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# The Hedgehog's Curse: Knowledge Specialization and Displacement Loss

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**Abstract**

This paper studies the impact of knowledge specialization on earnings losses following displacement. We develop a novel measure of the specialization of human capital, based on how concentrated the knowledge used in an occupation is. Combining our measure with individual labor histories from the NLSY 79-97 and Norway's LEED, we show that workers with more specialized human capital suffer larger earnings losses following exogenous displacement. A one standard deviation increase in pre-displacement knowledge specialization increases the earnings losses post-displacement by 3 to 4 pp per year in the US, and by 1.5 to 2 pp per year in Norway. In the US, the negative effect of higher pre-displacement knowledge specialization on post-displacement earnings is driven by the negative impact of knowledge specialization on well-paid outside opportunities. By contrast, this association between outside opportunities and knowledge specialization plays no role in post-displacement earnings losses in Norway, where the negative effect of specialization is in part explained by its association with the routine content and the offshoring probability of the occupation.

**Keywords:** Displacement, Earnings Loss, Knowledge Specialization, Unemployment, Human Capital

**JEL Codes:** J31, J62, J63

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*"The fox knows many things, but the hedgehog knows one big thing."*

*Archilochus*

*"(...) we are in a wicked work world, and there, sometimes hyperspecialization can backfire badly."*

*David Epstein*

# 1 Introduction

Job displacement leads to permanent earnings losses, greater job insecurity, more volatile earnings, increased mortality, and worse health outcomes.[1] While there is clear evidence of the negative impacts of displacement, there is less agreement on the causes of the earnings losses. Are they due to specific human capital loss when displacement happens? Do workers move down the job ladder after a displacement?[2] Do displacements destroy intrinsically good matches, creating new ones where the worker's productivity at the new firm is lower?[3] While all these factors may play a role,[4] in this paper we focus on the link between displacement and specific human capital losses.

While the loss of human capital due to displacement has been analyzed in the literature, previous work has failed to distinguish general from specific human capital empirically. While the key distinction between these two types of human capital is anchored in transferability, finding an empirical counterpart for this concept has proved to be challenging. We propose to solve this problem by assuming that while human capital is mostly transferable, the knowledge needed to perform the tasks required by the detailed occupations may differ significantly. If workers' human capital evolves based on what knowledge they use on the job, the occupation in which a worker is currently employed may shape the knowledge that a worker possesses. If this knowledge is concentrated in a few areas, a long tenure in such an occupation may hinder the worker's ability to perform the tasks needed by most other occupations, restricting the worker's job prospects. Thinking about the specificity of human capital in this way has two key benefits. First, it allows us to have an empirical counterpart based on O*NET's knowledge requirements data. Second, it allows us to tie displacement losses to the degree of knowledge specificity in a given occupation.

[1] See Davis and von Wachter (2011), Stevens (1997), and Sullivan and von Wachter (2009), among others.

[2] The previous literature has considered different ideas of job ladders. For instance, in Burdett and Mortensen (1998), a worker climbs the job ladder through on-the-job search, moving to higher-paying employers. Differently, in Krolikowski (2017) and Karahan et al. (2022) workers climb the job ladder by drawing better job matches through on-the-job search (regardless of whether it is at the same or at a different firm), or by receiving positive shocks in the stochastic component of the match. Regardless of the framework, displacement induces wage losses by moving the worker down the job ladder, toward a lower-paying firm or a job with a worse match.

[3] In Gibbons and Katz (1992) workers' ability is differently valued depending on the skill requirements of the employer. Displacement shifts workers to jobs with a lower match quality, generating earnings losses.

[4] Lachowska et al. (2020) argue that moving down the job ladder (from high- to low-paying employers) accounts for 9 percent of the earnings losses after displacement, while match effects can explain up to 57 percent.

The distribution of how important the different knowledge requirements are allows us to define the degree of concentration of an occupation's knowledge. An occupation (and by extension a worker) has a high concentration of knowledge if one or a few knowledge categories represent the bulk of the knowledge categories necessary for the occupation. We refer to this knowledge concentration as *knowledge specialization* and propose it as a novel measure for the specificity of human capital. Note that our proposed measure does not describe the total amount of knowledge required for an occupation (although we will also keep track of this), but its distribution. The specialization of the human capital will be higher for a worker in a high-concentration occupation, than a worker in an occupation that requires more diversified knowledge.[5]

Using this new measure of human capital specialization we analyze its relevance to the earnings losses of displaced workers in the US and Norway. Similar to Couch and Placzek (2010) and Schmieder et al. (2022), we first rely on a non-parametric matching empirical strategy. We complement the matching approach with an extension of the identification strategy proposed by Jacobson et al. (1993) (JLS (1993)) and reach several novel findings.

First, an additional standard deviation of pre-displacement knowledge specialization increases the earnings losses of a displaced worker by an average of 3.7 percentage points per year in the US, and by an average of 2.0 percentage points per year in Norway.[6] This result is robust to the inclusion of other worker characteristics at the point of displacement that the previous literature has identified as important in explaining the heterogeneity of the earnings losses post-displacement. Taking into account the effect of the worker's age, experience, job tenure, knowledge level, education, gender, industry, and occupation group at the point of displacement makes little difference in the estimated effect of the pre-displacement knowledge specialization on the earnings losses of displaced workers.

Second, in the US, higher pre-displacement knowledge specialization increases the earnings losses post-displacement because occupations with higher levels of knowledge specialization have fewer and worse possible outside options. Both the share of employment in possible (or similar) occupations and the difference between the current occupation's wages and the average wage of the occupation's possible outside options are decreasing in the level of knowledge specialization. Once we control for this, the negative effect of higher pre-displacement specialization on re-employment earnings disappears. On the other hand, the relevance of the outside options in Norway is much more limited, and cannot explain the negative impact of pre-displacement knowledge specialization on re-employment earnings.

[5] Conceptually, we exploit the idea that two workers with a similar level of aggregated knowledge/skills might have a different distribution of that knowledge in different areas. A good example of this is to think about a psychologist and an education administrator. While both are highly skilled types of jobs that require high levels of education, the distribution of that knowledge importance across different domains is different. The psychologist primarily needs knowledge about psychology and some social skills, while the education administrator uses a similar "amount" of knowledge in accounting, economics, finance, management, human resources, social skills, etc. Thus, one could argue that, despite both being highly skilled jobs, the latter has a more diversified knowledge portfolio than the former.

[6] Compared to the US wages in Norway are more compressed. The return to skill is lower and the age profiles of wages are flatter.

Finally, we test several alternative mechanisms through which higher knowledge specialization could affect re-employment earnings. For the US, we find them to be either uncorrelated with the occupations' knowledge specialization or irrelevant in explaining the earnings losses after displacement. The distance (in the task sense) between occupations, the type of tasks performed in the occupation, or the likelihood of the occupation (or its tasks) being offshored/automated cannot explain the negative effects of higher pre-displacement knowledge specialization on re-employment earnings. Similarly, a higher likelihood of changing industry, occupation, or main skill is not the reason why higher pre-displacement knowledge specialization affects re-employment earnings. In Norway's LEED, as well, most of the alternative channels are muted. However, we find some evidence that the negative effect of specialization is partially related to the routine intensity of the job's tasks and the likelihood that the job will be offshored.

This paper contributes to the literature that exploits the information available on the tasks and skills of different occupations to understand the degree of heterogeneity of the earnings losses after job displacement and the transferability of human capital. Our contribution lies in defining the specificity of human capital based on the degree of concentration of the occupation's knowledge, instead of determining it based on the similarity between an occupation's skills and the skills required in different occupations. We build upon the work of Poletaev and Robinson (2008)[7] and Gathmann and Schönberg (2010),[8] and highlight the riskiness of concentrated knowledge profiles that can turn into dead ends in the case of a dismissal, even if the specialization offered positive returns while a worker was employed in that job. This is something impossible to capture with the distance between jobs or with the changes in the occupations' main skills because, by construction, these dimensions ignore the importance of the direction of the change.

Similarly, we take the work of Macaluso (2017)[9] one step further. We show not only that the uniqueness of workers' skills (relative to their labor market) affects their post-displacement earnings losses, but that the concentration of the workers' knowledge profiles determines the quality of their outside options and impacts their earnings path after a dismissal.

