Workers' Task and Employer Mobility over the Business Cycle[*†]

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Abstract

We investigate cyclical changes in workers' task portfolios, highlighting their direction, magnitude, and distribution. Task changes are not only very common but provide information about the skills required across jobs. During recessions, a larger share of employer switches do not involve task changes. When changes occur, they tend to be more substantial. The cyclicality of task changes among employer-to-employer movers contrasts sharply with that of hires from unemployment. We link our findings to the "sullying" and "cleansing" effects of recessions, uncovering a novel cleansing effect associated with employer-to-employer transitions and a sullying effect tied to employer changes through unemployment.

Keywords Career Change, Occupational Mobility, Tasks, Business Cycles

JEL Codes E32; J24; J62; E24

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1 Introduction

Modern labor markets are characterised by large and cyclically varying number of workers who change employers, either directly (EE) or through intervening spells of unemployment (EUE). Job ladder models describe these patterns quite well (see e.g. Menzio and Shi (2011), Moscarini and Postel-Vinay (2013) and Lise and Robin (2017)). These models highlight two cyclical effects: first, during recessions, reduced upward movement on the job ladder causes a 'sullying effect', as the slowed reallocation of labor hinders the shift to more productive jobs. Second, increased inflows into unemployment create a 'cleansing effect', where job destruction offers an opportunity to redirect labor towards more productive roles.[1] These opposing effects are crucial to gauge the (net) costs of business cycles (see e.g. Mortensen and Pissarides (1994), Caballero and Hammour (1994) and Barlevy (2002)).

The upward and downward movements of workers on the job ladder are often accompanied by changes in job tasks. However, not much attention has been given to understanding how these task changes relate to the sullying and cleansing effects. This is important as job tasks can be considered fundamental units of production (e.g., Acemoglu and Autor (2011)) and have been shown to be key drivers of human capital accumulation (e.g., Lise and Postel-Vinay (2020)). In this paper we investigate how task changes associated with employer switches differ between recessions and expansions, analyzing these patterns separately for EE and EUE transitions and comparing them to their long-run trends. By examining task changes we provide insights into the 'quality' of worker reallocation and offer a deeper understanding of the sullying and cleansing effects of recessions.

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[1]Fundamentally these models imply that during recessions job opportunities are scarce due to reduced vacancy openings, hence workers' ability to step into or climb the job ladder diminishes, while the probability of falling from it through a layoff rises.

Our analysis is based on confidential data from the Canadian Labor Force Survey for the period 1997 to 2015. We consider over 20 job aspects across 4-digit occupations, and condense these job aspects into the three most important orthogonal dimensions. These turn out to have intuitive interpretations as 'cognitive', 'high-physical' (referring to physical work that requires dexterity and dealing with complexity), and 'low-physical' (brawn or muscle) dimensions. We subsequently represent each 4-digit occupation as a three-dimensional vector, with each of its elements indicating the intensity level of cognitive, high-physical, and low-physical tasks associated with that occupation. This representation of jobs as task portfolios allows us to study how worker reallocation across jobs translates to changes in task portfolios both in terms of magnitude and direction of change. We highlight three key findings.

First, the extensive and intensive margins of task portfolio changes exhibit contrasting cyclical patterns. On the extensive margin, the probability that a worker changes their task portfolio when changing employers decreases in recessions for EE and for EUE transitions. In contrast, on the intensive margin the magnitude of change increases in recessions for those who change task portfolio.[2] For each task dimension, in recessions relative to expansions, EUE movers experience larger average losses along the cognitive and high-physical dimensions, but larger average gains along the low-physical one. EE movers experience larger average *gains* along the cognitive and high-physical dimensions, with no change along the low-physical dimension.

Second, the magnitudes of these gains and losses vary significantly across the different quantiles of the *distribution* of task changes. Moreover, the size of the task change at a given quantile varies significantly across the cycle. During recessions, EUE task movers more frequently experience large losses along the cognitive and high-physical dimensions. Large increases in low-physical intensity also become more frequent for these workers. In contrast, during recessions EE task movers experience more fre-

[2]By construction, this contrasting behavior is missed when treating all changes of occupational code as having the same distance between them. See e.g. Moscarini and Thomsson (2007), Kambourov and Manovskii (2008) and Carrillo-Tudela et al. (2016), among many others. More generally, the same contrast is by construction still missed when using a strictly positive cutoff level for binary mobility on a continuous underlying task distance measure, as in Baley, Figueiredo, and Ulbricht (2022).

quently very large cognitive gains. At the same time, EE task movers are less likely to experience large declines in high-physical intensity.

Third, there are significant differences in the cyclicality of the task distributions of the jobs that ended with an EU or an EE transition, and with the jobs that started after an UE and EE transition. In recessions, unemployed workers who change their task portfolio upon re-employment leave more cognitive-intense jobs behind. We observe a particularly strong increase in the probability that such EUE task changers separate from high cognitive intensive jobs. On the other hand, the distribution of cognitive intensities of jobs taken after unemployment varies little over the cycle. EE task changers exhibit a different pattern. During recessions they leave behind more often jobs with low cognitive intensities, while they take up jobs that are more cognitive intense.

These findings suggest that, contrary to the literature's emphasis on a cleansing effect that operates through the EUE margin, there may be a significant countervailing sullying effect along these task dimensions, as EUE movers seem to reallocate to jobs that require less skill (cognitive or high-physical) during recessions compared to expansions. Similarly, while a sullying effect may operate along the EE margin, it may be mitigated by a cleansing effect along the task dimension, where EE movers transition from lower-skilled jobs to higher-skilled ones in recessions relative to expansions. Given the long-run increase in the cognitive intensity of jobs and the long-run decline in the high-physical intensity, the cleansing effect operating along the EE margin appears to help accelerate the economy's transformation towards more cognitive jobs and slow down the decline of high-physical ones. Along the EUE margin the opposite happens. The sullying effect accompanying task changes seems to accelerate the decline of high-physical intensive jobs and slow down the rise of cognitive ones.[3]

[3] Jaimovich and Siu (2020) link the cyclical patterns of routine and non-routine jobs to their long-run trend, showing that recessions are times where the destruction of routine jobs and the creation of non-routine accelerates, exacerbating their long-run trends.

Related Literature

Our methodology leans heavily on Robinson (2018), who uses factor analysis to study the direction and Euclidean distance of task portfolios following involuntary job loss and contrasts it to total overall occupational mobility. More generally, we build on the earlier contributions of Poletaev and Robinson (2008) and Gathmann and Schönberg (2010), who emphasize continuous notions of distance in the evolution of workers' task portfolios and their relation with workers' mobility and the evolution of their wages.[4]

Our analysis also relates to the literature on routine-biased technological change (e.g. Autor et al. (2003), Goos and Manning (2007), Autor and Dorn (2013)). The high-physical dimension and its behavior emphasized in this paper connects closely to the skill-replacing routine-biased-technological change of Danieli (2022). He argues that skill-replacing routine-biased-technological change provides a better explanation for wage trends than standard (skill-neutral) routine-biased technological change. The cognitive dimension, in turn, links with the notion of complex-task biased technological change (Caines, Hoffmann, and Kambourov (2017a)).

A number of recent papers have proposed structural models that incorporate multidimensional task/skill portfolio dynamics to investigate the interplay between task mobility of individual workers and employer mobility (see e.g. Lindenlaub (2017), Lise and Postel-Vinay (2020), Guvenen et al. (2020), Busch (2020)).[5] Our analysis complements these papers by documenting novel business cycle patterns along several task dimensions. Our investigation of the cyclical behavior of the distributions of workers' task changes further relates conceptually to the literature that studies the behavior of earnings change distributions over the cycle, following Guvenen et al. (2014). As in

[4]Focusing on a few (but key) archetypical task dimensions, Autor et al. (2003) is an early example of how the shifting importance of certain tasks can affect workers' outcomes. See e.g. Acemoglu and Autor (2011) and Sanders and Taber (2012) for overviews on the importance of tasks for labor market outcomes.

[5]While our focus is on continuous measurement of the intensities along a limited set of task dimensions, an alternative approach is to group occupations into coarse categories based on their task content and study mobility across these. A prime example of the latter is Cortes et al. (2020) who relate worker mobility across four aggregate occupation categories to flows through unemployment, nonparticipation or directly within employment, to study long-run shifts of employment in these four aggregate categories.

this literature, we find particularly strong cyclical responses in the tails of the distribution.

Closest to our paper is Baley et al. (2022), who also considers the sullying and cleansing effects of recessions in terms of tasks. A key difference is that we evaluate changes in workers' task portfolios along multiple dimensions and centre our analysis on a continuous measure of change. They define a career change if a worker's task changes is sufficiently large that it supersede a strictly positive angular distance cutoff (defined as in Gathmann and Schönberg (2010)). Using this binary measure they find that EUE movers *more* often change careers in downturns.[6]

The latter finding in Baley et al. (2022) appears to stand in contrast with the procyclicality of occupational code changes found among employer movers and pooled samples of employer movers and stayers across various levels of aggregation (see e.g. Moscarini and Thomsson (2007), Kambourov and Manovskii (2008) and Carrillo-Tudela and Visschers (2023), among many others).[7] Our analysis can reconcile these results. We find that during recessions both task staying and extreme task changes become more common, while moderate task changes become less common. Measuring mobility as a change of occupation code, as done in much of the literature, emphasizes task staying; while the Baley et al. (2022) analysis emphasizes extreme task changes found in the tails of the task portfolio distribution, giving the appearance of a contradicting result. Hence, when investigating worker reallocation one should consider the large heterogeneity of workers' task intensities changes. Similarly, to better gauge cleansing and sullying effects, it is important to consider the cyclical behavior of the entire distributions of task intensities of the jobs left behind and of the new jobs taken.

The rest of the paper is organized as follows. In Section 2 we discuss our data sources and the construction of our task measures. In Section 3 we then consider how

[6]See also Robinson (2018), who documents higher average task distances among displaced workers during recessions; and Bizopoulou and Forschaw (2018) who use the UK LFS in combination with US O*NET and focus on EE movers, they find these cover on average less angular distance in a downturn.

[7]Huckfeldt (2022) finds countercyclical occupational mobility of *displaced workers* using this metric, where it's helpful to note that the set of displaced workers does not equal the set of unemployed: a meaningful part of the latter does not satisfy the CPS Displaced Worker Survey definition of displacement, while conversely not all displaced workers enter unemployment.

task intensity changes behave (on average) over the business cycle. We subsequently turn to the cyclical behavior of the task change distributions in Section 4. In Section 5, we investigate the distribution of tasks that are terminated with a worker moving to unemployment or another firm, and how this behaves over the cycle. We also consider how the distribution of tasks started with a new hire, changes with the business cycle. Section 6 concludes and further relates our findings to theories of the labor market.

2 Measuring Tasks and Worker Mobility

In this section we describe how we measure workers' employer mobility and their task portfolio changes. In Appendix A, we provide further details, covering technical issues and additional data patterns, including the long-run evolution of tasks in the economy and the relationship between tasks and aggregate occupations.

2.1 Worker Flows and Occupations

Our analysis is based on a sample of workers who changed employer (hereafter employer movers) drawn from confidential versions of Canada's Labor Force Survey (LFS) between 1997 and 2015.[8] Monthly surveys include the employment and personal information of workers, as well as information about employer tenure, employer transitions and occupations. The LFS re-samples respondents so that each of them is interviewed for up to 6 consecutive months, with one-sixth of the sample replaced every month. By constructing person identifiers, we are able to follow workers across surveys and observe both employer and occupation changes during a worker's sampling window. For workers observed in unemployment, we have information on the most recently held occupation beforehand (within the last 12 months), allowing us to capture occupation changes for the unemployed as well.[9]

[8]We use LFS data from 1997 onward, because the Canadian unemployment insurance system was substantially reformed between 1994 and 1996, creating potential data comparability issues with prior years.

