at the second week of each month. The second relies on the monthly employment status recode. Using these two sources (and using the SIPP 2001 wording as an example) we consider a worker to be employed during a month if the individual reported in the second week of that month that he/she was "with job/business - working", "with job/business - not on layoff, absent without pay" or "with job/business - on layoff, absent without pay". The category "with a job" (Census 2008) is assigned if the person either (a) worked as paid employees (or worked in their own business or profession or on their own farm or worked without pay in a family business or farm) or (b) *"were **temporarily** [emphasis added] absent from work either with or without pay."* Thus, the employment status recode category "with job/business - on layoff, absent without pay" appears to capture temporary layoffs. Note that as a result our definition of employment differs from the CPS definition of employment. As the SIPP documentation points out: " "With a job" includes those who were temporarily absent from a job because of layoff and those waiting to begin a new job In 30 days; in the CPS these persons are not considered employed."

We consider a worker to be *employed* if the individual reported in the monthly employment status recode variable that he/she was "with a job entire month, worked all weeks", but also when "with a job all month, absent from work without pay 1+ weeks, absences not due to layoff", or "with a job all month, absent from work without pay 1+ weeks, absences due to layoff". If workers have spent part of the month in employment and part of the month in unemployment, workers are nonemployed only if they are nonemployed in week 2 *and* have been nonemployed for at least four weeks in total. That is, those who have less than a month of nonemployment in week 2 are still counted as employed. If the worker is "no job/business - looking for work or on layoff" during one of the weeks in nonemployment (i.e. in the "no job/business") state, we consider the worker to be unemployed. We have chosen this classification, because we want entry into unemployment to capture the serious weakening of the link with the previous firm of employment, rather than to be a definite period of nonproduction after which the worker would return to the previous employer. The restriction of

[42] As agricultural occupations could be miscoded nonagricultural occupations and vice versa, in our code-error corrected measure, we take agricultural workers according to reported occupational codes into account, apply our correction method, and remove agricultural workers *after correction* from our sample and associated statistics.

nonemployment for at least four weeks is meant to further limit the role of short-term absences from the same firm and temporary layoffs. This is motivated by the analysis of Fujita and Moscarini (2017), who document that many workers with very short unemployment spells return to their previous employer. We want to focus on those unemployed who at least *consider* employment in other firms and possibly other occupations.



(a) Sample: quarters after seam-correction SIPP

(b) Sample: quarters with workers in sample >14months

Figure 28: Unemployment Rate SIPP (red, our measures) and BLS-CPS (blue, official)

With these restrictions, our measured unemployment rate is somewhat lower than the official unemployment rate. In Figure 28, we plot the unemployment rate in our SIPP sample, constructed according to our definition, next to the standard (CPS-based) unemployment rate from the BLS. The left panel displays the unemployment rate in the SIPP when excluding those quarters in which panels phase in or out. In this case all quarters considered are symmetric with respect to seams between waves: each month there is at least one rotation group which switches interview wave. The right panel considers only observations that have been in the sample for at least 14 months. This necessarily means bigger gaps between panels, but addresses issues of left-censoring when considering complete unemployment spells for which we can observe the occupational mobility. This is important when e.g. considering the distribution of unemployment durations of completed spells as at the beginning of the panel the only completed unemployment spells are necessarily those of short duration, which have a lower occupational mobility rate. Not taking this into account would lead to mistaken time series patterns of occupational mobility of the unemployed.

Both panels of Figure 28 show that our restrictions lower the unemployment rate by about 1.5pp. This level effect is nearly uniform over time and over the cycle. That is, the time-series evolution of our measure of unemployment follows BLS unemployment closely, while the level effect is nearly unaffected by the business cycle. If anything, our measure responds slightly stronger to the business cycle (a 1pp rise in the official rate raises our unemployment measure by 1.04pp, this is small but statistically significant). The correlation between our unemployment measure and the BLS measure (for those months for which we have our SIPP measure of unemployment) is 98-99% for both unemployment series in Figure 28. This implies that the cyclical pattern in unemployment, to a very large extent, originates in the set of unemployed we consider in this paper (see also Hornstein, 2013, and Ahn and Hamilton, 2019).