This paper also adds to the literature studying the degree of transferability of human capital across different jobs, as in Parent (2000), Kambourov and Manovskii (2009) or Pavan (2011). We present evidence that suggests that the transferability of human capital is not only a function of the task distances (or skill changes) between jobs, as previously documented in the literature, but also depends on the initial knowledge specialization of the worker. This suggests that similar exogenous job changes, in a task distance sense, could imply very different outcomes for different workers depending on how their knowledge portfolios looked before the change.

[7] Poletaev and Robinson (2008) show that larger earnings losses are associated with larger changes in the skills used in the new job relative to the old one, as well as with skill "downgrades."

[8] Gathmann and Schönberg (2010) show that involuntary job changes are to jobs further away in the task space than voluntary ones.

[9] Macaluso (2017) argues that earnings losses are an increasing function of the distance between the worker's skill portfolio and the average local labor market skill portfolio.

Our work also speaks to the literature studying the differences in lifetime earnings risk across occupations as in Cubas and Silos (2017) and Dillon (2018). While previous work emphasizes the role of occupational mobility in absorbing negative occupation-specific wage shocks, we propose a novel mechanism through which potentially involuntary occupational mobility can increase this risk. Workers with more specialized knowledge profiles trade higher current earnings for the risk of higher earnings losses in the case of a dismissal. This risk arises because high knowledge specialization jobs put workers on a path from which finding higher/equal paying jobs that use similar skills becomes harder.

Finally, this paper also improves upon the previous literature in identifying *ex-ante* who may suffer stronger consequences from displacement, an aspect that can be useful from a policy perspective. All industry, occupation, skill, and task changes are determined *ex-post* (i.e., they depend on the distance between the industry/occupation or skills of the new and old job, and cannot be determined by information on the displacement job). In contrast, the level of knowledge specialization is purely based on the job characteristics from which the worker is displaced, and thus known before a potential displacement happens.

The structure of the paper is as follows. Section 2 describes the creation of our measure of knowledge specialization and provides summary statistics of this measure for the US and Norway. Section 3 details the construction of the NLSY and LEED samples to analyze the earnings losses of displaced workers. Section 4 presents the empirical strategy and identification. The benchmark results are shown in Section 5, while Section 6 highlights the impact of pre-displacement knowledge specialization on post-displacement earnings losses. Section 7 explores several mechanisms that could explain why higher pre-displacement specialization leads to larger earnings losses after re-employment. Finally, Section 8 concludes the paper.

# 2 Knowledge Specialization

## 2.1 Data

We rely on three different data sets. For our summary statistics and to understand the relationship between knowledge specialization and labor earnings in the US, we primarily use the longitudinal CPS samples from the years 1990 to 2019. We complement the CPS with a combined NLSY 1979 and 1997 sample for the years 1986 to 2018.[10] For Norway, we take advantage of the LEED data

[10]We rely on two different data sets for the US because each data set has different limitations and strengths. The longitudinal CPS sample (Flood et al. (2022)) allows us to obtain a larger sample size than the NLSY, while limited on the length of the time series – only two different observations per worker – and a limited set of covariates. The NLSY has information on a much smaller sample of individuals but provides multiple years of data for each worker. Finally, in unreported results, we focused on the ACS samples for 2000 to 2019. In contrast to the CPS and the NLSY, the ACS provides a very large sample size and representativeness of the US population. However, the ACS has only one observation per individual and only for a much more recent period (2000–2019). Nevertheless, the results

for the years 2000 to 2014. Created by Statistics Norway, the LEED is an employer-employee panel that combines several administrative files, and it is the base for many of the aggregate labor market statistics published in Norway. We provide an overview of the LEED construction and its details in Section 3.2.

## 2.2 Main Variable Construction

We take advantage of the O*NET data to create a measure that captures the idea of human capital specialization.[11] O*NET contains hundreds of standardized, occupation-specific descriptors on 968 occupations covering the entire US economy. For each occupation, O*NET provides details for work activities or tasks (i.e., specific detailed activities carried out in the occupation), skills (developed capacities that facilitate learning or the more rapid acquisition of knowledge), abilities (enduring attributes of the individual that influence performance), and knowledge (acquired sets of principles and facts applying in broad domains or areas) along with other characteristics regarding work styles, environment, values, etc.

We exploit the section regarding the knowledge required to perform an occupation's tasks, which describes and quantifies the knowledge requirements in several different categories (or areas) for each of the included occupations.[12] The choice of the knowledge category instead of the most common skills category is directly driven by O*NET's own definition of what knowledge and skills are, in relation to human capital. Human capital is an intangible stock owned by a worker that makes her labor more productive. From O*NET's definition, skills reflect the pace at which a worker creates a new stock of knowledge, therefore representing a flow. Based on O*NET's definitions, skills are fully transferable, since they are mediators in the creation of knowledge. On the other hand, knowledge represents a potentially non-transferable stock, since the set of principles that apply in one domain may not be the same for a different domain, making it a more appropriate measure of human capital.

Our main measure of interest is *knowledge specialization*, which tells how disperse is the knowledge required to perform the tasks demanded by an occupation. In order to illustrate the concept, let's compare two occupations: a psychologist and an education administrator. Both occupations are performed by highly educated workers, and both are relatively high-paying jobs (see Table 1 for details). However, the distributions of their knowledge could not be more different. When looking at O*NET's distribution of knowledge importance for these occupations, we see a stark contrast. For psychologists, the distribution is heavily concentrated in a few categories (7 categories represent

are qualitatively the same as the ones obtained for the CPS and the NLSY.

[11]Specifically, we use version 23.0 of the complete O*NET data set. The data can be found here: https://www.onetcenter.org/db_releases.html.

[12]O*NET's knowledge section is subdivided into two parts for each of the 33 different knowledge domains included in the data set. The first one refers to the *importance* of the knowledge area and uses a scale from 1 to 5. The second part quantifies the required *level* of knowledge in that area with respect to an anchored benchmark that shifts from 0 to 7.

over 50 percent of the total knowledge importance, and the first three categories capture over 25 percent of the total). Differently, education administrators' distribution of knowledge importance is more evenly distributed (9 categories are required to reach the 50 percent mark, and the first three categories represent only 19 percent of the total). We construct a *knowledge specialization* index to summarize the information on the distribution of the occupations' knowledge available in O*NET's knowledge section. In particular, we follow the algorithm:

$$spec_o = \frac{1}{J}\sum_{i=1}^{J}\sum_{j=1}^{i}\frac{k_{jo}}{\sum_{l=1}^{J} k_{lo}} \tag{1}$$

where $k_{jo}$ represents the importance component of knowledge area $j$ for occupation $o$. Knowledge areas $j \in \{1, ..., J\}$ are sorted by level of importance (i.e., $k_{1o}$ is the most important knowledge component for occupation $o$, $k_{2o}$ the second most important, and so on).[13] For empirical purposes, we normalize the knowledge specialization measure to have a mean of zero and a standard deviation of one within each of our data sets.[14] Back to our example: the psychologist is assigned a *knowledge specialization* value of 0.78 (or a value of 1.59 after standardizing the variable in the CPS), which locates it above the $90^{th}$ percentile of the knowledge specialization distribution across all jobs in the 1990–2019 CPS. Therefore, psychologists have a heavily concentrated knowledge profile relative to other jobs. Performing the tasks required of a psychologist does not require knowledge in many different domains, but mastering a few. On the other hand, the education administrator has a knowledge specialization value of 0.68 (-0.89 after standardization in the CPS), which places it below the $20^{th}$ percentile of the knowledge specialization distribution across all jobs in the 1990–2019 CPS. Therefore, education administrators do not require extremely special knowledge in their jobs, since for them, the value lies in having similar amounts of knowledge in a vast array of domains.

While the distribution of knowledge across different categories is our main variable of interest, it is crucial to consider a measure of knowledge "depth." Two jobs with similar levels of knowledge concentration in specific areas may have very different requirements in terms of knowledge depth. For example, let's consider a designer and a cashier. Both jobs imply very similar levels of *knowledge specialization*.[15] However, these occupations require completely different *levels* of this knowledge across the different categories.[16] In order to summarize the degree of knowledge depth across O*NET's 33 knowledge categories, we follow the literature and perform a principal components

[13] For additional robustness, in Appendix D we create an alternative specialization index using a different specification. This alternative specification is calculated as an HHI index in the knowledge importance categories for each 4-digit occupation. The correlation between the alternative definition and the main one presented in the paper is in excess of 0.97.