[9]Excluding longer unemployment spells could lead to bias. However, we believe any bias is likely small because the average unemployment duration in Canada during 1997−2015 was 18.73 weeks. Excluded individuals are typically married males with an average age of 40 years that are slightly more

Our sample of employer movers is restricted to individuals fitting the description of a typical labor market participant: workers aged 16-65, excluding the self-employed and students. We further exclude temporary layoffs, who typically return to their previous employer (see e.g Fujita and Moscarini (2017)), and imputed records.[10] Our sample contains 76,623 observations, comprised of direct Employer-to-Employer transitions (EE) and transitions with intervening unemployment spells (EUE).[11]

An advantage of the Canadian LFS relative to other commonly used data sources is the high quality and consistently-coded information on both occupation and employer tenure, and the direct link of occupational codes with information on tasks. Four-digit National Occupational Classification (NOC) 2011 codes are provided throughout the data. Statistics Canada has back-coded occupations to cover the entire sample from 1987 forward with uniform coding. Occupations are coded by experts from survey responses that describe the "kind of work reported and the description of the most important duties" (Statistics Canada, 2012).[12] Moreover, Statistics Canada has emphasized the quality of occupation coding, suggesting that our data has relatively few spurious occupational transitions.[13]

likely to be university graduates.

[10]Imputations in the LFS are representative in the cross-section only. An occupation is imputed based on characteristics rather than carrying forward past values, leading to a high likelihood of false transitions. Dropping these observations does not meaningfully impact our results as imputations are few (essentially zero) until the mid 2000s, reaching a peak of about 5% of observations in recent samples.

[11]Table B.1 in the Appendix provides the summary statistics of this sample. Note that EUE spells may also contain short intervening non-participation spells between unemployment periods.

[12]Relative to surveys where respondents state their occupational title, this should help to capture task changes, because the fraction of "within occupational title" task changes may be non-negligible (Autor and Handel, 2013; Cassidy, 2017).

[13]Statistics Canada states that occupation coders are trained extensively and follow well-established coding rules. Coding further involves a quality assurance procedure where about 20% of the records are coded independently by a second person, and any non-matching codes were reviewed by a more experienced coder. Moreover, the employer changes and firm tenure variables also appear of high quality, with flags for employer changes coinciding with the correct value of the separate tenure variable essentially everywhere. It is worthwhile to note that, especially when not conditioning on the occurrence of an occupation code change, the impact of miscoding an occupation into another with similar tasks would be limited.

2.2 Task Dimensions

To measure the task (re)allocation of workers we represent each four-digit occupation with a low-dimensional vector of tasks that summarizes this occupation's attributes. Attributes from Canada's Career Handbook (CH), the Canadian analogue of the US O*NET database, are condensed using Factor Analysis, resulting in three orthogonal task measures each with population average 0 and length 1. The CH is advantageous because it is a component of the NOC occupation coding framework meaning that we can generate tasks for almost all LFS four-digit occupations.[14] Our approach to describe occupations is similar to the ones proposed by Autor et al. (2003), Poletaev and Robinson (2008), Yamaguchi (2012), among others.

Our three task dimensions have straightforward interpretations that can be seen by comparing generated tasks to original CH components (see factor loadings in Appendix A). In descending order of explanatory power, Task 1 appears to measure cognitive occupational attributes, correlating heavily (and positively) with education, complex use of data, and other aptitudes such as general or verbal ability and social interactions. We refer to this dimension as 'cognitive', abbreviated as **COG**. Task 2 appears to capture high-level physical attributes, correlating positively with aptitudes like perception and motor-coordination and loading heavily on "complexity of things", while having no clear relationship with educational attainment. Rather than 'brain' or 'brawn', this category could be described by 'trained dexterity'. In abbreviated form, we refer to this task dimension as **H-PHYS**. Task 3 picks up lower-level physical tasks, correlating with measures of environmental hazards and physical strength and exertion. We refer to it as **L-PHYS**. Together, these three tasks explain 73% of the differences across Canadian occupations.[15]

[14]Our mapping results in unique task vectors for 520 LFS occupations. As the CH is built on the 2006 NOC codes, we step-back the uniform 2011 NOC codes to the 2006 NOC codes using a concordance provided by statistics Canada, preserving the uniformity of coding between CH and LFS data. A cross-walk provided by Statistics Canada to O*NET suggests that a broadly similar picture would arise when adding a further translation step from CH to O*NET.

[15]Robinson (2018) uses O*NET and obtains similar task dimensions/factors in the same order of importance: "general" and "analytic" skills; "fine motor skills"; "physical strength", explaining 72% of variance.

Table 1 provides intuitive confirmation of our labeling at the one-digit occupation level, while Appendix A further confirms this labeling at a two-digit occupations. COG task intensity is on average higher for the skilled white-collar occupations, those we would traditionally associate with cognitive tasks. H-PHYS is more intense among occupations requiring trained physical dexterity, including artists, sport and recreational, health, science and skilled trades. L-PHYS stands out in occupations typically found in primary industries such as operators of heavy machinery and manufacturing occupations, as well as health occupations.

Due to the orthogonal nature of our task measures, each task dimension contains unique information. Within 1-digit occupations, there is substantial heterogeneity in workers' task portfolios (as discussed in Appendix Section A.5). Table 1 shows that some occupations are more intense along all 3 dimensions, while others are low in all three; compare e.g. health occupations with sales and services. Although less visible in 1-digit occupations, task portfolios are not located throughout the entire task space. We observe apparent 'task frontiers': the most COG-intense occupations are low on L-PHYS and vice versa; while the most H-PHYS intense occupations are associated with at least average (and above) COG intensity. Appendix Figure 1 shows these relationships graphically and depicts these task frontiers.

The factor analysis procedure above is data-driven (as opposed to narrative-driven) and completely agnostic with respect to which CH measures contribute to a task dimension. Nevertheless, the three task dimensions have an intuitive (though not fully overlapping) relation with the standard task-based approach in the literature, as discussed e.g. in Acemoglu and Autor (2011). The COG dimension naturally relates to the abstract or non-routine cognitive dimensions of Autor et al. (2006)[16] Because the H-PHYS dimension is closely related to finger and manual dexterity, and motor coordination skills, it relates to routine tasks as defined by Autor et al. (2003), where "finger

[16] In Autor et al. (2006) 'abstract tasks' are measured by directly looking at two specific characteristics in the DOT: "direction control and planning", meant to capture managerial and interactive tasks, and "GED Math", to capture mathematical and formal reasoning requirements (see Dorn (2009) for more discussion. For a further investigation into the role of social attributes, see Cortes et al. (2021).

Table 1: Task Intensity by 1-Digit Occupation

		Task 1	*Task 2*	*Task 3*
NOC		**COG**	**H-PHYS**	**L-PHYS**
Code	Broad Occupation Group	Mean	Mean	Mean
0	Management Occupations	1.194	-0.859	-0.230
1	Business/Finance/Administration	-0.065	0.097	-0.861
2	Natural & Applied Science Occupations	0.893	0.490	-0.432
3	Health Occupations	0.327	0.506	0.482
4	Social Sciences/Education/Gov/Religion	1.061	-0.770	-0.121
5	Art, Culture/ Recreation & Sport	0.778	0.847	-0.153
6	Sales & Service	-0.642	-0.427	-0.009
7	Trades, Transportation & Operators	-0.526	0.516	0.504
8	Primary Industry Occupations	-0.818	0.167	0.653
9	Processing, Manufacturing, Utilities Occ.	-1.039	-0.042	0.373

Source: 2006 Career Handbook. Occupation categories according to 2006 NOC codes. Mean task values by 1-digit occupation. Task values specific to 4-digit NOC occupation codes. Tasks created from career handbook occupational ratings using population weights from the LFS data.

dexterity" is a defining characteristic of routine manual jobs.[17] But the importance of 'complexity of things' for H-PHYS in the factor loading matrix suggests that H-PHYS also emphasizes acquired skill and knowledge. Occupations that are high in H-PHYS intensity therefore appear closer to 'routinizable occupations with high complex content' in the parlance of Caines et al. (2017b) and the skilled routine jobs of Danieli (2022). Finally, that the L-PHYS task captures strength (rather than dexterity), the endurance of discomfort and the relatively higher importance of 'vision', imply this dimension relates to the 'manual' or 'low-skilled' labor component in Acemoglu and Autor (2011).[18]

To fully understand the cyclical task changes arising from workers' EE and EUE transitions as well as the scale of these changes, we first consider these changes against the long-run aggregate shifts in the economy-wide task distribution. Table 2 shows that the Canadian economy has been characterized by increased aggregate COG intensity and decreased H-PHYS intensity over the period 1997-2015. The bottom row of this table shows, along both of these dimensions, that the average task intensity among

[17]The other two task measures are included in routine manual tasks in a robustness exercise in Autor et al. (2003).

[18]Autor et al. (2006) measure the manual nature of a job by looking at the "eye-hand-foot coordination".

Table 2: Evolution Aggregate Task Portfolio Canada 1997-2015 (All Employed)

	Occupation (1d NOC)	Task Changes within Occ. COG	H-PHYS	L-PHYS	Occupation Size Change 1997 Size	Δ Size	Pct Change
0	Management	0.055	0.016	-0.045	0.09	-0.022	-24.7%
1	Business & Admin.	0.127	-0.322	0.064	0.20	-0.002	-1.1%
2	Nat.& Appl. Science	0.006	-0.189	-0.047	0.07	0.024	34.8%
3	Health	-0.081	-0.082	0.032	0.06	0.017	28.6%
4	Educ/Gov/SocSci	-0.131	-0.043	-0.039	0.07	0.015	20.6%
5	Arts, Leisure & Sports	-0.014	0.088	0.014	0.02	0.002	12.9%
6	Sales & Service	0.082	-0.038	0.028	0.22	0.012	5.3%
7	Trades, Transport, Op's	0.015	-0.054	-0.044	0.16	-0.009	-5.5%
8	Primary Industry Occ	0.155	0.024	-0.074	0.02	-0.002	-10.0%
9	Manufacturing & Utils	0.118	-0.017	-0.039	0.09	-0.035	-39.3%
	Aggregate	0.100	-0.085	-0.018	1.00	0.000	0.0%

Table captures average task portfolio of all employed workers (in an occupation, and in the aggregate), i.e. employer stayers and employer switchers.

employed workers changed by about 10% of the cross-sectional standard deviation. Given the vast heterogeneity of jobs in the economy, this is a substantial change. The intensity of 'brawny' L-PHYS tasks experienced a much smaller decline (about 2%) during the same period. Table 2 also shows that the economy-wide task-intensity changes occurred not only because occupations changed size but also because task-intensity changed within occupations, even within those occupations not typically associated with a particular task dimension; e.g. H-PHYS tasks in business and administration. Appendix A.6 provides the full time series describing these trends.

These aggregate changes appear not to be unique to Canada. The rise of COG intensity tracks closely the documented rise, in the US and elsewhere, of abstract tasks over our sample period (e.g. Autor and Price (2013) and Dickerson and Morris (2019) for the UK). The decline in H-PHYS relates to the well-known loss of routine work over the last two decades, especially to the already-mentioned *skill-replacing* routine-biased technological change in Danieli (2022) and the decline of skilled manual workers in Wilson et al. (2020).[19]

[19]It is also intuitive to map the decline in H-PHYS to the narrative of the "loss of the good blue-collar jobs" in the popular press.

2.3 Task Changes of Employer Movers

Task portfolios often change when workers change employers.[20] We observe changes in task portfolios in around 70% of employer transitions. Table 3 displays the 1997-2015 average of individual task intensity changes associated with EE and EUE movers who also change occupation. We label this sub-group of employer movers '**task switchers**', while we label '**task stayers**' those EE and EUE employer movers who did not experience any task change as a result of their employer move.[21]

The first three columns of Table 3 shows that EUE task switchers are associated with a considerable loss of COG intensity, while the change along the H-PHYS and L-PHYS dimensions are closer to zero. In contrast, EE task switchers make moves toward jobs that exhibit a higher COG and H-PHYS intensity dimension, and to a lesser extent toward jobs with higher L-PHYS intensity dimension.[22] Note, however, that the variance of task changes is large: many EE moves incur losses in intensity along the cognitive or physical dimensions while many EUE moves experience increases in COG or H-PHYS intensity.