We further check that these properties also hold when we restrict unemployment to those who *start* and *end* unemployment within the SIPP sample, taking care to address both the left- and right-censoring involved in this measure. The correlation of this unemployment rate (smoothed, because of the smaller set of observations) with the BLS unemployment rate is over 94% when considering nonemployment spells that include months of unemployment, and 93% when considering pure unemployment spells, where workers are unemployed in every month of nonemployment.

Assigning "source"/"destination" - occupations to unemployed workers. The SIPP collects information on a maximum of two jobs an individual might hold simultaneously. For each of these jobs we have information on, among other things, hours worked, total earnings, 3-digit occupation and 3-digit industry codes. We drop all observations with imputed occupations (and industries). If the individual held two jobs simultaneously, we consider the main job as the one in which the worker spent more hours. We break a possible tie in hours by using total earnings. The job with the highest total earnings will then be considered the main job. In most cases individuals report to work in one job at any given moment. In the vast majority of cases in which individuals report two jobs, the hours worked are sufficient to identify the main job. Once the main job is identified, the worker is assigned the corresponding two, three or four digit occupation.[43]

Each unemployment spell that is started and finished inside the panel can be assigned a "source"-occupation (main occupation right before the start of the unemployment spell), and a "destination"-occupation (main occupation right after becoming employed again). If the occupation code is missing just before the unemployment spell (e.g. due to imputation) and an occupation code is reported in a previous wave, while employment is continuous from the time that the occupation was reported until the start of the unemployment spell under consideration, we carry the latter occupation forward as source occupation. A worker is an occupation mover if source and destination occupations do not coincide. We thus conservatively count the following situation also as an occupational stay: the worker is simultaneously employed in two firms at the moment the worker becomes unemployed, and finds a job afterwards in an occupation that matches the occupation in one of the two previous jobs, even when it matches the job with less hours. The effect on the occupational mobility statistics of counting as occupational stays the unemployment spells with two simultaneous jobs at either side is small.

We construct the occupational mobility statistics from transitions of the form: at least a month in employment (with a non-imputed occupational code), followed by an unemployment spell which has a duration of at least a month, followed by at least a month in employment (with a non-imputed occupational code). We label these transitions as EUE transitions. We also consider transitions of the form: at least a month in employment (with a non-imputed occupational code), followed by a non-employment spell which has a duration of at least a month and involved at least one month of unemployment. We call these E-NUN-E transitions, or NUN-spells of nonemployment. Further convexifying the space between EUE and E-NUN-E, we also consider spells that started with a EU transition, i.e. employment directly followed by unemployment (though later the worker can report to stop looking for work), and those that ended with UE transition. We label these transitions as E-UN-E, E-NU-E, and if both restrictions apply, E-UNU-E transitions. We also tried other versions of the latter in which the full jobless spell was non-employed (ENE).

Occupational Classifications. The SIPP uses the Census of Population Occupational System, which relates closely to the Standard Occupational Code (SOC). The 1984-1991 panels use the 1980 Census Occupational classification, while the 1992-1996 and 2001 panels use the 1990 Census Occupational classifications. These two classifications differ only slightly between them. The 2004 and 2008 panels use the 2000 Census occupational classification, which differs more substantially from the previous classifications. We use David Dorn's recoding of the 1980 and 2000 Census Occupational Classification (Dorn, 2009, and Autor and Dorn, 2013)

[43] For the 1990-1993 panels we correct the job identifier variable following the procedure suggested by Stinson (2003).

into the 1990 Census Occupational Classification to have a uniform coding system. In robustness exercises, we instead use the IPUMS crosswalk to map the 1980 and 1990 Census occupational system into the 2000 Census occupational system.