[14] The normalization does not affect any of the results shown in the paper, which are identical in its absence.

[15] At 0.72 (or 0.20 for the former vs. 0.19 for the latter when normalizing the variable in the CPS)

[16] Both jobs presenting almost equal levels of *knowledge specialization* does not imply that the concentration of that knowledge is in the same categories.

analysis.[17] We use the first principal component as our measure of *knowledge level*.[18] Back to the designer vs. cashier comparison: according to our measure, the designer's knowledge level is 6.61 ($60^{th}$ percentile in the CPS), while the cashier's knowledge level is 6.07 ($20^{th}$ percentile in the CPS). In our original comparison between the psychologist and the education administration, the knowledge level for both jobs is similar. The psychologist has a level of 6.91, while the education administrator's level is 7.08, with both occupations above the $85^{th}$ percentile of the distribution of knowledge level in the CPS.

**Table 1:** Occupational Examples

| | % of Total | Knowledge | | Share | | Earnings |
|---|---|---|---|---|---|---|
| Occupation Name | Employment | Spec | Level | Male | College | Percentile |
| Education Administrators | 0.71 | -0.89 | 7.08 | 0.36 | 0.79 | 69 |
| Psychologists | 0.18 | 1.59 | 6.91 | 0.34 | 0.94 | 64 |
| Designers | 0.57 | 0.20 | 6.61 | 0.44 | 0.50 | 54 |
| Cashiers | 1.18 | 0.19 | 6.07 | 0.19 | 0.09 | 19 |

### 2.3 Knowledge Level and Specialization: Characteristics and Comparison to Task Measures

Given the novelty of our variable of interest, we briefly present how this measure correlates with common covariates found in the literature. In Appendix B we offer a more detailed evaluation. Table 2 presents a linear regression of our variable of interest on the common covariates in the CPS as well as the LEED. Remarkably, results are quite similar for both databases. In particular, occupations with higher knowledge specialization are more likely to be offshorable in both the CPS and the LEED. Differently, knowledge specialization is unrelated to traditional task content measures (routine vs. non-routine, cognitive vs. manual) as measured by Acemoglu and Autor (2011) and only marginally positively correlated to task complexity (see Caines et al. (2017)) in the case of the CPS. Furthermore, specialization's relationship with educational level is somewhat distinct between samples. While it is increasing at lower levels of education in the CPS sample, the relationship is pretty mute in the LEED. Finally, the relationship between the probability of automation (see Frey and Osborne (2017)) and specialization is distinct across the samples. While specialization is positively correlated to the probability of automation in the CPS, there is no correlation between the two variables in the LEED.

[17] For a more technical note regarding the principal component analysis, see Ingram and Neumann (2006), Poletaev and Robinson (2008), or Yamaguchi (2012).

[18] The final calculation of knowledge level takes the log of the variable after re-scaling it relative to the occupation with the lowest knowledge level, such that the log version of the variable for the occupation with the lowest knowledge level has a value of zero after the transformation $knw = ln((PC^{knw}_{occ} - min_{occ}(PC^{knw}) + 0.01) \times 100)$.

In terms of knowledge level, Table 2 shows that it is increasing in education attainment up to college in both samples. Similarly, it is higher for occupations with more complex tasks and with higher cognitive and non-routine scores, while it is lower for occupations with high manual task content.

Figure B.2 in the appendix shows the mean knowledge level and specialization for different industry and occupation groups. Results for industry groups are similar between the CPS and the LEED. The education, public administration, real estate, health care, finance, and professional sectors display the highest knowledge levels, while jobs in manufacturing present some of the lowest knowledge levels. Knowledge specialization is the highest in the finance, professional, wholesale, and retail sectors, with information showing quite high levels of knowledge specialization in the LEED. Our conclusions remain similar when considering occupational groups, even if STYRK-08 groups in the LEED are significantly coarser.

However, even within industry and occupation groups we still find significant variation in knowledge level and specialization. The within-industry group variation in knowledge level and specialization represents over 85 percent of the total variance in both samples. Similarly, the within-occupation group variation in knowledge level is approximately 50 percent in the CPS and the LEED.[19] The main difference between both samples is found in the within-occupation group variation in knowledge specialization, which represents 56 percent of the total variance in the CPS but almost 90 percent in the LEED.

Table 3 shows some of the most common occupations (6- and 5-digit SOC) in the CPS, sorted by knowledge specialization, along with their knowledge level, and other covariates of interest. These occupations represent 58 percent of the total employment in the CPS. Within this group of occupations, accountants and auditors have the highest knowledge specialization, followed by bookkeeping, accounting and auditing clerks, customer service representatives, psychologists, and computer systems analysts. On the other hand, we see construction laborers at the bottom of the distribution, followed by secondary school teachers, and farmers, ranchers, and other agricultural managers.

Finally, we consider the relationship between knowledge specialization and level of the occupation, and the individual's labor earnings. Table 4 summarizes our main findings. Column (1) shows the estimated relationship between the knowledge specialization and the log annual labor earnings, controlling by the knowledge level, as well as state, year, education, age, and gender fixed effects. Column (2) adds additional control variables to the specification of column (1).[20] Finally, column (3) adds variables related to the cognitive, manual, and routine dimensions for each occupation, the complexity of its tasks, and three measures of the likelihood of the occupation, or its tasks,

[19] See Section 3.2 for a description of the occupation categories in the LEED.

[20] In the CPS sample, we include industry and occupation group fixed effects. In the sample from the NLSY 79-97, controls include the log of experience and job tenure as well as industry and occupation group fixed effects.

being offshored or automated. Columns (4) to (6) repeat the specifications from columns (1) to (3), respectively, but add individual fixed effects.

In the US samples, regardless of the specification, we find that there's a positive association between knowledge specialization and earnings, significant at the 1 percent level in all specifications. While the inclusion of additional controls and individual fixed effects reduces the coefficient of interest, our results suggest that one additional standard deviation of knowledge specialization increases annual earnings by at least 1.6 to 1.8 percent. Remarkably, when comparing equivalent specifications, we find extremely similar coefficients in the CPS and NLSY,[21] even when each sample covers different time periods and uses different control variables. Results for the LEED are similar with two key distinctions. First, the magnitude of the impact of knowledge specialization on compensation is smaller, regardless of the specification. Second, this impact becomes statistically insignificant once we include different measures related to the types of tasks of the occupation (i.e., routine, manual cognitive scores, offshoring and automation probabilities, and task complexity), even though it still has a positive coefficient.

## 3 Sample Construction

To analyze the effects of displacement on earnings and its connection with the worker's knowledge specialization, we rely on the NLSY 79 & 97 and the Norwegian LEED.

### 3.1 NLSY 1979 & 1997

We use the NLSY 79 and the NLSY 97 weekly employment roster, from their respective start dates until the end of 2018. For each job contained in the weekly roster, we attach the job characteristics for the specific sample year. Similarly, we attach a unique job identifier to each job in the employment array following the mapping provided in the NLSY.

We start with the complete NLSY samples and make the following two restrictions. First, we define a unique job spell as the time from the first to the last week the job appears in the sample, even if for periods during these two dates the worker works zero hours or has zero earnings in that job. The length of the spell as previously defined determines the job tenure variable in the NLSY sample. Thus, even if the worker has zero hours in a specific job during one week, that week counts toward their job tenure (with zero earnings and zero hours for the specific job). After updating the employment roster, we discard all individuals who have 4 or more jobs simultaneously, even if some of those jobs have zero hours and earnings in the specific period. This restriction removes

[21] In fact, results are also quite similar with the ACS. For brevity, we omitted the results here but they are available if requested. In the case of the ACS, controls include a categorical variable for the education degree, marital status, immigration status, class of worker, occupational scores as well as industry and occupation group fixed effects.

411 individuals from the NLSY 79 (3.2 percent of the original sample) and 383 individuals from the NLSY 97 (4.3 percent of the original sample).