The fourth column of Table 3 shows a one-dimensional distance measure summarizing these three-dimensional task intensity changes. Specifically, we define the overall distance between two task portfolios, $T_{j,it}, T_{j,it-1}$, using a weighted Manhattan distance, $\sum_{j=1}^{3} \rho_j |T_{j,it} - T_{j,it-1}|$ where $T_{j,it}$ is the index value of task j for the occupation of person i (in period t). The task differences are weighted with ρ_j, which denotes the share of the overall variation explained by each task, 0.36, 0.22 and 0.15 for COG, H-PHYS, L-PHYS respectively, normalized by the sum of these three shares. We observe that the overall task distance when changing employers is substantial for both EE and EUE moves, with quite similar magnitudes and variances. This occurs even though the average direction along each task dimensions differs, especially along the

[20] Appendix B.1 provides details of the summary statistics of our sample of employer movers.

[21] Appendix B.2 shows comparison between the intensity of old and new jobs along the three task dimensions using the entire distributions.

[22] The move to jobs with a higher L-PHYS intensity dimension could reflect that some jobs that require dexterity skills also have a higher opportunity cost of an idle worker. While this feature may not apply to every job, we can observe in Section 5 that jobs in the upper tail of the H-PHYS intensity distribution tend to be jobs with high levels of L-PHYS as well.

Table 3: Task Changes of Task Switchers among Employer Movers, pooled sample

Simultaneous Employer and Task Switchers through Unemployment (EUE)							
	Changes in intensity in job switch				Intensity in old job		
	COG	H-PHYS	L-PHYS	DIST	COG	H-PHYS	L-PHYS
Mean	-0.078	0.0003	-0.0069	0.5928	-0.4569	-0.1083	0.0319
SD	1.0089	1.1314	1.0572	0.3158	0.8925	0.8463	0.8806
Obs	24,205	24,205	24,205	24,205	24,205	24,205	24,205
Task Switchers who change Employers Directly (EE)							
	Changes in intensity in job switch				Intensity in old job		
	COG	H-PHYS	L-PHYS	DIST	COG	H-PHYS	L-PHYS
Mean	0.0235	0.0312	0.0182	0.5877	-0.3719	-0.129	-0.0254
SD	1.0133	1.1263	1.022	0.318	0.9096	0.845	0.8221
Obs	30,419	30,419	30,419	30,419	30,419	30,419	30,419

COG dimension. In the next section, we will study how the business cycle affects the average direction, distance and distribution of task moves.

The last three columns of Table 3 show the tasks that are typically left behind in a previous job when a worker moves employers and changes tasks. We find that relative to the average job in the economy (which has a normalized task intensity at 0), both EE and, in particular, EUE movers typically leave jobs that are less intense in cognitive tasks. These workers also leave behind jobs that are on average lower in H-PHYS intensity. Workers who become unemployed tend to come from jobs with a higher L-PHYS intensity than the economy-wide job average, while the opposite is true for EE task movers, for whom the L-PHYS intensity is typically lower than the economy-wide average. In Section 5 we study how the economy-wide task intensity distributions of origin and destination jobs changes over the business cycle, for EE and EUE employer movers.

3 Cyclical Task Changes by Employers Movers

We now turn to investigate how task intensities change over the business cycle for employer movers. Our analysis captures the business cycle using the aggregate unem-

Table 4: Occupational Code Mobility and the Business Cycle

Occupational Switching Propensity when Changing Employer						
	EUE Transition			EE Transition		
	1-digit	3-digit	4-digit	1-digit	3-digit	4-digit
UR_t	-0.009**	-0.015***	-0.016***	-0.005	-0.009***	-0.007***
	(0.0042)	(0.0039)	-0.0039	(0.0040)	(0.0034)	(0.0024)
Lin. trend	x	x	x	x	x	x
Month FE	x	x	x	x	x	x
Monthly Obs	190	190	190	190	190	190

ployment rate, UR_t.[23] We rely on two major economic slowdowns during the period 1997-2015 to obtain business cycle variation. From October 2008 to May 2009 the economy experienced a drastic increase in unemployment due to the global financial crises (Cross and Bergevin, 2012). Between 2002-2003, the economy also experienced a noticeable uptick in unemployment. Although, this episode was not officially classified as a recession, it nevertheless represented a period with considerably increased slackness in the labor market, impacting occupational mobility patterns.

3.1 Workers' Occupational Mobility over the Cycle

The most conventional measure of reallocation across different job types is a change in these jobs' occupational code (at one's preferred level of aggregation). Implicitly, this imposes a discrete distance metric: occupational stayers have zero distance, while any change of occupational code has a distance of one. Before analyzing our gradual measure of change we briefly describe the cyclical behavior of this discrete measure. Our aim is to place the Canadian experience in context with comparable international evidence.

Table 4 reports the cyclicality of occupation switches, separately for EE and EUE workers. Similar to the prior literature, results are generated from OLS regressions of the average monthly occupational mobility rates (at 1-, 3- and 4-digit NOC level), on the Canadian unemployment rate, a linear trend and dummies for calendar months.

[23] Since the LFS data are the source of Canada's official statistics on employment and unemployment, we generate the aggregate unemployment rate directly from the LFS, prior to sampling restrictions.

The estimates show a clear pattern: when unemployment rates are high, more unemployment spells end with workers taking a job in their previous occupation. In other words, during recessions unemployed workers display stronger (realized) attachment to the their old occupation, whether by choice or by constraint. This result holds at all three levels of aggregation.[24] Similarly, in downturns EE movers are more often occupation stayers, most evident among 4- and 3-digit levels of occupational aggregation and weaker and statistically insignificant at the 1-digit level.

These results are consistent with the international evidence. The empirical elasticity of the (pro)cyclicality of occupational mobility of the unemployed is comparable to what Carrillo-Tudela and Visschers (2023) find for the Survey of Income and Program Participation and the Current Population Survey (CPS) in the US. Procyclicality of sectoral or occupational mobility, at different aggregation levels for both EUE and EE movers is also observed in the CPS in Hobijn (2012) (industries) and Carrillo-Tudela et al. (2015) (occupations) and in the UK Labour Force Survey (Carrillo-Tudela et al., 2016).

3.2 Workers' Task Mobility over the Cycle

We now turn to our continuous measure of task changes and show it uncovers further insights on the nature of workers' reallocation over the cycle. We use the full depth of the individual-level panel data in the LFS, separately considering the samples of EE and EUE movers, and estimating linear probability models of the following form

$$\textit{Task Change}_{j,it} = \alpha + \gamma UR_t + \delta(UR_{\ell_{it}t} - UR_t) + X'_{it}\beta + J'_{it}\Omega + \mu(t) + \tau t + \eta(\ell_{it}) + \epsilon_{it}. \quad (1)$$

The outcomes we examine in equation (1) include task changes of individual i at time j along each of the three orthogonal task dimensions j: COG, H-PHYS, and L-PHYS, as well as the total change along all three dimensions (DIST) measured as Man-

[24]The average occupational mobility rates for employer movers across the entire sample are, at 1-, 3-, and 4-digit level, resp., 0.43, 0.67, and 0.70.

Table 5: Unemployed Workers' Task Mobility over the Cycle

	EUE Task Changers Only				EUE incl. Task Stayers			
	Δ COG (1)	Δ H-PHYS (2)	Δ L-PHYS (3)	DIST (4)	Δ COG (5)	Δ H-PHYS (6)	Δ L-PHYS (7)	DIST (8)
	PANEL A. Unemployment Rate Only							
UR_t	-0.029**	-0.027**	0.024*	0.006	-0.020**	-0.019**	0.017*	-0.010**
	(0.012)	(0.013)	(0.013)	(0.004)	(0.009)	(0.010)	(0.009)	(0.004)
	PANEL B. With Controls, also for Education, Marital Status, Public Sector Job							
UR_t	-0.025**	-0.028**	0.022*	0.005	-0.017*	-0.020**	0.016*	-0.009**
	(0.013)	(0.014)	(0.013)	(0.004)	(0.009)	(0.010)	(0.009)	(0.004)
Age	-0.005***	-0.001	0.002**	-0.001***	-0.003***	-0.001	0.001**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Male	0.013	-0.073***	0.025	-0.019***	0.015	-0.053***	0.019	-0.032***
	(0.017)	(0.022)	(0.017)	(0.005)	(0.012)	(0.016)	(0.013)	(0.006)
Obs	24,205	24,205	24,205	24,205	33,368	33,368	33,368	33,368

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by month. Educ are education dummies for less than high school, HS grads, some College, College graduates. MS=marital status. Pub Sector: last job was a public sector job. All regressions includes month-of-year dummies, linear trend, and regional unemployment rates.

hattan distance.[25] Task changes are regressed against the national unemployment rate UR_t, regional deviations from the national unemployment rate $(UR_{\ell_{it}t} - UR_t)$, month-of-year indicators $\mu(t)$ to capture any seasonality, and a linear time trend t. In further specifications, we include worker characteristics, X_{it}, and last job, J_{it}, characteristics and economic region ℓ_{it} fixed effects, $\eta(\ell_{it})$.

Employer changers through Unemployment In Table 5 we report regression results for EUE movers.These results are presented for two populations: (i) the subset of task changers, or EUE movers who also change tasks; and (ii) the set of all EUE movers, which includes both task changers and task stayers. Results for the former, presented in columns (1)$-$(4), show how the business cycle affects task mobility of those who left behind their 4-digit occupation. Results for the latter, presented in columns (5)$-$(8), show what happens to task mobility among the unemployed in general.

Panel A presents the results from the specification with limited controls (month-of-year dummies, linear trend, regional deviations from aggregate unemployment rate). Panel B shows the results with added controls, such as gender, age, marital status, and

[25]For EE transitions, $t-1$ captures the previous job. For EUE transitions, the previous occupational information is carried forward to $t-1$, mimicking the reporting in the LFS.

whether the last job was a public sector job.[26] Adding these controls does relatively little to the observed *cyclical* relationship.

We find that workers who changed tasks after an unemployment spell during downturns get reemployed in jobs that exhibit lower cognitive intensities relative to expansions. Column (1) shows that for a 1 percentage point rise in unemployment, the average loss of COG intensity increases by 3%. Likewise, workers going through unemployment on average lose more H-PHYS intensity when unemployment is high, similar in magnitude to COG losses. These are large effects. To put them into perspective, if the unemployment rate were 1 percentage point above trend, our estimates imply that an unemployed worker would lose about one third of the average (per capita) COG and H-PHYS loss in the economy over the entire 1997-2015 period. These loses contrast with the gains unemployed workers make in their new jobs on the L-PHYS intensity dimension during downturns.

Thus, during downturns EUE task changers end up employed in jobs exhibiting substantially lower COG and H-PHYS intensities, but higher L-PHYS intensities. Interestingly, when aggregating these changes into an overall distance, column (4) reveals much smaller cyclical changes. This highlights once again that important cyclical sensitivities can be hidden in less responsive binary or one-dimensional distance measures. Including task stayers in columns (5)-(8) (that are more common during recessions) attenuates the coefficients on individual task dimensions but does not change our conclusions.

In the context of economy-wide long-run task trends, Table 2 and Table 5 imply that the loss in COG intensity when unemployment is high during a recession, works against the economy's long-term trend increase in COG intensity. The larger H-PHYS losses during recessions, however, amplify its aggregate long-term trend.

Unemployment Duration In Table 6 we add unemployment duration to our regressors. Carrillo-Tudela and Visschers (2023) document that workers with higher unemployment durations change occupational codes more often. Here we show that the

[26] Public sector jobs tend to be more cognitive, for given worker characteristics. Leaving such a job is associated with a larger COG loss.

direction of the adjustment of the task portfolio does also changes with unemployment duration. Task changers with higher unemployment durations end up falling deeper down the COG dimension; while the longer the unemployment spell, the stronger also the increase in L-PHYS intensity. This suggests that occupation-specific human capital depreciates faster than general human capital, as longer durations are associated with moves to a more dissimilar task portfolio.

Table 6: Workers' Unemployment Duration and Task Mobility over the Cycle

	EUE Task Movers Only				EUE incl. Task Stayers			
	Δ COG (1)	Δ H-PHYS (2)	Δ L-PHYS (3)	DIST (4)	Δ COG (5)	Δ H-PHYS (6)	Δ L-PHYS (7)	DIST (8)
UR_t	-0.019	-0.028**	0.021*	0.005	-0.012	-0.020**	-0.016**	-0.010**
	(0.013)	(0.014)	(0.013)	(0.004)	(0.009)	(0.010)	(0.009)	(0.004)
Unemp.	-1.882**	-0.458	1.583*	0.093	-1.730***	-0.380	1.208*	1.153***
Duration	(0.885)	(1.067)	(0.924)	(0.282)	(0.664)	(0.794)	(0.688)	(0.278)
Obs	22,948	22,948	22,948	22,948	31,082	31,082	31,082	31,082

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by month. See Table 5 for more details. Regressors also include age, gender, marital status, education and public sector dummies.