We aggregate the information on "broad" occupations (3-digit occupations) provided by the SIPP into "minor" and "major" occupational categories.[44] Measurement error in occupational codes might give rise to spurious transitions, as discussed for example in Kambourov and Manovskii (2008, 2009) and Moscarini and Thomsson (2007). We correct for coding error using the $\mathbf{\Gamma}$-correction method we propose in Supplementary Appendix A. The occupational categories of the classifications used can be found in Tables 4 and 5 of that appendix.

Time series construction. We construct monthly time series for the unemployment rate, employment to unemployment transition rate (job separation rate), unemployment to employment transition rate (job finding rate), occupational mobility rates and the other measures described in the main text. Job finding rates are simply UE_t/U_t, the proportion of unemployed at time t that moves to employment at time $t+1$. Similarly, the separation rate is EU_t/E_t, the proportion of employed at time t that moves to unemployment at time $t+1$. We start measuring job finding and separation rates at the first month were we have information for all four rotation groups.

For construction of de-trended time series we have to address the issue of gaps (missing observations) in time series. There are a few quarters that are not covered at all by the 1984-2008 SIPP panels: 2000Q2-2000Q3, and 2008Q1. The gaps around these times can become larger, and new gaps can be created, when censoring issues cause us to drop further quarters from the analysis. We discuss this in more detail below.

To cover the missing observations we interpolate the series using the TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) procedure developed by Gomez and Maravall (1999), with interpolation of missing observations through regression ("Additive Outlier Approac").[45] In our baseline cyclical timeseries, de-trended data series are produced with after HP-filtering the resulting (logged) time series, with smoothing parameter 1600.

Two aspects are especially important for the time series of the propensity of hires from U to start in a new occupation: (1) the code error correction, and (2) addressing censoring issues, to counter noise and bias due to shifts in the duration distributions between adjacent quarters that are orthogonal to the business cycle.

We select only observations of individuals who have been in sample for more than 14 interviews and are hired beyond wave 4. Given this, we correct for coding error at the level of quarter $\times$ (completed) spell duration. This means that, for all hires from unemployment with a given completed duration in a given quarter, we calculate the transition matrix of occupational mobility and correct it using the appropriate $\mathbf{\Gamma}$ (code-error) correction matrix. We then calculate the cumulative mobility of all hires with unemployment durations up to (and including) 12 months, and in an alternative measure, up to and including 14 months. We find little difference across these two measures, and hence report only the former measure. The same corrected observations at the

[44] In any of these classifications we have not included the Armed Forces. The 1980 and 1990 classifications can be found at https://www.census.gov/people/io/files/techpaper2000.pdf. The 2000 classification can be found in http://www.bls.gov/soc/socguide.htm. Additional information about these classifications can be found at http://www.census.gov/hhes/www/ioindex/faqs.html.

[45] See also Fujita, et al. (2007) for a similar procedure using the SIPP. Tramo/Seats is a parametric, ARIMA model based method (AMB), that works in two steps. In the first step (TRAMO) the series is interpolates missing observations and deals with outliers. The second step (SEATS), among other things, decomposes the time series resulting from step 1 into e.g. a trend-cycle, an irregular, and a seasonal component. Seasonal adjustment is broadly similar to the Census Bureau's X12 procedure, and is used e.g. by Eurostat. (Hood et al. (Hood, Ashley, Finley, US Census Bureau: "An Empirical Evaluation of the Performance of Tramo/Seats on Simulated Series"), who also argue that SEATS does better than X12-ARIMA with longer time series that have large irregular components.)

SIPP Panels	Qtr from	Qtr to (inclusive)
1984,85,86,87,1988	1985q1	1989q3
1990,91,92,1993	1991q2	1995q3
1996	1997q3	1999q4
2001	2002q2	2003q4
2004	2005q1	2007q3
2008	2009q3	2013q3

Table 19: Quarters included in time series for overall occupational mobility rate of all unemployed (with unemployment duration between 1-14 months

level of duration×quarter will subsequently be used to calculate the mobility-duration profile shift from times of low unemployment to times of high unemployment.