Second, we remove all individuals who present an invalid skip (or who refuse to answer) on the reason why they left a job. This procedure eliminates an additional 471 and 75 individuals from the NLSY 79 and NLSY 97 samples, respectively. Finally, as documented by the NLSY, hourly wages are neither capped nor corrected and sometimes present extreme values. To deal with this problem, we winsorize the bottom 5 and top 1 percentiles of the hourly wage distribution, per year. The restriction at the bottom roughly equates to removing all hourly wages below the minimum federal wage for the year.

We define a job separation as a displacement when the worker: a) loses her job involuntarily after 1983 (layoff; job eliminated; company, office, or workplace closure); b) has at least 104 weeks of prior tenure in the job; c) is at least 25 years old at the time of dismissal; and d) worked at least 25 hours per week (on average) in that job for the duration of the job. This creates 2,790 displacements in our NLSY 79 sample, of which 2,249 are first displacements. The number of displacements in our NLSY 97 sample is significantly smaller, at 731, of which 691 are first displacements.

To understand the relevance of the measures of knowledge specialization and level in explaining the earnings losses of displaced workers, the data from the O*NET are then matched to the NLSY 79 and NLSY 97. The occupational data in the NLSY contain multiple occupational classifications within the data set, depending on the cohort and the year. The years prior to 2002 use the 1970 Census occupational codes while 2002 uses the 2000 Census occupational codes and the years from 2004 onward use the 2002 system. To standardize the classification, we convert all occupational codes to the 2000 Census codes and match them to the 2010 SOC occupational codes used in the O*NET, using the crosswalk provided by the BLS.

### 3.2 Norway's Administrative Data

Our sample combines information from two restricted-access databases provided by Statistics Norway. First, we obtain education information from the registers of the population's education. This database is drawn directly from the National Education Database (NUDB) and includes all residents in Norway who are 16 years old or older, and reports information at an annual frequency. An individual's educational attainment is the highest level in the Standard Education Group (NUS2000), which is a 6-digit code system that classifies education activities by level and field. In order to make our results comparable to the NLSY, we collapse the education information into the same categories presented in the NLSY 1979 and 1997.

Second, we use the linked employer-employee database (LEED) from Statistics Norway. This database combines several administrative files. The main source of data is the employer-employee registry from the Norwegian Labor and Welfare Administration (NAV) and it is linked to the administration of the sick pay scheme for employees. All employers are obliged to register in the employer's section of the register, which in practice means the Register of Legal Entities. In order to obtain information on unemployed workers, Statistics Norway matches the data to the NAV's ARENA register of job seekers, providing a measure of labor force participation during the reference week (third week of November). Finally, the data include information on self-employed workers, merged to the LEED from the tax return register from the Norwegian Directory of Taxes.

The LEED covers the period 1995–2014. However, since information on occupation codes is only available starting in 2003, our sample focuses on the period 2000–2014. Occupation information is at the job level and it is reported by employers. The reported occupation codes follow, or can easily be converted to, the standard for occupation classifications (STYRK) for 2008.[22] STYRK is an adapted Norwegian version of ISCO-08 which is EUROSTAT's version of the ILO Standard. Using a crosswalk provided by Statistics Norway and by inspecting the names for the very few categories in which we see a mismatch, we were able to confirm that the two systems line up quite well. We then use a crosswalk between ISCO-08 and SOC-10 provided by EUROSTAT in order to create our measures of knowledge level and specialization based on the O*NET measures. While this conversion may introduce some measurement error, this practice has been common in the literature (see Goos and Manning (2007), Goos et al. (2014), and Dingel and Neiman (2020), among others).

To assign one value of knowledge specialization and level to each ISCO-08 occupation we start with EUROSTAT's crosswalk, which connects each ISCO-08 occupation to one or more SOC-10 occupations. To each SOC-10 occupation, we attach the total share of employment in the economy it represents. To calculate these shares we rely on the 2000 to 2019 samples of the ACS. Since each SOC-10 occupation can be matched to more than one ISCO-08 occupation, we assume that the SOC-10's share of total employment is evenly distributed across all the different ISCO-08 occupations it is matched to.[23] After this step, we calculate the relative share of each SOC-10 occupation within each ISCO-08 occupation. These relative shares are the basis of our ISC0-08 measures of knowledge specialization and level. For each ISCO-08 occupation, we calculate knowledge specialization and level as the weighted mean of the knowledge specializations and levels of each of the SOC-10 occupations they are matched to, using as weights the relative shares described above.

The LEED has an annual frequency, in particular on its compensation information. However, it contains detailed information on job spells' start and end dates, as well as the start and end dates of active work in a given job spell in a given year. The LEED also includes detailed information on

[22]Our LEED files include both STYRK-08 and STYRK-88 codes, where STYRK-88 is an adapted Norwegian version of ISCO88. We focus on STYRK-08 but use a crosswalk between STYRK-88 to STYRK-08 provided by Statistics Norway whenever the occupation code is only available for STYRK-88.

[23]For instance, if one SOC-10 is matched to three different ISCO-08 occupations, we assume that the share of employment from that SOC into each ISCO-08 occupation will be 1/3 of the original SOC's employment share.

aggregated work hours per year per job spell. Furthermore, compensation information in a given year is broken down per job spell for all but self-employed workers. Given the annual frequency of the data, we keep information on the worker's main job in a given year. We define a job as an employment spell based on the firm's, establishment's, and worker's unique identifiers. We consider the main job as the full-time job with the highest compensation in a given year. If two jobs have the same compensation, we keep the one with the longest duration in days. We combine multiple spells with the same firm at the same establishment in a given year as part of the same employment spell. Our main compensation variable is annual total real earnings. In order to calculate this value, we follow Dutz et al. (2021) and consider total compensation as the sum of cash salary (*k_lonn*), ordinary benefits in kind (*ord_nat*), and expense allowances (*utg_godt*). Values are then deflated based on the annual values for Norway's All-Items Consumer Price Index (2015=1) from the St. Louis Fed's FRED database.[24]

In order to construct our sample, we start with all workers who report being freely available and searching for work in the reference week as well as a 40 percent random sample of all workers who do not report an unemployment spell. We keep only the individuals with available information on education attainment and with clear occupation information for employment spells after 2003. We drop observations without information on firm identifiers or multiple occupation codes within the same job spell in the same year. We also drop individuals with gaps in their spells in our data.[25] Finally, we drop the few individuals for whom there are inconsistencies in their main job information within a given year (industry code and occupation code variations across within-year spells of the same job). However, this restriction affects only a small share of workers (84 individuals).

We define displacement in the LEED as job spell termination that is followed by a record in the NAV's ARENA register of job-seekers that indicates that the worker is completely available and looking for work (yrkstat=3) during the reference week. This is a less precise definition than the one we used for the NLSY, so we may be missing a significant share of short-duration unemployment spells. However, due to the significant fraction of non-employment spells in the LEED that are reported as voluntary (i.e., workers report being out of the labor force after the job end date – yrkstat=0), we believe that a measure that relies on a particular threshold between employment spells to classify unemployment may introduce significant noise into our analysis. Apart from this distinction, we follow the same restrictions imposed in the NLSY sample, i.e., a) having at least two years of prior tenure in the job; b) being at least 25 years old and at most 57 years old at the time of dismissal;[26] and c) worked at least 20 hours per week (on average) in that job for the duration of the job.[27] Moreover, since our data frequency is annual, we consider that the displacement occurred

[24] Series NORCPIALLMINMEI

[25] Keep in mind that the LEED keeps track of individuals even when they are out of the labor force.

[26] We impose a maximum age at displacement, since workers 60 years old or older in Norway can stay on unemployment benefits until they reach retirement age.

[27] As a robustness test, we raised the requirement to work at least 30 hours per week (on average). The results were quite similar to the ones presented in the paper.

at the year-end of the last job before the worker reported that she is completely available for work. Overall, we have 21,079 first displacements in the LEED in the period 2004–2009.

# 4 Empirical Strategy

We propose two different empirical strategies to assess the importance of pre-displacement knowledge specialization in the earnings losses of displaced workers. Throughout the main text, we focus on a matching empirical strategy, similar to that in Couch and Placzek (2010) and Schmieder et al. (2022). Each displaced worker is matched to one or more control units based on the characteristics of the worker and of the economy at the point of displacement. For additional robustness, in Appendix C we replicate the entirety of our results using the empirical strategy proposed in Jacobson et al. (1993),[28] the gold standard in the displacement literature. In both cases, the definition of the treatment group is identical and follows the criteria described in the previous section. However, each empirical strategy leverages a different control group and uses a different estimation strategy. At its core, each identification strategy imposes different assumptions and presents certain strengths and weaknesses that we detail in Appendix C.