Note that recessions continue to affect task intensity changes even conditional on unemployment duration. Unemployed workers lose more H-PHYS intensity in recessions and gain more L-PHYS intensity upon re-entering employment for any given unemployment duration. The effect on the COG intensity dimension remains negative, but attenuated.

Job-to-Job Employer Changers The task changes of EE movers, in Table 7, provide a contrast to the task changes of EUE movers. We again summarize the results across two populations using two corresponding sets of regressions. Columns 1–4 show the results for task changing EE movers, and columns 5–8 for all EE movers, incl. task stayers. Panel A displays the regressions of EE task intensity changes (and distance) on the aggregate unemployment rate and the same limited set of controls behind Panel A of Table 5. Panel B adds the same worker and job characteristics as in Panel B of Table 5, *plus* tenure in the last job. As before, we observe that controlling for workforce composition along these dimensions does little to affect the cyclical behavior of task intensity and distance changes, even though characteristics matter for the level of task mobility: older, male and high-tenure workers experience lower changes in COG and H-PHYS intensity during EE transitions.

Table 7: Task Mobility in Direct Employer-to-Employer Moves over the Cycle

	EE Task Changers Only				EE incl. Task Stayers			
	Δ COG (1)	Δ H-PHYS (2)	Δ L-PHYS (3)	DIST (4)	Δ COG (5)	Δ H-PHYS (6)	Δ L-PHYS (7)	DIST (8)
PANEL A. Unemployment Rate Only								
UR_t	0.017*	0.029**	0.005	0.010***	0.011	0.019**	0.003	0.002
	(0.010)	(0.011)	(0.010)	(0.003)	(0.007)	(0.008)	(0.00)	(0.003)
Panel B. With Controls, also for Education, Marital Status, Public Sector Job								
UR_t	0.018*	0.029**	0.007	0.011***	0.012*	0.019**	0.005	0.005*
	(0.010)	(0.012)	(0.010)	(0.003)	(0.007)	(0.008)	(0.007)	(0.003)
Age	-0.002***	-0.002**	0.000	-0.001***	-0.002***	-0.001**	0.000	-0.004***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Male	-0.023*	-0.045**	0.080***	-0.002	-0.019**	-0.032**	0.057***	-0.018***
	(0.014)	(0.018)	(0.016)	(0.005)	(0.009)	(0.013)	(0.011)	(0.005)
Job	-0.686***	-0.12	0.071	-0.140***	-0.405***	-0.085	0.042	-0.144***
Tenure	(0.137)	(0.166)	(0.164)	(0.048)	(0.085)	(0.102)	(0.099)	(0.045)
Obs	30,419	30,419	30,419	30,419	43,255	43,255	43,255	43,255

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by month. See Table 5 for more details.

Comparing Table 5 (for EUE movers) and Table 7 (for EE movers), we find opposing cyclical COG and H-PHYS task intensity changes among these two types of transitions. While EUE task changers lose more on the COG and H-PHYS task dimensions during recessions, EE task changers gain more on these dimensions, with no change in the L-PHYS dimension. Column 4 shows that this implies that EE task changers cover more overall distance in recessions relative to expansions than EUE task changers.

When considering the entire set of EE movers, we observe two opposing forces at work: in downturns task staying becomes more common, while workers who are task changers exhibit larger changes in their tasks. Although the increased presence of task stayers in recessions dampens the patterns discussed above for each dimension, the main conclusions remain.

4 Cyclicality of the Distribution of Task Intensity Changes

We now move away from average changes and investigate how the *distributions* of task intensity changes of EE and EUE movers evolve over the business cycle. This is

Table 8: Cyclicality of the Distribution of Individual Task Changes

	Panel A: EUE Task Changers, coefficient on UR_t				
LHS quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	-0.0513***	-0.0501***	-0.0217**	-0.0350**	-0.0012
	(0.0197)	(0.0180)	(0.0110)	(0.0176)	(0.0209)
Δ H-PHYS	-0.0266	-0.0667***	-0.0075	-0.0296	-0.0279
	(0.0208)	(0.0250)	(0.0089)	(0.0234)	(0.0206)
Δ L-PHYS	0.0297	0.0412**	0.0152	0.0186	0.0251
	(0.0186)	(0.0165)	(0.0134)	(0.0150)	(0.0213)
	Panel B: EE Task Changers, coefficient on UR_t				
LHS var quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	-0.0283	0.0030	0.0093	0.0476***	0.0637***
	(0.0205)	(0.0163)	(0.0100)	(0.0165)	(0.0187)
Δ H-PHYS	0.0379**	0.0580**	0.0209***	0.0332	0.0317
	(0.0189)	(0.0245)	(0.0067)	(0.0216)	(0.0196)
Δ L-PHYS	0.0260	-0.0020	0.0045	0.0098	-0.0065
	(0.0172)	(0.0136)	(0.0114)	(0.0143)	(0.0203)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported numbers are coefficients on UR_t in quantile regression, with LHS variable (in row) and quantile (in column). Standard errors in parentheses robust to heteroskedasticity. Additional regressors include month dummies for seasonality and a linear time trend

interesting for multiple reasons. Comparing the standard deviations in Table 3 with the coefficients in the regression tables or the bottom row of Table 2, one can observe that the dispersion of task intensity changes of EE and EUE movers is sizeable relative to both the cyclical and structural shifts in mean task changes. As a result, the behavior of different quantiles of the distribution can highlight the inequality among task changers across the cycle.[27] Further, from a more theoretical perspective, theories built to explain cyclical task mobility could have differing implications for the cyclical behavior of the *distribution* of task changes. As such, the plausibility of these theories can be judged better using the documented cyclical distributional patterns.

Table 8 shows the cyclical response of the task change distribution at the respective 10th, 25th, 50th, 75th and 90th percentiles, denoted by q. The values reported on the first line (ΔCOG) correspond to the coefficients of the aggregate unemployment rate

[27]For example, the behavior in the distributions' 'lower' tails could weigh heavily on workers' risk-averse/precautionary behaviour. The wide dispersion of task intensity changes of EE/EUE movers is consistent with the wide dispersion of earnings changes of EE/EUE movers (see e.g. Busch (2020), Carrillo-Tudela et al. (2022)).

estimated from a quantile regression with robust standard errors,

$$\textit{Task Change}(q)_{it} = \alpha(q) + \gamma(q)UR_t + \mu(q,t) + \tau(q), t + \epsilon(q)_{it} \tag{2}$$

which includes month fixed effects $\mu(q,t)$ and a linear time trend $\tau(q)$. The columns in Table 8 correspond to different quantiles q and the rows correspond to different task measures under consideration.

The first row of Panel A shows that decreased COG intensity among EUE task changers during recessions, previously documented for the mean in Table 5, is mimicked across the distribution. Specifically, the COG intensity change distribution is first-order stochastically dominated by the same distribution in expansion. The cyclical response is stronger in the lower tail, where large losses of COG intensity are more likely in recessions.[28] Instead, for EE task changers, the first row in Panel B shows the opposite pattern. The improvement in the average COG intensity dimension is reflected across the task change distribution, with the distribution shifting up in recessions. In this case, the stronger cyclical response lies in the right tail.

The H-PHYS task change distribution, specific to EUE task changers, also moves down as a whole during recessions with higher cyclical sensitivity in the left tail. The corresponding task change distribution of EE task movers again moves in the opposite direction, but now with a particularly pronounced upward shift of its left tail in recessions. Finally, the mean increase in the L-PHYS dimension among EUE workers during recessions is observed throughout the distribution, although most of the coefficients are not statistically significant. These regressions also confirm that among EE task movers there is no significant change on the L-PHYS dimension between recessions and expansions.

Appendix B.3 provides a graphical representation of the above results. In this ap-

[28]Because cognitive tasks earn higher wages (Autor and Handel, 2013, for example), the large losses in the COG intensity dimension at essentially all quantiles mirror the sharp recessionary drops in the right tail of the earnings growth distribution documented in Guvenen et al. (2014) and, conditional on EUE moves, in Carrillo-Tudela et al. (2022). The large drops in COG task intensity and in wages during recessions suggest that the wage patterns documented in the literature go beyond merely a shift in rent division but also reflect changes in tasks.

pendix we also show that including EE and EUE task stayers, creates a mass point at zero in each respective task change distribution. In downturns, the increased incidence of task staying among EUE movers implies that there are fewer large increases in COG and H-PHYS, more mass at zero, and a longer left tail of deeper losses of COG and H-PHYS intensity.[29] In other words, the COG and H-PHYS task change distributions of EUE movers become (weakly, in the case of H-PHYS) more left-skewed in recessions, consistent with the increased left-skewness of the earnings change distribution documented in Guvenen et al. (2014). For EE movers, however, the task change distributions of COG and H-PHYS move in opposite direction and become more right-skewed.

5 Cyclical Differences in Origin and Destination Task Portfolios

Building from the previous results, we now separately investigate the cyclical task distributions of old jobs, from which workers separate, and of new jobs. Again, we consider all employer movers separately from the subset that are also task changers. Shifts in the task distributions of *all* employer movers will describe the dynamics of task space by illustrating where new jobs were created, where old jobs were destroyed, and where there was no change. Distribution shifts among *task changers* will illustrate more clearly any cyclical loses and gains across task space specific to *reallocating* workers which, by its nature, is more closely related to cyclical economy-wide task reallocation.

5.1 Employer Movers with Intervening Unemployment Spell

Table 9 displays quantile regression coefficients for the unemployment rate, separately for the three dimensions of the task. In the following, we discuss each task dimension in turn.

[29]The results of the quantile regressions of all EUE and EE employer movers are in Appendix Tables B.2 and B.3.

Table 9: Changes in the Task Intensity Distributions over the Cycle: Quantile Regression coefficients of Unemployment Rate, for EUE moves

PANEL A: Previous Jobs of all EUE Movers (incl. Task Stayers)					
Task Distr. Last Job	Q10	Q25	Q50	Q75	Q90
COG intensity	0.0124***	0.0046	0.0178	0.0213	0.0269*
	(0.0046)	(0.0073)	(0.0136)	(0.0134)	(0.0145)
H-PHYS intensity	0.0110**	0.0000	0.0642***	0.0400***	0.0286**
	(0.0048)	(0.0014)	(0.0190)	(0.0127)	(0.0135)
L-PHYS intensity	-0.0011	-0.0000	0.0279**	0.0226**	0.0162***
	(0.0050)	(0.0036)	(0.0134)	(0.0113)	(0.0057)
PANEL B: New Jobs of all EUE Movers (incl. Task Stayers)					
Task Distr. New Job	Q10	Q25	Q50	Q75	Q90
COG intensity	-0.0000	-0.0000	-0.0031	-0.0106	0.0000
	(0.0092)	(0.0078)	(0.0156)	(0.0214)	(0.0154)
H-PHYS intensity	-0.0000	-0.0000	0.0186	0.0285**	0.0001
	(0.0035)	(0.0009)	(0.0191)	(0.0128)	(0.0111)
L-PHYS intensity	0.0000	0.0041	0.0454***	0.0337***	0.0146
	(0.0051)	(0.0027)	(0.0126)	(0.0090)	(0.0091)
PANEL C: Previous Jobs of EUE *Task Changers*					
Task Distr. Last Job	Q10	Q25	Q50	Q75	Q90
COG intensity	0.0098**	0.0026	0.0135	0.0387*	0.0620**
	(0.0047)	(0.0069)	(0.0187)	(0.0203)	(0.0256)
H-PHYS intensity	0.0082*	0.0033	0.1015***	-0.0023	0.0171
	(0.0045)	(0.0023)	(0.0333)	(0.0144)	(0.0135)
L-PHYS intensity	-0.0000	-0.0000	0.0085	-0.0000	0.0000
	(0.0071)	(0.0067)	(0.0148)	(0.0102)	(0.0187)
PANEL D: New Jobs of EUE *Task Changers*					
Task Distr. New Job	Q10	Q25	Q50	Q75	Q90
COG intensity	0.0000	0.0000	-0.0107	-0.0178	0.0156
	(0.0008)	(0.0076)	(0.0174)	(0.0221)	(0.0195)
H-PHYS intensity	0.0000	-0.0000	-0.0000	-0.0000	-0.0179
	(0.0044)	(0.0020)	(0.0296)	(0.0088)	(0.0114)
L-PHYS intensity	0.0068	0.0074	0.0319**	-0.0000	0.0197
	(0.0063)	(0.0054)	(0.0135)	(0.0071)	(0.0181)

COG Task Dimension Panel A illustrates that the COG dimension of destroyed jobs after an EU move shifts towards higher COG intensities during recessions. This is most clearly visible at the 10th and 90th percentiles: the intensity of the low COG-intense and high COG-intense jobs destroyed increases.[30] In contrast, there is no signif-

[30]These pattern presents an interesting counterpart to Mueller (2017)'s finding that in recessions the pool of unemployed shifts towards previously high-wage workers. Here, the shift is towards workers

icant shift of the COG distribution of reemployment jobs in Panel B. Thus, the cyclical composition shift along the COG dimension for EUE employer movers is characterized largely by shifts in the intensity of jobs destroyed, rather than the the intensity jobs created. Panels C and D show similar patterns when only EUE *task changers are considered*. In this case, we observe stronger effects on the intensity of the highest COG-intense jobs that are destroyed, further suggesting that adverse labor market conditions hit the higher COG intensities jobs harder.