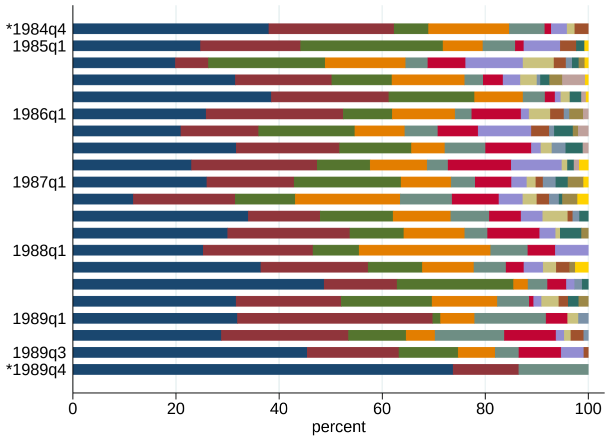
While time series gaps are small for many statistics, this issue is more important for the average occupational mobility of all hires from unemployment (of $\leq$ 12-14 months). The restriction to wave 5 and beyond means that, by default, we leave out those observed unemployment spells that arise from workers losing their jobs and being hired within the first 16 months of each panel. As argued above, this is to make sure that we capture the nearly full duration distribution of unemployment at each quarter considered in our analysis. This is especially important here as not doing so would generate a downward bias in the occupational mobility rates at the beginning of a panel, which is particularly strong in e.g. 2004. In addition, we take into account that, given the rotating survey design, some further quarters early in the panel do not have a seam in each month (this is also a relevant issue for the job finding and separation time series). We are also conservative on this issue and disregard those quarters as well.

We also note that censoring issues may arise at the very end of the panel, where again a quarter may contain varying proportion of monthly observations that are the final seam. We observe that in practice, some of these "ending" quarters have duration distributions that are very different from the duration distributions in previous quarters. As we show below, this variation is significantly larger and more abrupt than changes that appear to move with business cycle conditions. For this reason, we also exclude the last quarter of the 1988 panel and all panels from the 1993 panel onwards, with the exception of the 2001 panel. The quarters which are used for our analysis are then given in Table 19. These observations span a number of different moments during multiple business cycles and therefore the cyclical patterns can indeed be clear and significant, as is shown in Section 2.5 of the main text and this appendix.

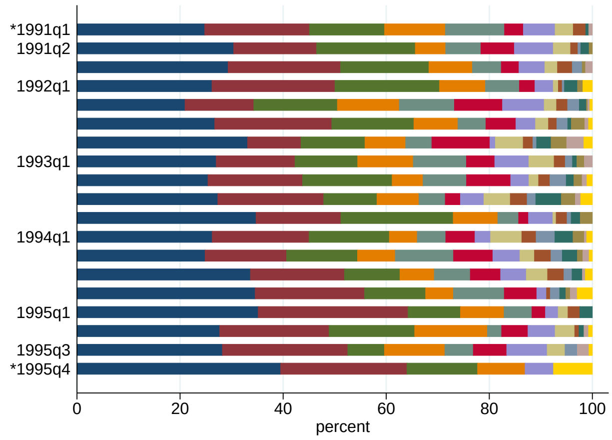
To visualize the impact of censoring, Figure 29 presents the duration distribution of hires from unemployment per quarter. Each horizontal bar specifies the unemployment durations of hires (from 1 month to 14 months, in order). On the y-axis are the quarters in which we have observations beyond wave. Those quarters that we exclude from our time series calculations, due to one of the reasons mentioned above, are prefaced by an $*$.[46]

Here we can indeed observe the some of the last and first of the quarters considered are affected by these (censoring) issues and hence are excluded from our analysis. We also observe that the remaining duration distributions are relatively stable across individual quarters, with the amount of quarter-to-quarter variation dropping with the 1996 panel and thereafter. This occurs because the sample sizes per panel are larger, while