## 4.1 Empirical Strategy: Matching

### 4.1.1 Matching: NLSY 79-97

For our main empirical strategy, we propose a matching approach, where we match each worker in the displacement job and year to a set of workers that, during the same year, are similar in pre-specified worker and job characteristics. To implement this strategy, we only look at the worker's first displacement and consider 14 different characteristics of the worker-job at the point of displacement, unless otherwise presented. Specifically, we focus on the skill level, knowledge level, knowledge specialization, occupation group, industry group and job tenure of the displacement job, the year of the displacement, the average weekly hours worked during the displacement year, the average hourly wage during the displacement year, the experience, age, and education level at displacement, as well as the gender and race of the worker. When the variable is dichotomous or categorical, we keep it as it appears in our sample originally (age, displacement year, education, gender, race, industry, and occupation group), while for continuous variables (skill level, knowledge level, knowledge specialization, experience, job tenure, average weekly hours worked and average hourly wages) we create 20 different ventiles.

From here, for each displacement, we look in our sample for the closest observation to the displacement, based on the previously mentioned characteristics. Specifically, we follow the following

[28] We refer to this identification strategy as Jacobson et al. (1993) or JLS (1993) throughout the paper.

algorithm. First, we match on the year. Second, for each observation in our sample of a worker who is never displaced or has not yet been displaced, we consider the total number of remaining 13 characteristics that match the characteristics of our displacement. For each displacement, we keep all job-year-worker observations that match the maximum number of characteristics, independently of whether all characteristics or only a subset of them are matched. Even if an observation has already been matched to a displacement we maintain it in our sample and allow other displacements to match again with that observation.

**Matching Summary Statistics NLSY 79-97**

Using this procedure, we match all displacements with at least 1 job-year-worker observation that satisfies the above conditions. While we do not have a limit on how many observations a job-year-worker observation can be matched to, no job-year-worker observation is matched to more than 4 different displacement events. Specifically, of all job-year-worker observations matched to a displacement, 87.9 percent of them are only matched to one displacement event, 11.2 percent are matched to two, and less than 1 percent to three or more. On the other hand, looking at the best job-year-worker observation matches for each displacement, the median number of characteristics matched is 11 of 14 (0.7 percent of all displacement match in 7 characteristics, 5.0 percent in 8, 14.1 percent in 9, 30.0 percent in 10, 33.1 percent in 11, 14.5 percent in 12, 2.5 percent in 13 and 0.1 percent in all 14). The median displacement event is matched to two different job-year-workers observations (44.0 percent of all displacements are matched to one single job-year-worker observation, 20.5 percent to two, 12.0 percent to three, 7.7 percent to four, 4.8 percent to five, and the remaining 11 percent are matched to six or more). Table 5's panel (a) shows additional statistics on the joint distribution of matched covariates and the number of matches recovered for the control group.

For estimation purposes we only keep the observations from five years prior to the displacement (or to the match year in the case of the control units) to seven years post-displacement. This results in an estimation sample that, conditional on having non-zero earnings, contains approximately 90,300 worker-year observations, with 21,400 observations from the treatment group and 68,900 observations in the control group. We have an average of 7.4 observations per worker in the displaced group, and an average of 8.6 observations per worker in the control group.

#### 4.1.2 Matching: Norway's LEED

There is significant variation in annual earnings and hours worked in the LEED. In particular, as presented in Huttunen et al. (2011), displaced workers are significantly more likely to exit the labor force. Furthermore, as we see in our analysis, displaced workers are also more likely to significantly reduce the number of hours worked per year after displacement.[29] Consequently, in order to match all displacements with at least 1 job-year-worker observation, we consider a hierarchical approach in terms of the matching characteristics. First of all, we match exactly on year and gender. Second, we give priority to control observations that match on the largest number of pre-displacement periods available in terms of log(annual earnings).[30] Once we match on pre-displacement earnings, we consider matching on industry 2-digit sector, average weekly hours, and aggregate hours (split into 10 deciles) during the pre-displacement year. Finally, we consider matches in terms of knowledge specialization and knowledge level, detailed industry and occupation groups, employment tenure, age (split into 10 deciles), employment tenure (in years), labor market experience, and education groups. Since we have this 4-layer hierarchy in the matching procedure, we only consider as potential controls in the next matching layers the observations that perform best in previous rounds. Finally, since our potential control group is quite large, we only consider individuals who are never displaced in our matched sample.

**Matching Summary Statistics Norway's LEED**

Table 5's panel (b) shows the result of our matching exercise. Specifically, of all job-year-worker observations matched to a displacement, 97.1 percent of them are only matched to one displacement event, 2.8 percent are matched to two, and less than 0.2 percent to three or more. On the other hand, looking at the best job-year-worker observation matches for each displacement, the median number of characteristics matched is 12 of 22. However, the low median is somewhat misleading since the highest match value of layoffs that occurred in 2004 (21 percent of the total) is 20 – due to missing information for pre-displacement years -4 and -5 – and in 2005 (16 percent of the total) the highest match value is 21. The median displacement event is matched to one different job-year-worker observation (79 percent of all displacements are matched to one single job-year-worker observation, 14 percent to two, 4 percent to three, and the remaining 3 percent are matched to four or more). As in the NLSY, we only keep the observations from up to five years prior to the displacement (or to the match year in the case of the control units) to five years post-displacement.

## 4.2 Estimation

After implementing the matching algorithms described above, we estimate equation (2):

$$Y_{it} = \sum_{k=-5}^{k=7} \eta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k D_{it}^k \times Disp_i + \eta Disp_i + \boldsymbol{\beta X_{it}} + \alpha_g + \gamma_t + \epsilon_{it} \tag{2}$$

where $D_{it}^k$ are dummy variables around the displacement event. $D_{it}^k$ are defined at the displacement group level, which includes both the displaced worker as well as workers in the matched control group. For instance, for an individual displaced in 1999, $D_{i,1999}^0 = 1$ while all other $D_{i,1999}^j$ are

[29]This result may be driven by temporary contracts. Unfortunately, we have no temporary contract identifier in our data, so we are unable to distinguish between a low-duration job spell and a temporary contract.

[30]Up to 5 years pre-displacement when data availability permits.

zero. That same individual in 2004 has $D^5_{i,2004} = 1$ and all other $D^j_{i,2004} = 0$. Similarly, for all individuals matched to this specific 1999 displacement, $D^0_{i,1999} = 1$ (and all other $D^j_{i,1999}$ are zero). These same matched individuals in 2004 have $D^5_{i,2004} = 1$ and all other $D^j_{i,2004} = 0$. The dummy variable $Disp_i$ takes the value of 1 for the individual within the displacement group that will be (or has already been) displaced and zero for all other individuals in the group. The dependent variable $Y_{it}$ represents any measure of interest to be analyzed around the displacement event (i.e., real annual earnings or hours, hourly wages, etc.). $\alpha_g$ are match fixed effects (i.e., we assign a unique identifier to all year-worker observations matched to a displacement event, including the observations of the displaced worker), $\gamma_t$ are year fixed effects and $\boldsymbol{X_{it}}$ is a vector of individual controls including non-parametric controls by gender, race,[31] age, education, and the interactions of education with time fixed effects, and, for the NLSY, education with NLSY round, NLSY round with time fixed effects, and NLSY round with time fixed effects and education. We cluster the standard errors at the match level.[32]

The identification of the effects of displacement using the empirical strategy in equation (2) differs from the standard Jacobson et al. (1993) empirical strategy (shown in Appendix C) significantly. Note that equation (2) does not include individual fixed effects but match (or displacement group) fixed effects. This implies that conditional on the match group and the other covariates, workers in the control group set the baseline from where the $\delta_k$ coefficients are derived for dismissed individuals. Thus, as opposed to the Jacobson et al. (1993) case, the control group is not only crucial to identify the effects on the outcome of all the control variables (i.e., gender, age education, NLSY group, and year fixed effects, etc.) but it also set the baseline earnings path from where the treatment group is benchmarked pre- and post-displacement. In short, this empirical strategy works as a within-match difference in differences, conditional on covariates, under the assumption that, in the absence of displacement, the evolution of earnings for the displaced worker within the match would have been the same as that of the matched control workers.