H-PHYS Task Dimension The H-PHYS dimension of the distribution of destroyed jobs also moves up in recessions, and this shift is stronger than the one observed along the COG dimension of destroyed jobs, especially at the median and in the upper tail. In contrast to the COG dimension, Panel B shows that the H-PHYS dimension of the distribution of re-employment jobs does shift up, but the increase remains weaker than for the distribution of destroyed jobs, and only visible between the median and the 75th percentile. Panel C shows a similar pattern for the distributions of destroyed jobs among task changers. However, for this group the cyclical change is much weaker. This is also reflected in Panel D, where we observe that the distribution of re-employment jobs does not change over the cycle along the H-PHYS task dimension. These results then suggest that task stayers are driving most of the aggregate results, such that during recessions more workers in jobs with higher H-PHYS intensities become unemployed, and a large proportion of these workers return to their old task portfolio in their re-employment jobs.

L-PHYS Task Dimension Panels A-D show that along the L-PHYS dimension we observe a pattern similar to the H-PHYS dimension. Among all EUE workers, destroyed and re-employment jobs have a stronger intensity on the L-PHYS dimension during recessions than during expansions. One notable difference is the strength of the upward shift of the L-PHYS dimension of the re-employment job distribution. New jobs taken by the unemployed during recessions have a much stronger L-PHYS dimension compared to the H-PHYS dimension. Among task changers, the only significant cycli-

with previously high COG-intense jobs.

Table 10: Changes in the Task Intensity Distributions over the Cycle: Quantile Regression coefficients of Unemployment Rate, for EE moves

Panel I: Previous Jobs of EE Task *Changers*					
Task Distr. Last Job	Q10	Q25	Q50	Q75	Q90
COG intensity	-0.0125***	-0.0225**	-0.0016	0.0138	0.0137
	(0.0042)	(0.0111)	(0.0089)	(0.0140)	(0.0175)
H-PHYS intensity	-0.0049	-0.0019	-0.0494	-0.0000	-0.0103
	(0.0047)	(0.0034)	(0.0303)	(0.0062)	(0.0130)
L-PHYS intensity	0.0143	0.0057	0.0000	0.0000	-0.0011
	(0.0131)	(0.0048)	(0.0074)	(0.0164)	(0.0208)
Panel II: New Jobs of EE Task *Changers*					
Task Distr. New Job	Q10	Q25	Q50	Q75	Q90
COG intensity	0.0032	-0.0010	0.0178	0.0250*	0.0159**
	(0.0037)	(0.0080)	(0.0128)	(0.0151)	(0.0078)
H-PHYS intensity	0.0048	0.0000	0.0555*	0.0285**	0.0091
	(0.0043)	(0.0014)	(0.0298)	(0.0130)	(0.0110)
L-PHYS intensity	0.0000	0.0000	0.0222*	-0.0000	0.0153
	(0.0051)	(0.0062)	(0.0127)	(0.0076)	(0.0167)

cal variation is observed at the median in the L-PHYS distribution of re-employment jobs.[31] These results suggest the following pattern during recessions: more workers in jobs with higher H-PHYS *and* higher L-PHYS intensities become unemployed, and these workers subsequently return to jobs with an even higher L-PHYS intensity.

In summary, during recessions the distribution of the COG, H-PHYS and L-PHYS dimensions of jobs destroyed shifts up, such that more of these type of jobs get destroyed. At the same time, the distribution of the H-PHYS and L-PHYS dimensions of re-employment jobs shifts up, driven by task stayers. This suggests that while there is worker reallocation across jobs with similar task portfolios in the H-PHYS and L-PHYS dimensions, jobs with a high COG dimension are lost and appear not to return after re-employment. Thus, the sullying effect of recessions among EUE transitions arises from the lack of a significant response of the job COG dimension of re-employment jobs.

[31] This could reflect the stronger *net* inflow into non-routine manual jobs in recessions, documented in Jaimovich and Siu (2020) and Carrillo-Tudela and Visschers (2023)

5.2 Direct Employer-to-Employer Movers

A key message of this paper is that the tasks distributions of the jobs of EE and EUE movers have strikingly different patterns. We observe this feature once again when analyzing the distributions of destroyed and new jobs. Table 10 shows this difference based on task changers only as, in contrast with EUE movers, the inclusion of task stayers does not meaningfully change the conclusions obtained from EE task changers alone.

The top and bottom panels of Table 10 show that, conditional on an EE transition, workers leave behind jobs with low cognitive intensity and move to jobs with much higher cognitive intensity. This reallocation is very different from the cyclical patterns documented along the COG dimension for EUE movers and emphasizes the cleansing effect of recessions along the COG dimension among EE movers. A similar pattern is evident for the H-PHYS dimension, but mainly in terms of new jobs and between the median and the 75th percentile. EE moves along the L-PHYS dimension exhibit few meaningful cyclical shifts, with the exception around median where mostly sales and services occupations are located.

In contrast to EUE transitions, where new-job task distributions change little across the cycle, we observe meaningful changes among EE transitions at the upper tail of the COG and H-PHYS distributions. Thus, in recessions, the jobs reached through EE moves are proportionally more often among the most COG and H-PHYS intense.

6 Further Discussion and Conclusion

Overall, the task portfolio dynamics of workers changes significantly with the business cycle. This applies to the magnitude, direction, and dispersion of task portfolio changes among workers that changed employer. It also applies to the locations in the 'task space' where these task portfolio changes originate and terminate. The direction and magnitude of task portfolio changes, which can be thought of as a measure of the *quality* of employer and task moves, reveal valuable lessons for theories and suggest new underlying mechanisms applicable to the study of labor market dynamics. These lessons would be obscured when we consider only the propensity or the frequency with which workers change their task portfolio, i.e the quantity of such moves.

Consider the cyclicality of the task mobility of the unemployed. In recessions, we observe that these workers more often return to their previous task portfolio. If they do not, they typically lose more along the COG and H-PHYS intensity dimensions than they would in expansions, where particularly extreme losses of COG and H-PHYS intensity become more likely.

One possible explanation for this pattern is that in recessions the distribution of possible alternative task portfolios for the unemployed shifts down in quality relative to their pre-displacement jobs. This is consistent with the larger COG and H-PHYS intensity losses observed during recessions.[32] In response to worse alternative task portfolios, the unemployed would try to return to their similar portfolios. Alternatively, the particularly strong increase in *large* losses of COG and H-PHYS intensities could also suggest that in recessions the layoff shock that “pushes" workers out of their old task portfolio (or occupations) may become stronger relative to the probability of finding jobs that “pulls" these workers towards new portfolios. Therefore, it seems important to disentangle the relative roles played by the returns to mobility versus the job loss and job finding probabilities along task portfolios in structural models that incorporate worker reallocation, e.g. through cyclically varying obsolescence shocks (as done in Huckfeldt (2022)) or occupation separation shocks (as in Carrillo-Tudela et al. (2022)).

The magnitude and direction of task changes in EE transitions can inform whether there is any recovery from an EUE transition. In downturns, drops of COG intensity among EUE movers are larger, start from more cognitively intense jobs than they would during expansions, and end in the typical jobs workers take out of unemployment. At the same time, EE moves during recessions start at lower COG intensities and bring

[32] In Carrillo-Tudela and Visschers (2023), we argue that the lower expected outcomes of occupational reallocation play an important role in the lengthening of unemployment spells in recession, particularly the increase in long-term unemployment.

workers to highly COG-intense jobs. Therefore, EE and EUE mobility along the COG task intensity dimension suggests a job ladder that operates differently over the business cycle than the one proposed in standard job ladder models. In this alternative task job ladder the loss in COG intensity from EUE transitions can be recouped by a subsequent EE transition, working as a sort of 'bungee' jump that has a longer elastic during recessions, and where the extent of the bounce-back determines the scarring effect of recessions.

The patterns documented here appear to connect better to theories of cyclical mismatch and cyclical underemployment than standard job ladder models. They strongly hint at a cyclical shift in which more cognitively skilled workers take jobs that could also be done by less cognitively skilled workers. In this sense our results relate to Devereux (2002), Summerfield (2021), Barnichon and Zylberberg (2019) and can rationalize the increase in skill requirements among vacancies, as documented by Modestino et al. (2020).[33] This also applies to the H-PHYS task dimension as well because this dimension exhibits cyclical patterns similar to those of the COG dimension. A key difference lies in their long-term trends, where the COG intensity of the economy is steadily increasing, while the H-PHYS intensity is steadily decreasing. It is natural to connect these trends to job destruction patterns and worker flows. In addition, the reallocation of workers throughout the business cycle is often linked to the direction of longer-term trends. For example, Jaimovich and Siu (2020) link the multi-decade job polarization trend to cyclical employment patterns. In this context, the similarity in the cyclical H-PHYS and COG task change patterns may appear surprising.

Overall our task-based approach to worker reallocation reveals the need for nuance when characterizing recessions as either cleansing or sullying. That is, unemployment in recessions could be associated with 'cleansing' along the H-PHYS dimension (at least when considering EUE flows), but at the same time with 'sullying' along the COG dimension. One key aspect is to what extent these dimensions operate separately or are intertwined. This is important to inform labor market policy, particularly to know

[33] See Dolado et al. (2009) for a (non-cyclical) frictional labor market model where skill mismatch is transitory due to job-to-job mobility.

whether any recessionary losses along the cognitive dimension could be mitigated independently from potentially more beneficial cleansing along other task dimensions. This may or may not be the case: some of the COG and H-PHYS intensities could be tied together at the level of individual jobs and workers.[34] This highlights that, when investigating the micro-level of task portfolio changes, we learn lessons that are of great relevance for the macro level.

Although we do not analyze the earnings changes associated with task changes in this paper, there is now strong evidence showing that earnings growth distribution exhibits procyclical skewness. This implies that during recessions there are more and larger earnings losses in the left of the distribution and less and smaller earnings gains in the right tail of the distribution (see Guvenen et al. (2014)). Further, the cyclical behavior of the tails are dominated by the cyclical behavior of EUE and EE movers who also change occupations (see Carrillo-Tudela et al. (2022)). Our results imply that larger earnings losses in recessions among EUE movers are accompanied by worker reallocating across jobs that are more intensive in high-physical and low-physical tasks, while smaller earnings gains among EE movers are accompanied by worker reallocation towards jobs that exhibit higher cognitive and high-physical intensities. We leave a further exploration of the interrelation between task and earnings changes to future research.

[34] In the Appendix, we show that, among the higher H-PHYS intensities, as the H-PHYS intensity increases, cognitive intensity increases as well. This pattern suggests that higher levels of H-PHYS intensity require non-trivial levels of cognitive intensity as well.