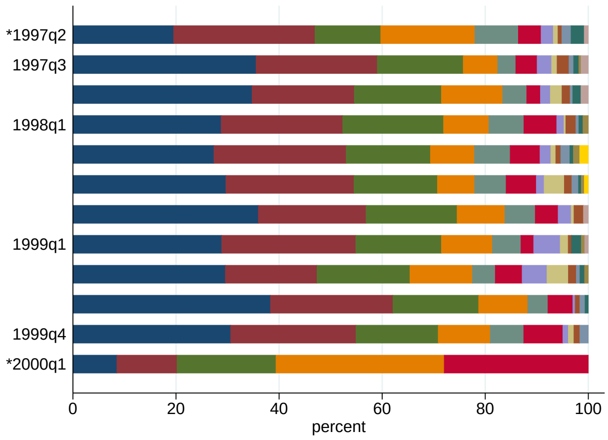
[46]One can distinguish some cyclical patterns directly, clearest perhaps when comparing across panels, where the red bands (hires after 6 months of unemployment) in the early 1990s panels are to the left of those in the 1996 panel, and likewise for the 2001 SIPP vs the 1996 and 2004 SIPP, and the 2008 vs the 2004 SIPP, signifying more long-term unemployment in the "recession" 1990-1993, 2001, and 2008 SIPP panels.



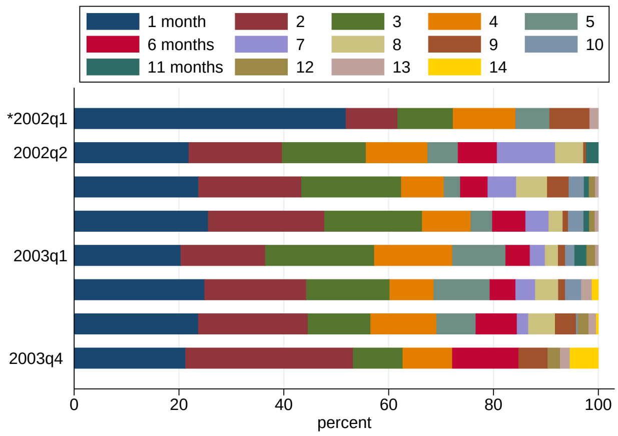
(a) 1984-1988 SIPPs



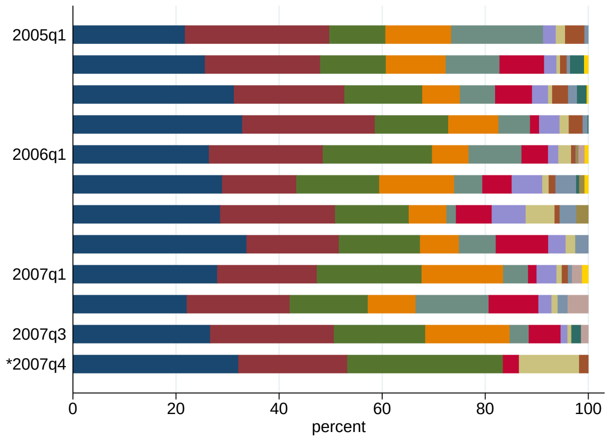
(b) 1990-1993 SIPPs



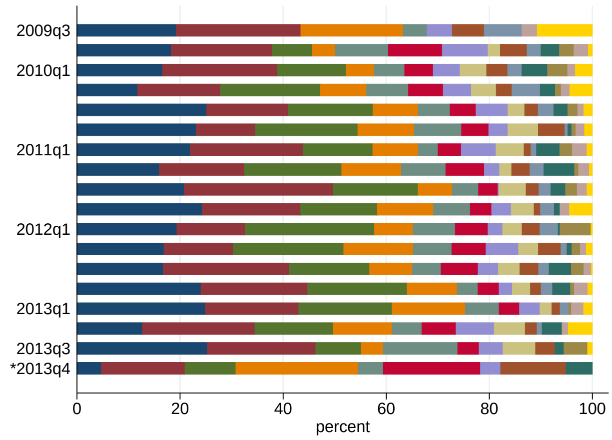
(c) 1996 SIPP



(d) 2001 SIPP



(e) 2004 SIPP



(f) 2008 SIPP

Figure 29: Completed Unemployment Duration of Hires from U, per quarter

the overlapping nature of panels beforehand imply that some additional noise is generated when panels are phased in and out, while other panels are ongoing. We also tried to further restrict the sample to exclude observations from these phase-in and -out, but the impact of this on time series patterns is minor.