Our baseline specification estimates the average effect of displacement on hours, wages, and earnings. However, this specification does not allow us to speak about the heterogeneity of the losses. To account for loss heterogeneity, we extend the baseline model in order to include the interaction of the dummy variables $D^k$ with the value of knowledge specialization at the displacement job. Given the strong correlation between a job's knowledge specialization and knowledge level, we also include the interaction between the displacement dummies and the knowledge level in the pre-displacement job. In this way, we can understand the role of higher or lower pre-displacement levels of specialization, conditional on a knowledge level. Therefore, we augment equation (2) to:

[31] We do not include race in the LEED since we do not observe it.

[32] Clustering the standard errors at the individual level results in identical estimates.

$$Y_{it} = \sum_{k=-5}^{k=7} \eta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k D_{it}^k \times Disp_i + \eta Disp_i + \sum_{k=-5}^{k=7} \eta_k^{sp} D_{it}^k \times sp_{i,0} + \sum_{k=-5}^{k=7} \delta_k^{sp} D_{it}^k \times Disp_i \times sp_{i,0} + \eta^{sp} Disp_i \times sp_{i,0}$$
$$+ \sum_{k=-5}^{k=7} \eta_k^{kn} D_{it}^k \times kn_{i,0} + \sum_{k=-5}^{k=7} \delta_k^{kn} D_{it}^k \times Disp_i \times kn_{i,0} + \eta^{kn} Disp_i \times kn_{i,0} + \boldsymbol{\beta X_{it}} + \alpha_g + \gamma_t + \epsilon_{it} \quad (3)$$

One of the main concerns of the previous specifications is the fact that knowledge specialization at displacement is strongly correlated with other worker characteristics at displacement, which are unaccounted for in equation (3). If those other factors drive the difference in earnings losses post-displacement, the estimated effect of knowledge specialization at displacement could simply reflect differences in other pre-displacement characteristics. For example, if highly specialized workers are systematically longer-tenured when displaced, the coefficients $\delta_k^{sp}$ could be picking up the fact that longer-tenured workers suffer longer displacement losses (see Topel (1990) or Davis and von Wachter (2011)) while masking it as the effect of specialization.

We use two alternative solutions to account for these worker characteristics at displacement. First, we augment equation (3) by including new interactions of the dummy variables $D_{it}^k$ with a series of job and worker observed characteristics, at the point of displacement. These variables are all taken in their values for $k = 0$ for all the pre- and post-displacement periods of interest (from $k = -5$ to $k = 7$). Thus, on top of the pre-displacement knowledge specialization (and knowledge level), we include experience, job tenure, education (high school or less or some college or more), age, gender, industry, and occupational group.[33] In addition to worker and job characteristics at the point of displacement, we also include the level of unemployment at the time the worker was displaced.[34]

The updated equation (3) is equation (4):

$$Y_{it} = \sum_{k=-5}^{k=7} \eta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k D_{it}^k \times Disp_i + \eta Disp_i + \sum_{k=-5}^{k=7} \eta_k^{sp} D_{it}^k \times sp_{i,0} + \sum_{k=-5}^{k=7} \delta_k^{sp} D_{it}^k \times Disp_i \times sp_{i,0} + \eta^{sp} Disp_i \times sp$$
$$+ \sum_{w \in W} \Big[ \sum_{k=-5}^{k=7} \eta_k^{W} D_{it}^k \times W_{i,0} + \sum_{k=-5}^{k=7} \delta_k^{W} D_{it}^k \times Disp_i \times W_{i,0} + \eta^{W} Disp_i \times W_{i,0} \Big] + \boldsymbol{\beta X_{it}} + \alpha_g + \gamma_t + \epsilon_{it} \quad (4)$$

where each $w_{i0}$ is one of the previously mentioned job and worker observed characteristics at displacement.

The estimation period by period combined with a large number of control variables and the individual fixed effects generates large standard errors for the interactions of interest. To gain power, we combine all pre-displacement periods and post-displacement periods in the dummy variables

[33] Previous findings in the literature drive our selection of the additional controls. In other words, these variables were identified as sources of heterogeneity in either the depth or the recovery of displaced workers' earnings losses.

[34] This follows the findings of the previous literature, such as Davis and von Wachter (2011) or Huckfeldt (2022), in that earnings losses of displaced workers vary significantly with the aggregated macroeconomic conditions at the time they lose their job. The inclusion of the unemployment rate in $k = 0$ aims to account for this effect.

$D_{it}^{PRE}$ and $D_{it}^{POST}$, respectively. This approach mimics the one proposed by Jacobson et al. (1993). Therefore, $D_{it}^{PRE}$ takes value 1 starting five years prior to the displacement event up to the year before the dislocation happens, and zero otherwise. $D_{it}^{POST}$ shifts to value 1 in the year when the worker loses her job and remains 1 up to 7 years after displacement, with all other periods being zero. This results in the following equation (5):

$$Y_{it} = \sum_{k=-5}^{k=7} \eta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k D_{it}^k \times Disp_i + \eta Disp_i + \sum \sum_{k=Pre}^{k=Post} \eta_k^{sp} D_{it}^k \times sp_{i,0} + \sum_{k=Pre}^{k=Post} \delta_k^{sp} D_{it}^k \times Disp_i \times sp_{i,0} + \eta^{sp} Disp_i \times sp$$
$$+ \sum_{w \in W} \Big[ \sum_{k=Pre}^{k=Post} \eta_k^W D_{it}^k \times W_{i,0} + \sum_{k=Pre}^{k=Post} \delta_k^W D_{it}^k \times Disp_i \times W_{i,0} + \eta^W Disp_i \times W_{i,0} \Big] + \boldsymbol{\beta X_{it}} + \alpha_g + \gamma_t + \epsilon_{it} \quad (5)$$

The second alternative is to residualize the knowledge specialization variable. Specifically, we run a linear regression of the knowledge specialization on a set of covariates including knowledge level, gender, age, education, job tenure, experience, and industry and occupational group dummies. The regression's sample includes only non-displaced workers in all periods. The use of knowledge specialization residuals, instead of the original variable, allows us to get rid of the heterogeneous effects of displacement driven by other variables in $k = 0$ (such as industry, age, etc.). Hence, this approach eliminates the fear that our results are driven by confounding effects by omitted observed characteristics. The residualized variable gives us an intuition of how specialized an individual is, conditional on her age, experience, education, tenure, industry, etc. Therefore, instead of equation (5), we estimate equation (6):

$$Y_{it} = \sum_{k=-5}^{k=7} \eta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k D_{it}^k \times Disp_i + \eta Disp_i + \sum_{k=Pre}^{k=Post} \eta_k^{sp} D_{it}^k \times usp_{i,0}$$
$$+ \sum_{k=Pre}^{k=Post} \delta_k^{sp} D_{it}^k \times Disp_i \times usp_{i,0} + \eta^{sp} Disp_i \times usp + \alpha_g + \gamma_t + \epsilon_{it} \quad (6)$$

Identification of the effects of the pre-displacement knowledge level and knowledge specialization on the post-displacement losses is based on conditional independence. We require that there are no other unobserved characteristics at the point of displacement that affect the recovery path of earnings post-displacement and are correlated with knowledge specialization in $k = 0$. A simple example of this problem could arise through the ability of the worker. If more specialized workers tend to be higher-ability individuals, and the ability is a determinant of the magnitude and persistence of a worker's earnings losses, our estimates of interest would be biased.[35]

[35] Regarding the just mentioned example, we do not include ability as a control (or variable to residualize with respect to). The reason is that once all other control variables are included, we find the worker's ability (AFQT) irrelevant in explaining the heterogeneity of earnings losses.

# 5 Earnings Losses of Displaced Workers

We estimate the effects of displacement on earnings using equation (2). The results are shown in Figure 1. Panel (a) of Figure 1 shows the estimated $\delta^k$ coefficients for the NLSY. Compared to two years prior to the displacement, we find minor differences in earnings between treatment and control groups, which reach, at most, 2 percent of annual earnings three to five years pre-displacement. Similarly, we do not see any significant difference in total earnings in the year before the worker is displaced (we normalize the difference to 0 in the period -2). This is followed by a large drop that reaches 24 percent[36] in the displacement year (period 0), 36 percent during the first full year after displacement (period 1), and recovers relatively constant to levels around 16 percent 7 years after the displacement event. Our estimated earnings losses in the US are in line with those reported in previous work (see Couch and Placzek (2010) and Lachowska et al. (2020)).