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Online Appendix

A Data and Task Measurement

A.1 Data Source

The Canadian Labor Force Survey (LFS) is a nationally representative survey of the Canadian labor market, akin to the Current Population Survey (CPS) for the United States. Surveys are administered monthly at the household level, with households rotating in and out of the sample every 6 months. We employ the confidential version of the LFS, available to researchers through Statistics Canada Research Data Centres. This has several advantages over the public-use version of the LFS, it allows linking persons longitudinally (required for studying transitions) and includes considerably more detail on worker and job characteristics.

The Canadian LFS has two desirable traits that assist in addressing our research questions. First, the data employ a consistent occupational coding for the period from 1987 to December 2015 and thereby avoid the somewhat inconveniently-timed occupational code changes of the Current Population Survey (CPS) in 1992 and 2003. However, due to the redesign of unemployment policies in the mid-90s, we have chosen to confine ourselves to 1997-2015. Second, the occupational data we employ from Canada's Career Handbook (CH) was designed *in parallel with* the Canadian occupation structure ensuring a seamless match to the data at hand.

A.2 Task Measurement

To measure the task (re)allocation of workers, we start with a list of the four-digit occupation codes present in the full LFS samples. We then turn to the CH, which contains occupational attributes and core worker competencies. The CH is Canadian analogue of the US O*NET database and its predecessor, the Dictionary of Occupational Titles (DOT). As mentioned above, a main advantage of the CH as our source for task information is that the CH is built directly on-top of the 2006 NOC occupation coding framework. Thus, tasks generated from the CH integrate seamlessly into the LFS data to provide task measures for essentially all recorded occupations. We step-back the uniform 2011 NOC occupation coding to the 2006 NOC structure using the concordance provided by Statistics Canada, preserving the uniformity of coding between the CH and the LFS data.[1]

A.3 Job Attributes in the Career Handbook

The Career Handbook lists 23 occupational attributes. These attributes are divided into broad categories, including nine "Aptitudes" (such as finger dexterity, verbal ability or spatial perception) grouped by position in the distribution of the working population; three categories describing the complexity of occupational elements "Data/Information, People and Things"; three Environmental condition measures that describe workplace hazards; and six "Physical Activities" (such as vision, strength or hearing).[2] Further, the CH collects the level of required education, and potential additional requirements for training outside the standard educational framework.[3]

A.4 Factor Analysis of CH Occupational Task Mapping

We re-scale all 23 measures to be ascending from a lowest value of 0 to a maximum of 1. The exception is education, which we re-code as approximate years of education.[4]

[1] A crosswalk provided by Statistics Canada to O*NET suggests that a broadly similar picture to the one sketched in this paper would arise when adding a further translation step from CH to O*NET.

[2] We normalize these scales below, but for completeness: aptitude measures are scaled from 0 to 8, environmental conditions from 1 to 5, and physical activities from 1 to 4.

[3] Also available are five "occupational interests" from the Canadian Work Preference Inventory. These are not used as they describe worker preferences rather than job characteristics or requirements. The additional requirements do not, in practice, appear to refer to training on the job in general but rather to certification or validated experience as e.g. accountant; engineers, computer programmer, religious worker, sales worker, material handler.

[4] Years of education are informed from Statistics Canada encoding categories used in the Survey of Labour and Income Dynamics (SLID), which have more detail than the LFS. We encode this variable as follows: 0 if "The occupation does not require formal education or training"; 10 if "Some high school education is required, or on-the-job training or previous related experience alone is adequate", or if "Some high school education may also be combined with on-the-job training or previous experience related to the occupation"; 12 if "The completion of high school is required"; 13 if "The completion of course work, training, workshops and/or experience related to the occupation, usually on completion of high school, is required. Course work refers to courses taken at special training institutes, colleges,

Second, we measure the number of workers in each 4-digit occupation in the LFS data to use as weights in the factor analysis procedure.

We use Factor Analysis to boil down the list of CH occupational attributes to a manageable set of basic tasks that are present in all occupations with varying magnitude. Factor Analysis allows us to identify the common sources of variation, in descending order such that the principal factor explains the most variation and the last factor explains the least. It estimates a model that explains each of the $p = \{1, \ldots, 23\}$ CH elements as a linear combination of $j = \{1, \ldots, K\}$ common factors T_j, weighted by a matrix of factor loadings Λ:

$$CH = \Lambda T + e. \tag{3}$$

Our estimation of this model returns 13 orthogonal factors, decreasing in order of their importance in explaining the common variation across the observable CH characteristics. We identify and retain only those factors that are significant, which is determined by selecting factors with eigenvalues greater than one.

Factor analysis estimates both T and Λ from the covariance of the matrix CH and thus can produce an infinite set of solutions, none of which is preferable to any of the others on a statistical basis. However, different arrangements of the model may produce factors that are easier to interpret if the original elements CH each load more heavily on to a single task from the vector T. To facilitate interpretation of factors, we rotate the factor matrix orthogonally using the varimax rotation, which maximizes the variance of the squared loadings of each of the original 23 CH elements onto the resulting three task measures. This procedure produces task measures so that each CH element loads heavily onto a single factor. As a result, the factors/tasks are more likely to have an interpretation based on the collection of original CH measures that are strong contributors.

universities and/or other training venues, but does not include the completion of a program." or "Vocational schooling: 2-5 years with 8 weeks per year"; 14 if "Completion of a program at a college or technical school is required. A program could lead to a certificate or a diploma"; 16 if "Completion of a university degree at the bachelor's level is required"; and 18 if "Completion of a university degree at the master's or doctoral level is required. Professional degrees that require additional education beyond the bachelor's level, such as law, dentistry, pharmacy and veterinary medicine, are also included".

Table A.1: Factor Analysis Results

Factor	Share Explained (ρ)	Interpretation
Task1	0.361	Cognitive
Task2	0.216	H-level Physical
Task3	0.147	L-level Physical

Factor analysis output with varimax rotation. Three principal factors retained. Canadian occupational distribution used as weights.

Table A.1 presents the results of the factor analysis procedure, including the "importance" or overall share of variation explained by each of the three tasks.[5] Table A.2 shows each of the CH elements and their intensity along these three task dimensions. Given that task 1 appears more important on CH elements that can be related to cognitive activities like education, learning, verbal and numerical abilities as well as complexity of data/information and people, we label such task as 'cognitive' (COG). Similarly, task 2 appears to weigh more heavily on CH elements that relate to physical work that requires perception, dexterity, motor coordination and complexity of things we label it 'high-physical' (H-PHYS). As task 3 is associated with physical activities that require strength, body position and limb coordination, we label it 'low-physical' (L-PHYS).

These tasks are then matched into our sample of LFS employer movers. This process allows each of the 520 occupations in our data to be described as a set of task magnitudes rather than an arbitrary numerical code. As a result each four-digit occupation can be interpreted as a location in the 3-dimensional task space, where the distance between any two occupations varies according to the magnitudes of the various task measures. In the main text we present the task intensity by 1-digit Major Occupational Groups. Table A.3 below does so for 2-digit occupations.

[5]Factor analysis generates a measure of uniqueness - the proportion of variance not explained by common factors that is unique to an original CH element. CH inputs with high uniqueness are not well-described by the resulting factors. In our analysis, only three have uniqueness greater than 0.5: Physical activities Hearing and Color discrimination and Environmental Condition Discomforts with values of 0.54, 0.67 and 0.51, respectively.

Table A.2: Factor Loading Matrix

CH Elements	Task 1 COG	Task 2 H-PHYS	Task 3 L-PHYS
Aptitudes			
General Learning Ability	0.8442	-0.0282	-0.2329
Verbal Ability	0.8659	-0.0845	-0.2182
Numerical Ability	0.6640	-0.1317	-0.1461
Spatial Perception	0.2579	0.3816	0.0249
Form Perception	0.3500	0.5384	0.1298
Clerical Perception	0.2281	-0.1563	-0.4262
Motor Co-ordination	-0.1476	0.8399	0.0653
Finger Dexterity	-0.0253	0.7629	-0.0437
Manual Dexterity	-0.2647	0.6484	0.3320
Complexity of...			
Data/Information	0.8785	-0.0102	-0.0443
People	0.8227	-0.2487	-0.1205
Things	-0.1873	0.7032	0.2040
Physical Activities			
Colour Discrimination	-0.0167	0.2898	0.0339
Vision	-0.1821	-0.0758	0.1738
Hearing	0.4519	-0.0482	-0.1620
Body Position	-0.2613	0.0924	0.7437
Limb Co-ordination	-0.4158	0.416	0.1946
Strength	-0.4770	0.1691	0.6403
Environmental Conditions			
Discomforts	-0.3096	0.1012	0.2882
Location	-0.1535	0.1248	0.4422
Hazards	-0.1420	0.3595	0.5376
Education/Training			
Years of Education	0.6919	-0.0373	-0.1490
Additional Requirements	0.5614	0.0066	0.1962

Factor loadings after varimax rotation. Factor loadings represent how each original CH element contributes to the task measures created by factor analysis. Additional requirements for education and training include “extensive experience, demonstrated or creative ability, appointments, etc." All elements scaled 0-1 except for years of education, scaled 0-18.

A.5 Task Space

In Figure 1 we display the distribution of the task intensities of *two*-digit occupations. Pairwise comparisons across any two of the three dimensions are used to illustrate averages calculated from the entire sample period, with the size of each bubble cor-

Table A.3: Task Intensity by 2-Digit Occupation

NOC Code	2-Digit Occupation Title	Distribution Proportion	Task1 COG Mean	Task2 H-PHYS Mean	Task3 L-PHYS Mean
00	Senior Management	0.001	1.749	-0.823	-0.304
01	Middle and Other Management (professional)	0.010	1.550	-0.842	-0.409
06	Middle and other Management (services)	0.012	0.631	-0.916	0.067
07	Middle and other Management (trades and manufacturing)	0.004	1.222	-0.793	-0.383
11	Professionals: Business and Finance	0.016	1.113	-0.840	-0.511
12	Skilled Admin & Business	0.030	0.261	0.110	-0.837
14	Clerical	0.093	-0.555	0.313	-0.960
21	Professionals: Natural &App. Sciences	0.019	1.363	-0.172	-0.588
22	Technicians: Natural &App. Sciences	0.024	0.378	1.214	-0.261
31	Professionals: Health	0.009	1.241	0.664	0.413
32	Technicians: Health	0.007	0.089	1.155	0.331
34	Assistants: Health	0.011	-0.855	-0.389	0.740
41	Professionals: Soc. Sci, Educ, Gov & Religion	0.026	1.360	-0.783	-0.108
42	Paraprofessionals: Law, Soc. Services, Educ & Religion	0.026	0.173	-0.730	-0.158
51	Professionals: Art & culture	0.017	1.242	0.024	-0.343
52	Technicians: Art, Culture, Rec. & Sport	0.004	0.554	1.243	-0.062
62	Skilled Sales and Service	0.052	0.254	0.088	0.019
64	Intermediate Sales and Service	0.121	-0.501	-0.721	-0.190
66	Elemental Sales and Service	0.126	-1.387	-0.447	0.168
72	Trades & Skilled Transp. + Equip. Operators (incl. supervisors)	0.088	-0.049	0.886	1.014
73	Trades & Skilled Transport + Equip. Operators	0.029	-0.146	1.054	1.132
74	Interm. Transport, Equip. Operators and Maint. (incl. drivers)	0.092	-1.039	0.205	-0.651
76	Trades Helpers	0.043	-1.232	-0.985	1.613
82	Skilled Occupations in Primary Industry (incl. Supervisors)	0.013	0.100	0.179	0.658
84	Intermediate Primary Industry	0.033	-1.071	0.276	0.645
86	Labourers in Primary Industry	0.027	-1.410	-0.040	0.661
92	Supervisors & Skilled Operators : Manufacturing & utilities	0.003	0.392	-0.039	0.008
94	Processing & Manufacturing Machine Operators and related	0.036	-1.226	0.242	-0.020
95	Assemblers in Manufacturing	0.006	-1.175	-0.132	1.033
96	Labourers in Manufacturing & Utilities	0.028	-1.364	-0.667	1.263

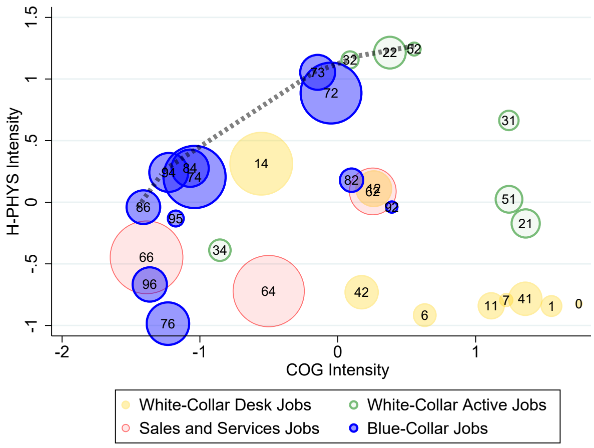
Source: 2006 Career Handbook. Occupation categories according to 2006 NOC codes. Mean task values by 2-digit occupation. Task values in this paper calculated for 4-digit NOC occupation codes (with substantial heterogeneity even within 2-digit occupations). Tasks created from career handbook occupational ratings using population weights from the LFS data.

responding to relative employment of the two-digit occupation.[6] We group those occupations further into four intuitive occupational super-categories (OSCs): blue-collar occupations that correspond industrial and trade occupations; sales and services occupations; and two groups of white-collar occupations termed ‘desk jobs' and ‘active jobs' according to the average L-PHYS intensity at the *one*-digit level.