Aggregate Series Productivity, Unemployment, Vacancy Series For output per worker, we take nonfarm business output from the Major Sector Productivity and Costs section of Bureau of Labor Statistics (series id: PRS85006043), and divide this by the sum of employment of private industry wage and salary workers (not in agriculture) and employment of self-employed unincorporated workers in these sectors (series LNS12032189Q and lns12032192q, respectively) Unemployment rates in the cyclical analysis are BLS Unemployment rates (UNRATE in the St. Louis Fred data). We take the vacancy data from extended Help-Wanted Index constructed by Regis Barnichon.

Repeat Mobility In our baseline repeat mobility measures, we concentrate on pure u-spells that follow pure u-spells within a SIPP panel, for workers that are at least 4 years in sample. To avoid including seasonal unemployment in our measures (which are not informative about attachment as interpreted in the model), we exclude construction and agricultural workers. We are left with 610 observations of repeat unemployment. For our NUN measures, we consider NUN-spell following NUN-spells with the same restrictions, leaving 1306 observations of repeat unemployment. We average the measures that consider the occupation of intermediate employment at the beginning and end of that spell. We correct coding errors using the procedure described in footnote 13 in the main text. Finally, to gauge occupational moving, we exclude any observations of return movers.

7.2 Panel Survey of Income Dynamics

Following Kambourov and Manovskii (2008) sample restrictions, we consider the 1968-1997 period as during these years the PSID interviews were carried out annually. We also consider males head of households between the ages of 23-61 years who were not self- or dual-employed and were not public sector works. This sample restriction then gives 1,643 employed individuals in the year 1968 and 2,502 employed individuals in 1997. In an alternative sample we also included women, younger workers and self or dual-employed workers with no meaningful change in our main results.

To construct the *across-employer* occupational mobility rate we compute the fraction of employed workers who's occupational code differs between years t and $t+1$ and have reported an employer change between these years, divided by the number of employed workers in year t that have reported an employer change between years t and $t+1$. As Kambourov and Manovskii (2009), to identify employer changes in the PSID we use Brown and Lights' (1992) Partition T method. As robustness we also use Brown and Lights' (1992) Partition 24T method. To identify employer changes using these two methods we followed exactly the same procedure as specified in Appendix A1 of Kambourov and Manovskii (2009). In addition, we used Hospicio's (2015) method to identified employer changes in the PSID, as described in Hospido (2015), Section 3.2. We find that our conclusions are not affected by the method used.

When constructing the ENE occupational mobility rate we consider (i) those workers who were employed at the interview date in year $t-1$, non-employed at the interview date in year t and once again employed at the interview date in year $t+1$; and (ii) those workers employed at the interview dates in years t and $t+1$ but who declared that they experienced an involuntary employer change during these two interviews. In an alternative specification we also added those workers who were employed at the interview date in year $t-2$, non-employed at the interview date in years $t-1$ and t and once again employed at the interview date in year $t+1$. Given the small number of workers in the latter category the results hardly change.

We follow Stevens (1997) and Hospido (2015) and classify an involuntary employer change as those cases were the worker declared a job separation due to business or plant closing, due to being laid off or were fired or their temporary job ended. We also added an "other" category as a reason why workers left their employers to increase the number of observations. This category encompasses other reasons such as military draft. Pooling together the "involuntary" and "others" categories and computing the ENE occupational mobility rate gives very similar results. Further, in constructing the ENE occupational mobility rates we were not able to eliminate those workers in temporary layoff. The analysis of Fujita and Moscarini (2016), however, suggests that unemployed workers in temporary layoff will bias downwards our ENE occupational mobility rates as these workers have a very high probability of re-gaining employment in the same occupation.