Panel (b) of Figure 1 shows the estimated $\delta_k^k$ coefficients from equation (2) using the Norwegian sample. Looking at the pre-displacement period, we find some significant differences in the years 3 to 5 before dismissal, although the magnitudes are small compared to the earnings losses post-displacement (at most 3.6 percent) and do not follow any particular trend. However, during the year prior to the displacement, we do not observe any significant differences in annual earnings between the treatment and control groups. This is followed by a large drop in earnings that reaches 53 percent[37] the year we first observe the worker in unemployment (period 0), and 57 percent during the first full year after we first observe the worker in unemployment (period 1). Afterward, these losses recover at a relatively constant rate to a level around 26 percent below the pre-displacement baseline 5 years after the displacement. These losses are significantly larger than the ones discussed in the literature (see Huttunen et al. (2011)). However, differently from our specification, Huttunen et al. (2011) includes benefits received, including unemployment benefits. The inclusion of unemployment benefits significantly reduces annual earnings losses. Unemployment benefits normally provide an annual compensation of 62.4 percent of the previous income.[38] Furthermore, benefits can last between 52 and 104 weeks.

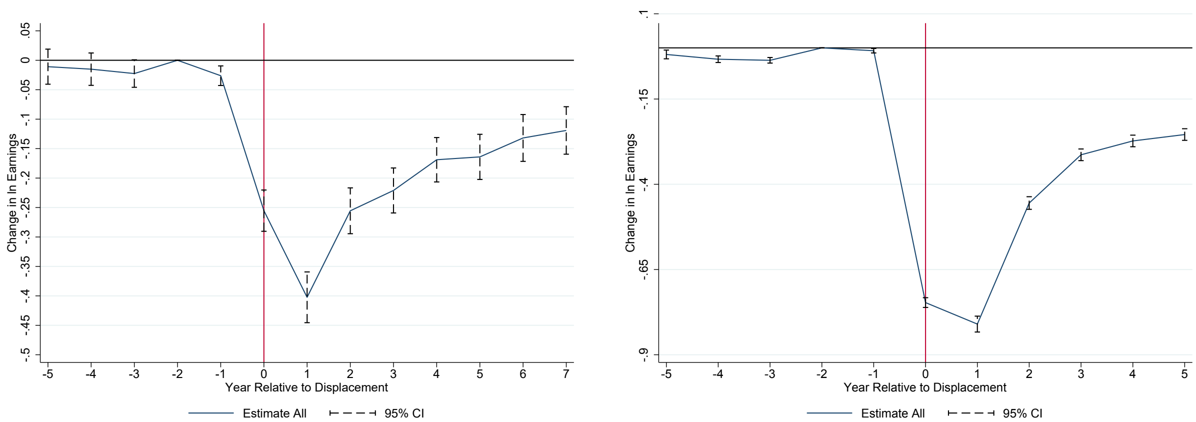
However, neither the NLSY nor the LEED results in this paper consider the provision of UI benefits post-displacement, and yet the estimated earnings losses in the LEED are twice as large as the NLSY ones. The main reason behind this difference comes from the definition of displacement in each data set. The NLSY allows us to identify displacements when they happen and follow the workers each week after it. Even if workers spend zero days unemployed after a displacement, we can identify those events and add them to our pool of displacements. The structure of the LEED does not allow us to identify a displacement event. We proxy displacements by looking

[36] $\exp(-0.270) - 1$=-0.237

[37] $\exp(-0.747) - 1$=-0.526

[38] The exact UI compensation will depend on the highest of either the income of the last preceding 12 completed calendar months prior to the application for unemployment benefits, or the average over the last 36 preceding calendar months prior to the application for unemployment benefits.

**Figure 1:** Displacement Effects on Earnings




(a) NLSY

(b) LEED

*Note:* This figure presents the estimated earnings losses from displacement, where the outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the matching empirical strategy outlined in the text and use the control group described in Section 4.1. The value on the y-axis captures the difference in earnings in the period relative to the difference between treatment and control two years prior to the dismissal, following equation (2). Black bars represent the corresponding 95% confidence intervals after clustering the standard errors at the match group level.

at the labor history of the workers, and define a worker as displaced when she is unemployed at the time of the survey but was employed in the year prior to the survey (similarly to Nilsen and Reiso (2011)). This definition has important implications in determining which workers we can observe as displaced. Displaced workers who quickly find a new job are highly unlikely to belong to our sample of displacements, since they would have to be dismissed close to the interview date to appear as currently unemployed. If a worker is dismissed in the previous year, but by the time of the interview in the subsequent year she has already found a new job, we will not be able to capture that displacement event. Similarly, we could be capturing quits as potential displacements. If a worker quits her job but is searching for a job by the interview date, we would classify it as a displacement. These measurement errors are likely to bias our results downward, generating larger earnings losses compared to the case where we could perfectly measure all displacement events.

We show evidence of how the different definitions of displacement generate the differential in earnings losses between the NLSY and the LEED by manipulating our definition of displacement in the NLSY. Specifically, within our original NLSY sample of displacements, we keep all workers who report not having a job during the third week of November during the displacement year (if they were dismissed prior to it), or in the following year (for those displaced during or after the third week of November). This results in a much smaller sample of displacements, with the total number dropping from 2,940 to 1,374. Within this sample, we replicate our matching empirical strategy and estimate the earnings losses post-displacement using equation (2).

The results are shown in Figure A.1 in the appendix, side by side with the original results from the NLSY and the Norwegian LEED. Changing our definition of displacement to one more similar to the LEED results in earnings losses in the NLSY that are extremely similar to those in the Norwegian sample. The first year after we first observe the worker in unemployment the earnings losses reach 56 percent, later tapering off to levels around 25 percent. The almost identical point estimates in both samples strongly suggest that the differences we initially observed were driven by the different definitions of displacement across data sets.

However, even if our estimates of the earnings losses after displacement are downward biased in the LEED (relative to using the same definition of displacement as in the NLSY) this does not necessarily invalidate our main results of interest in the paper. For the effect of higher pre-displacement knowledge specialization in the earnings losses post-displacement to be biased, we would require a correlation between the unemployment duration and the pre-displacement knowledge specialization. We provide evidence that this is not the case in the following section, where we compare the estimated effect of higher pre-displacement knowledge specialization in our original NLSY displacement sample and the reduced sample, where we require observing the workers without a job during the third week of November.

Table 6 shows the estimated coefficients for the effect of displacement on earnings and decomposes them into the effect coming from hours worked and that arising from changes to hourly wages. Neither hours worked nor hourly wages fully recover after dismissal, and remain depressed 5 to 7 years later in both samples. However, the LEED and NLSY show important differences in this decomposition. The decrease in hours worked is the main mechanism behind the earnings losses we estimate in Norway, while the drop in hourly wages explains most of the long-term losses in the US. While our definition of displacement in the LEED makes this effect more pronounced, this remains true even when compared to the estimation of the NLSY that uses the LEED definition of displacement. Hourly wages in Norway drop significantly during the first period of unemployment, but recover quickly to a level 4 percent below pre-displacement 4 to 5 years post-dismissal. In the US the initial drop in wages is not as extreme, but their recovery is very sluggish, remaining 8 percent below pre-displacement 4 to 5 years post-dismissal (or almost 14 percent below when using the LEED equivalent definition of displacement). On the other hand, hours worked drop sharply in both countries early after displacement, but recover quickly and constantly in the US, to a level 8 percent below pre-dismissal in 5 years (or 10 percent below when using the LEED equivalent definition of displacement). In Norway after the initial recovery, hours worked stagnate at a level around 20 percent below pre-dismissal for several years.

Finally, Appendix C.2 presents equivalent results of the effect of displacement on earnings using the JLS (1993) empirical strategy. While the results are qualitatively similar, in the appendix we highlight the main differences and the reasons behind those differences.