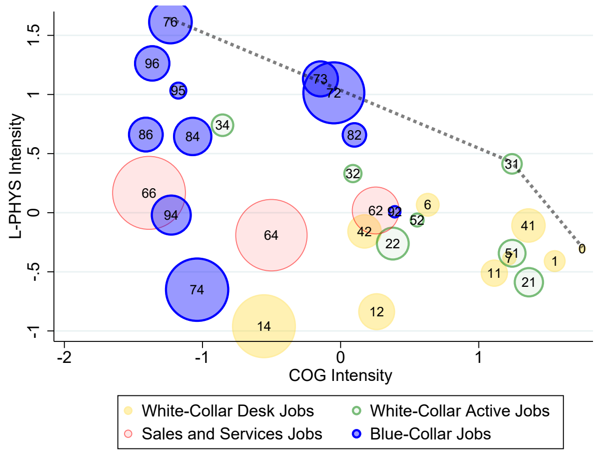
As discussed in the main text, we observe considerable heterogeneity in tasks, though some general tendencies are also evident across the four super-categories. As expected, blue-collar occupations are generally less cognitively intense, with most two-

[6]We calculate these by averaging (weighted by employment) over the four-digit task intensities that form the base of our analysis.

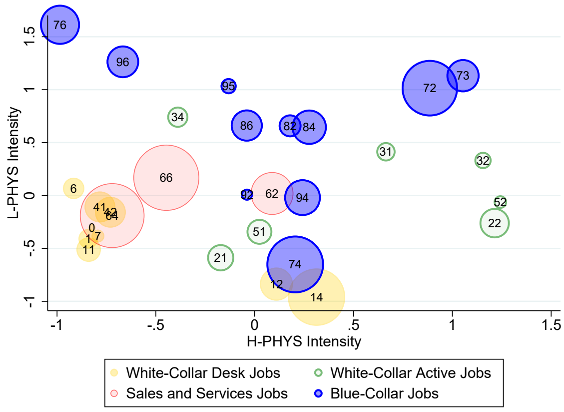
Figure 1: Two-digit Occupations in COG / H-PHYS / L-PHYS space



(a) COG vs H-PHYS intensities



(b) COG vs L-PHYS intensities



(c) H-PHYS vs L-PHYS intensities

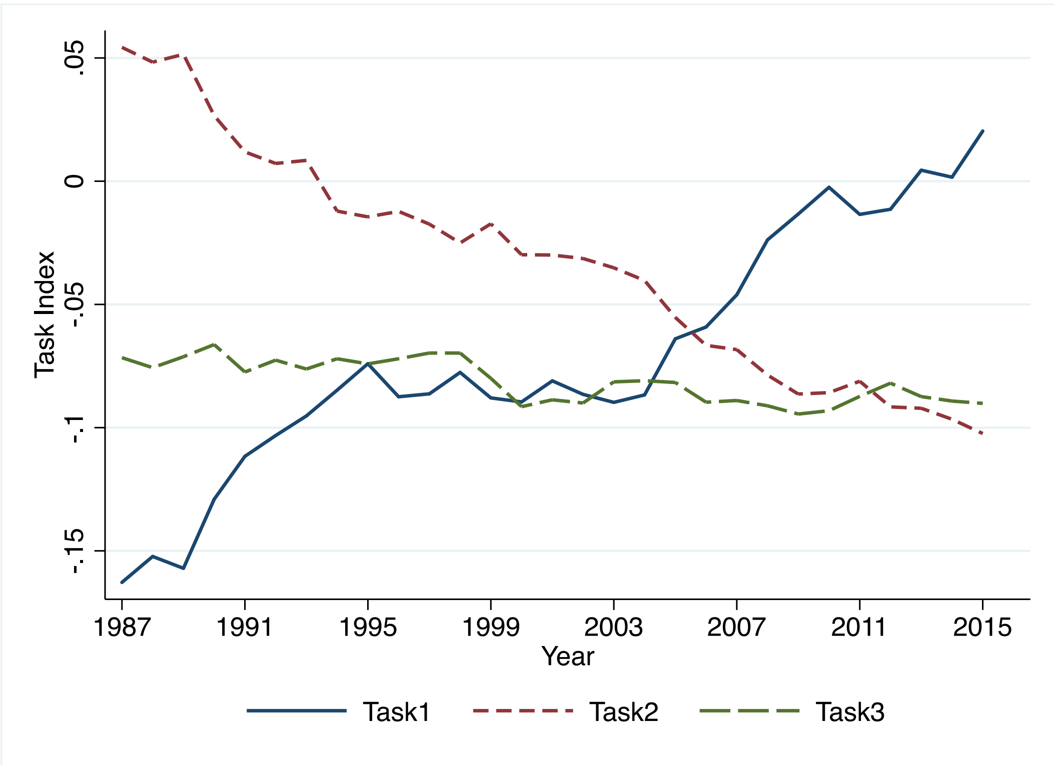
digit averages below the median COG intensity. Many, but importantly not all, blue-collar occupations are L-PHYS intense. They exhibit the largest span of H-PHYS/L-PHYS subspace. White-collar occupations tend to have a higher COG intensity, but with exceptions such as clerical work. Finally, sales and service occupations appear 'interior', characterized by below-median values on all dimensions.

One can draw *suggestive* 'task frontiers' to illustrate the outer borders of the (convexified) task set of observed occupational task vectors (the dashed lines in Figure 1) and speculate about the underlying mechanisms that dictate the employment of various tasks. For example, the highest H-PHYS intensities could require higher COG intensity (finely coordinated physical work may need a higher degree of 'knowing what you are doing'). Higher L-PHYS intensity, on the other hand, comes with less COG intensity, suggesting a rate of technical substitution across types of jobs of brain and brawn.

A.6 Task Evolution over Time

In the main text we showed that jobs have become more cognitive intensive over time, while they have lost intensity in high-physical tasks. Figure 2 shows these trends graphically. We observe a steep rise in the intensity of cognitive task during the late 80's and first half of the 90's, followed by stable period of bout 8 years. After that, we observe another steep increases in the intensity of cognitive tasks. In contrast, the intensity of high-physical tasks has been continuously decreasing during the entire period. This decrease is of the same order of magnitude as the overall increase in the intensity of cognitive tasks. We also observe a small decline in the intensity of low-physical tasks during the period of observation.

Figure 2: Trends in Occupational Tasks



Source: LFS 1987-2015 and 2006 CH. Annualized series. Tasks 1-3 represent cognitive, high-level physical and low-level physical work activities, respectively. Tasks are principal factors from the CH data weighted to match the Canadian occupational distribution over the period of analysis.

B Workers' Employer Transitions

B.1 Descriptive Sample Statistics

Our sample contains 90,463 observations of EE and EUE transitions. EE changes are defined as those who report a new employer (or one month or less of job tenure) in the current month. We further restrict EE transitions to those who go on to hold the current job for at least 2 months.[7] EUE transitions involve workers switching employer with an intervening unemployment spell. The LFS has two ways of identifying the occupational switches of these workers. Some workers report employment at the beginning and end of their 6 month sampling window, with a spell of unemployment in between. For these workers, identifying 4-digit occupational job mobility is done straightforwardly by comparing the occupations of the job in sample before and after the unemployment spell. Additionally, for workers who enter the sample as unemployed, typically the information for the most recently held job is reported.[8]

Table B.1 presents summary statistics describing the employer transitions in our sample. Panel A shows that about 48% of the transitions in our sample are EE transitions whereas 52% were EUE transitions. Importantly, not all employer transitions are career changes, where we define the latter as employer switches that also involve a occupational switch. Indicators for 1-4 digit occupation changes show the prevalence of career changes measured with differing levels of specificity. About 43% of employer transitions are also 1-digit career changes.[9] These career changes are significant, representing a move in major occupation category. For example, a worker might move from

[7] This further restriction avoids counting workers who (for example) work on a project basis, frequently changing location or firm, and keeps the focus on those who have a more standard relationship with an employer. Also helps with measurement error by eliminating potential "false" switchers (change and then change back and/or a miscode).

[8] The NOC codes of an unemployed worker represents the most recent job held, within the last 12 months. It may be possible to be recorded as unemployed in Canada for more than 12 months if a person is actively engaged in job search for the entirety of this period, although this is not common in the data. Unfortunately this information is not available for workers who are inactive or out of the labor force and so transitions from inactive to employed cannot be reliably observed.

[9] This number is well in line with 1-digit occupational changes in US data that is corrected for occupational miscoding.

Table B.1: Summary Statistics for Estimation Sample

	EUE Transition		EE Transition	
Panel A	**Mean**	**SD**	**Mean**	**SD**
SW OCC 1-D	0.457	0.498	0.419	0.493
SW OCC 2-D	0.619	0.486	0.574	0.495
SW OCC 3-D	0.701	0.458	0.651	0.477
SW OCC 4-D	0.734	0.442	0.684	0.465
Panel B				
Age	33.296	12.51	32.599	11.476
Male	0.59	0.492	0.577	0.494
Married/C.law	0.522	0.5	0.558	0.497
LHS	0.11	0.313	0.077	0.266
HS	0.295	0.456	0.278	0.448
OPS	0.116	0.32	0.106	0.308
PS	0.479	0.5	0.539	0.498
Pub. Sector$_t$	0.086	0.281	0.114	0.318
Pub. Sector$_{t-1}$	–	–	0.093	0.291
Union Covered$_t$	0.148	0.355	0.176	0.381
Union Covered$_{t-1}$	–	–	0.175	0.38
Panel C				
Agg. Unemp. Rate	7.343	0.936	7.248	0.908
Region Unemp. Rate	7.725	3.105	7.053	2.572
Unemp. Duraton$_{t-1}$	9.625	10.18	–	–

Source: LFS data 1997-2015, workers aged 16+ reporting an EE or EUE employer transition in the survey month. Excludes students, temporary job holders and LFS records with imputed information. Occupation categories according to 2006 NOC codes. Mean estimates employ population weights from the LFS data. EE sample $N = 43,255$. EUE sample $N = 33,368$ except for Unemp. Duration$_{t-1}$ which reduces sample size to $N = 31,082$.

an occupation in primary industry or manufacturing to an occupation in services. At higher levels of occupational specificity the number of career changes increase, reaching about 70% at the 4-digit level, where an individual would move to a much more similar occupation (for example, from Cook to Chef).

The Canadian LFS provides a set of worker and job characteristics that allows us to examine how task mobility vary with observable traits. These also help to control for the impact of potential composition shifts in workers by observable characteristics over the cycle. Educational attainment indicators are generated for four groups, including Less than High School (LHS), High-School graduates (HS), Other Post-Secondary (OPS) graduates, with a certificate or diploma less than 2 years, and traditional Post-

Secondary graduates (PS) including community college diplomas 2 years or longer and university education. Age, sex and an indicator for married/common-law are also used.