References

[1] Acemoglu, D. and D. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings," In D. Card and O. Ashenfelter (Eds.), *Handbook of Labor Economics*, Vol. 4, Part B, Chapter 12, Elsevier, The Netherlands.

[2] Autor, D. H. and D. Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, Vol. 103 (5): 1553-1597.

[3] Ahn, H. J. and J. D. Hamilton. 2019. "Heterogeneity and Unemployment Dynamics," *Journal of Business and Economic Statistics*, forthcoming.

[4] Autor, D. H., F. Levy and R. J. Murnane. 2003. "The skill content of recent technological change: An empirical exploration," *Quarterly Journal of Economics*, Vol. 116 (4): 1279-1333.

[5] Brown, J. N. and A. Light. 1992. "Interpreting Panel Data on Job Tenure," *Journal of Labor Economics*, Vol. 10: 219-257.

[6] Cortes, M., N. Jaimovich, C. J. Nekarda and H. E. Siu. 2016. "The Micro and Macro Disappearing Routine Jobs: A Flow Approach", Mimeo, Department of Economics, York University, Canada.

[7] Dorn, D. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." Dissertation no. 3613, University of St. Gallen, Switzerland

[8] Farber, H. S. and R. G. Valleta. 2015. "Do Extended Unemployment Benefits Lengthen Unemployment Spells? Evidence from Recent Cycles in the U.S. Labor Market" *Journal of Human Resources*, 50 (4): 873-909.

[9] Fujita, S. and G. Moscarini. 2017. "Recall and Unemployment", *American Economic Review*, Vol. 102 (7): 3875-3916.

[10] Fujita, S., C. Nekarda and G. Ramey. 2007. "The Cyclicality of Worker Flows: New Evidence from the SIPP". Federal Research Bank of Philadelphia, Working Paper No. 07-5.

[11] Gomez, V. and A. Maravall. 1999. "Missing observations in ARIMA models: Skipping Approach versus Additive Outlier Approach". *Journal of Econometrics*, 88: 341-363.

[12] Goos, M. and A. Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, Vol. 89 (1): 118-133.

[13] Hornstein, A. 2013. "Accounting for Unemployment: The Short and the Long of It". Working Paper Series, Federal Reserve Bank of Richmond, WP 12-07.

[14] Hospido, L. 2015. "Wage Dynamics in the Presence of Unobserved Individual and Job Heterogeneity," *Labour Economics*, Vol. 33: 81-93.

[15] Jovanovic, B. and R. Moffitt. 1990. "An Estimate of a Sectoral Model of Labor Mobility," *Journal of Political Economy*, Vol. 98 (4): 827-852.

[16] Kambourov, G. and I. Manovskii. 2009. "Occupational Specificity of Human Capital," *International Economic Review*, Vol. 50 (1): 63-115.

[17] Kambourov, G. and I. Manovskii. 2008. "Rising Occupational and Industry Mobilty in the United States: 1968-97," *International Economic Review*, Vol. 49 (1): 41-79.

[18] Kroft, K., F. Lange, M. Notowidigdo and L. Katz, "Long-term unemployment and the Great Recession: the role of composition, duration dependence, and nonparticipation." Journal of Labor Economics 34.S1 (2016): S7-S54.

[19] Murphy, K. and R. Topel. 1987. "The Evolution of Unemployment in the United States: 1968 - 1985," NBER Macroeconomics Annual 1987, Vol. 2: 11-68.

[20] Neal, D. 1999. "The Complexity of Job Mobility Among Young Men," *Journal of Labor Economics*, Vol. 17 (2): 237-524.

[21] Pavan, R. 2011. "Career Choice and Wage Growth", *Journal of Labor Economics*, Vol. 29 (3): 549-587.

[22] Stevens, A. H. 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses," *Journal of Labor Economics*, Vol. 15 (1): 165-188.

[23] Wiczer, David. 2015. "Long-term Unemployment: Attached and Mismatched?" Research Division, Working Paper Series, Federal Reserve Bank of St. Louis, WP 2015-042A.