We also generate variables that describe the job characteristics of employed individuals, including binary indicators union coverage and public sector employment and job tenure, which is measured as months with the same employer.[10]

Summary worker characteristics for the sample are presented in Panel B of Table B.1 above. The sample includes more men (57%) than women, which is reasonable given the fact that our sample is restricted to labor force participants. Of the respondents, the average age is 33 years and about 57% are married or in common-law relationships. The most common education level is traditional post-secondary, representing 46% of the sample. An additional 11% of respondents report some post-secondary certificate or diploma below university, for 31% of the sample high school is the highest education milestone achieved and 12% of respondents in the sample did not complete high school. About 17% of the workers in the sample are covered by collective bargaining agreements or union members, and 11% work in public sector jobs.

For unemployed workers, we have information on the duration of unemployment and the reason of job separation. Constrained by the relatively coarser information available before the mid 2000s, we summarize job leavers into three broad categories: voluntary leavers, involuntary leavers and "other".[11] The duration of unemployment, measured weekly, is also available for those classified as unemployed.

B.2 Distribution Difference Old and New Jobs

In Figure 3 we consider the *reallocation across task distributions* that is associated with worker flows, averaged over time. We display the *difference* between the task intensity distribution of the new job and the corresponding task distribution of the previous job,

[10]Union coverage includes union membership and non-members covered by collective agreements. Overlap between public sector and collective agreement coverage is considerable in Canada.

[11]Reasons for leaving are encoded are as follows. Voluntary: "Left job" due to change of residence, dissatisfaction or retirement. Involuntary: "Lost job" due to layoff, own illness or disability. Other: "Left job" due to personal or family responsibilities, to attend school or for "other" reasons.

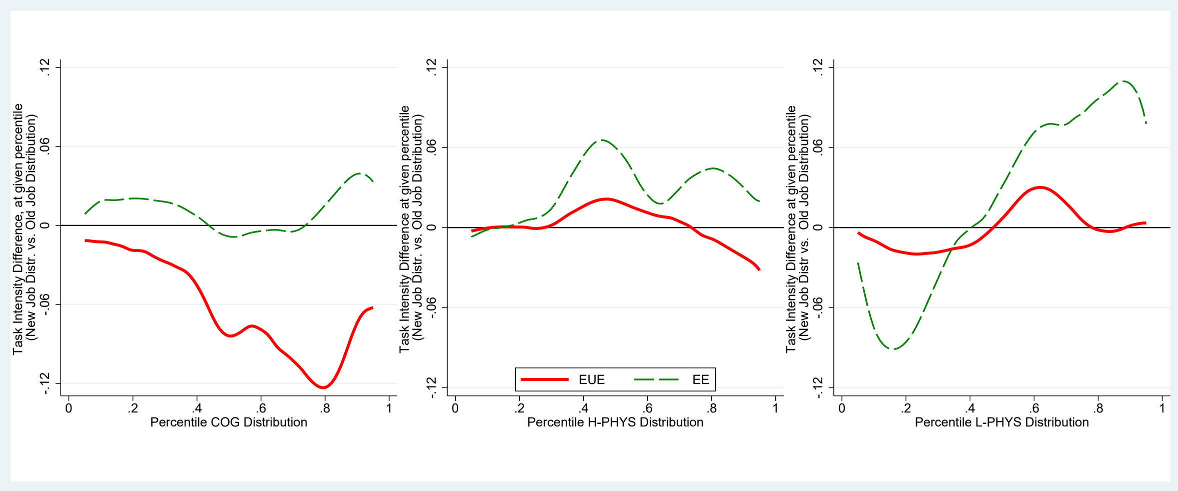


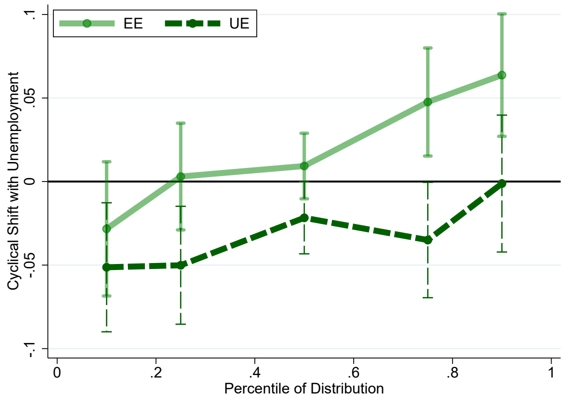
Figure 3: Shift of Task Distribution (New Job - Old Job) of Employer Changers

for EE transitions (in dashed green) and EUE transitions (in solid red), measured at each percentile on the x-axis. For example, a positive y-value at a value of, say, 0.8 on the x-axis means that the intensity at the 80th percentile of the task distribution in new jobs lies above the 80th percentile of the distribution of previous jobs.

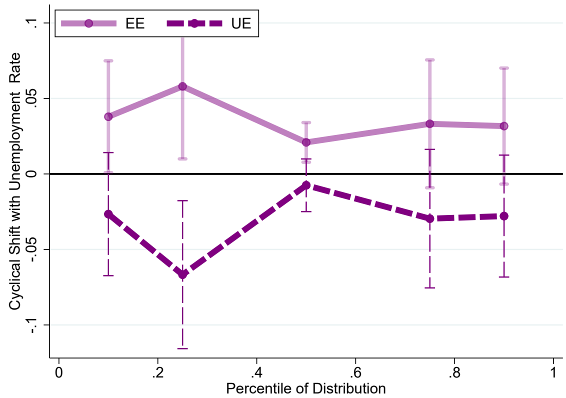
Among EUE movers, the COG intensity distribution in previous jobs stochastically dominates the distribution in new jobs. Interestingly, this difference is particularly pronounced in the upper tails: the highest COG intensities among post-unemployment jobs are much lower than the highest COG intensities among jobs that ended in unemployment. For EE movers, we see that the distribution of COG intensity in new jobs roughly stochastically dominates the intensities in previous jobs, and particularly so in both tails of the distribution.

For H-PHYS, we also see that the highest H-PHYS intensities before becoming unemployed are not recovered after unemployment, while direct job-to-job moves allow for recovery in the upper tail. For L-PHYS, we observe an increased intensity dispersion of the new jobs (relative to previous jobs) of EE movers: new jobs for job-to-job movers more often have very low L-PHYS intensity, but we also see more L-PHYS intensity in the upper tail. This is consistent with EE transitions that move a set of workers to jobs that are simultaneously more COG-/less L-PHYS intense, while simultaneously moving another set of workers up the H-PHYS ladder to jobs that also are more L-PHYS intense.

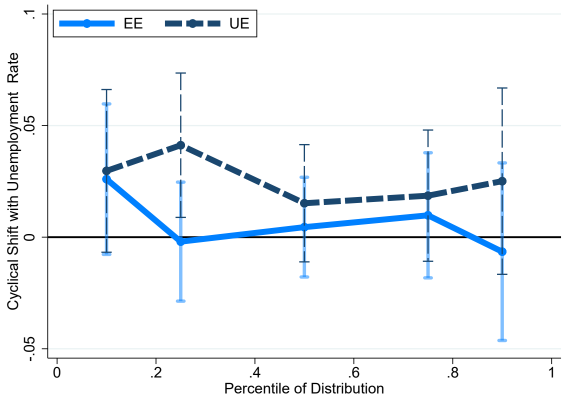
Figure 4: Cyclical Shift in Task Change Distributions



(a) COG intensity



(b) H-PHYS intensity



(c) L-PHYS intensity

B.3 Cyclical Shifts in the Task Change Distribution

In the main text we showed the cyclical shifts in the cognitive, high-physical and low-physical task change distributions, presenting the regression coefficients of the unemployment rate. The main takeaway from this analysis is that EUE task changers experience a larger decrease in cognitive and high-physical dimensions, while an increase in the low-physical dimension. We also showed that EE task changers gain in the cognitive and high-physical dimensions and experience no meaningful change in the low-physical dimension.

Figure 4 gives a graphical representation to better visualize these changes. It is clear that EE task changers who already experience an increase in the COG dimension when they change employers (located above the median) gain even more on this di-

Table B.2: EUE Movers - Cyclicality of the Distribution of Individual Task Changes

	Panel A: EUE Task Changers, coefficient on UR_t				
LHS quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	-0.0513***	-0.0501***	-0.0217**	-0.0350**	-0.0012
	(0.0197)	(0.0180)	(0.0110)	(0.0176)	(0.0209)
Δ H-PHYS	-0.0266	-0.0667***	-0.0075	-0.0296	-0.0279
	(0.0208)	(0.0250)	(0.0089)	(0.0234)	(0.0206)
Δ L-PHYS	0.0297	0.0412**	0.0152	0.0186	0.0251
	(0.0186)	(0.0165)	(0.0134)	(0.0150)	(0.0213)
Total Distance	-0.0010	0.0022	0.0081	0.0131**	0.0059
	(0.0030)	(0.0039)	(0.0053)	(0.0065)	(0.0066)
	Panel B: EUE Movers incl. Task Stayers, coeff. on UR_t				
LHS quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	-0.0302*	-0.0037	0	-0.0550***	-0.0448**
	(0.0180)	(0.0146)	-	(0.0132)	(0.0178)
Δ H-PHYS	-0.0040	0.0133	0	-0.0365**	-0.0423**
	(0.0187)	(0.0178)	-	(0.0185)	(0.0206)
Δ L-PHYS	0.0482***	0.0593***	0	-0.0165	0.0067
	(0.0155)	(0.0144)	-	(0.0155)	(0.0169)
Total Distance	0	0.0022	-0.0203***	-0.0002	0.0004
	-	(0.0076)	(0.0056)	(0.0053)	(0.0059)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported numbers are coefficients on UR_t in quantile regression, with LHS variable (in row) and quantile (in column).

mension when unemployment is high, while those EUE task changers who already lose the most along the COG dimension when changing employers, lose even more when unemployment is high. Similarly, EUE task changers who already lose the most along the H-PHYS dimension when changing employers, lose even more when unemployment is high. In contrast, EE task changers who make relatively smaller gains along the H-PHYS dimension gain more when unemployment is high. Along the L-PHYS we do not observe any significant change.

Tables B.2 and B.3 present the results of the quantile regressions for all EUE and EE employer movers. The results show that including EE and EUE task stayers, creates a mass point at zero in each respective task change distribution. In downturns, the increased incidence of task staying among EUE movers implies that there are fewer large increases in COG and H-PHYS, more mass at zero, and a longer left tail of deeper losses of COG and H-PHYS intensity. For EE movers, the task change distributions of

Table B.3: EE Movers - Cyclicality of the Distribution of Individual Task Changes

	EE Task Changers, coefficient on UR_t				
LHS var quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	-0.0283	0.0030	0.0093	0.0476***	0.0637***
	(0.0205)	(0.0163)	(0.0100)	(0.0165)	(0.0187)
Δ H-PHYS	0.0379**	0.0580**	0.0209***	0.0332	0.0317
	(0.0189)	(0.0245)	(0.0067)	(0.0216)	(0.0196)
Δ L-PHYS	0.0260	-0.0020	0.0045	0.0098	-0.0065
	(0.0172)	(0.0136)	(0.0114)	(0.0143)	(0.0203)
Total Distance	0.0082***	0.0025	0.0060	0.0162***	0.0142**
	(0.0027)	(0.0038)	(0.0046)	(0.0061)	(0.0056)
	EE Movers incl. Task Stayers, coeff. on UR_t				
LHS var quantile reg.	Q10	Q25	Q50	Q75	Q90
Δ COG	0.0057	0.0103	0	0.0147	0.0450***
	(0.0161)	(0.0128)	-	(0.0126)	(0.0172)
Δ H-PHYS	0.0462**	0.0321***	0	0.0096	0.0264
	(0.0202)	(0.0110)	-	(0.0135)	(0.0224)
Δ L-PHYS	0.0191	0.0099		0.0161	-0.0035
	(0.0127)	(0.0123)		(0.0128)	(0.0147)
Total Distance	0	0	-0.0056	0.0081*	0.0100*
	-	-	(0.0056)	(0.0053)	(0.0059)

COG and H-PHYS move in opposite direction and become more right-skewed.