# 6 Pre-Displacement Knowledge Specialization and Earnings Losses after Displacement

We now move to the main interest of this paper: the effect of higher pre-displacement knowledge specialization on the earnings losses of displaced workers. Figure 2 plots the estimated earnings losses of a worker one standard deviation above the mean (high specialization) and those of a worker one standard deviation below the mean (low specialization), estimated using the matching empirical strategy in equation (3).

Looking first at panel (a), where we use the NLSY, we do not observe any significant differences in the evolution of the earnings of workers with high vs. low pre-displacement knowledge specialization during the pre-displacement period. Similarly, during the displacement year, high- and low-specialization workers show extremely similar earnings losses. However, after this period, the earnings losses of high-specialization workers become 8 percentage points larger (36 percent vs. 28 percent) and remain in the 4 to 8 percentage point range for the following 5 periods. After 5 years, the gap narrows, and the earnings losses of high-specialization workers are only 2 to 4 percentage points larger than the losses of low-specialization workers (14 percent vs. 11 percent).

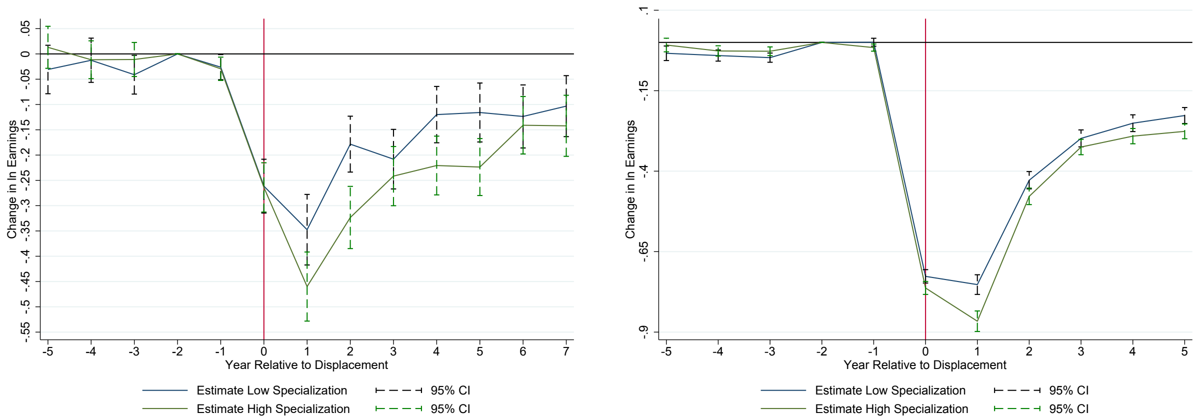
Moving to the Norwegian data in panel (b), our estimates paint a similar story, although the differences post-displacement between high- and low-knowledge-specialization workers are less pronounced and evolve slightly differently. As in the previous panel, we do not observe any significant differences in the evolution of the earnings of workers with high vs. low pre-displacement knowledge specialization during the pre-displacement period.[39] During the first year in which workers report being unemployed, we estimate earnings losses that are 3.6 percentage points larger for high-specialization workers, compared to their low-specialization counterparts. This gap increases drastically right after this period, reaching 11 percentage points during the first year after first reporting being unemployed, and 5 percentage points the following period. Afterward, the gap narrows marginally and stabilizes around 4 percentage points.

We provide additional evidence of these results in columns (1), (2), (5), and (6) of Table 7, where we show the estimated coefficients from equation (5). Looking first at columns (1) and (2), which use data from the NLSY, we find that one additional standard deviation of pre-displacement knowledge specialization increases the earnings losses of a displaced worker by an average of 3.6 to 4.2 percentage points per year, depending on whether we include the pre-displacement knowledge level as an additional control or not. Moving to columns (5) and (6), where we use the LEED, one additional standard deviation of knowledge specialization pre-displacement increases the earnings losses post-displacement by an average of 2.5 to 2.8 percentage points per year, depending on the specification. Both results are significant at the 1 percent confidence level.[40]

[39] Note that both types of workers show slightly lower earnings than those in the control group during the pre-displacement period, even if we do not observe any significant differences between high and low specialization.

[40] Table D.3 compare these results to the results from using our alternative measure of knowledge specialization,

**Figure 2:** Displacement Effects of Knowledge Specialization on Earnings




(a) NLSY (b) LEED

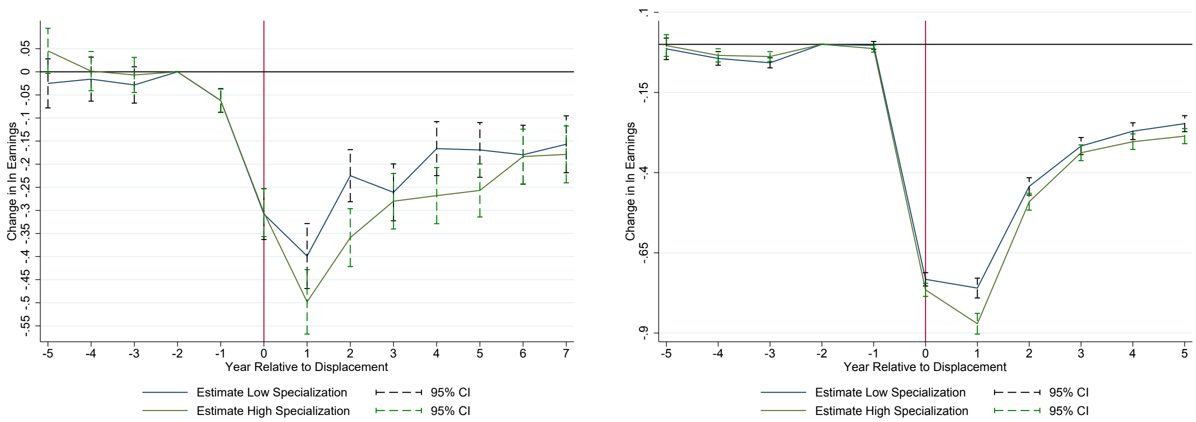
*Note:* This figure presents the estimated earnings losses from displacement for workers with high vs. low knowledge specialization pre-displacement. Low (High) knowledge specialization: Estimated earnings losses of a worker with knowledge specialization pre-displacement one standard deviation below (above) the median. The outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the matching empirical strategy outlined in the text and use the control group described in Section 4.1. The value on the y-axis captures the difference in earnings in the period relative to the difference between treatment and control two years prior to the dismissal for each type of worker, following equation (3). Black bars represent the corresponding 95% confidence intervals after clustering the standard errors at the match group level.

The potential correlation between the pre-displacement specialization and other covariates at the point of displacement could affect our estimate of the relevance of knowledge specialization for the earnings losses of a displaced worker. To account for this, columns (3) and (7) in Table 7 present the estimated coefficients from equation (4), where we additionally interact the displacement dummies with gender, age, tenure, education, experience, industry, and occupation group of the pre-displacement job as well as the unemployment rate at the point of displacement. Focusing on the US results in column (3), we find that even after controlling for this vast set of worker, job, and economy characteristics, one additional standard deviation of pre-displacement knowledge specialization increases the earnings losses of a displaced worker by an average of 3.7 percentage points per year. We extract a similar conclusion when we instead consider the data from Norway, and still control by the other worker, job, and economy characteristics at the point of dismissal, in column (7). In this case, one additional standard deviation of pre-displacement knowledge specialization increases the earnings losses after displacement by an average of 1.6 percentage points per year.[41] We provide additional evidence of these results in Figure 3, where we plot the estimated earnings losses of a high- vs. low-specialization worker, after controlling for the above-mentioned covariates interacted with the displacement dummies. The estimated earnings losses for a worker

the HHI index. We find very similar results regardless of the chosen measure.

[41] Columns (3), and (6) in table D.3 compare these results to the results from using our alternative measure of knowledge specialization. Regardless of the measure chosen, our conclusions remain unchanged.

**Figure 3:** Displacement Effects of Knowledge Specialization on Earnings




(a) NLSY (b) LEED

*Note:* This figure presents the estimated earnings losses from displacement for workers with high vs. low knowledge specialization pre-displacement. Low (High) knowledge specialization: Estimated earnings losses of a worker with knowledge specialization pre-displacement one standard deviation below (above) the median. The outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the matching empirical strategy outlined in the text and use the control group described in Section 4.1. The value on the y-axis captures the difference in earnings in the period relative to the difference between treatment and control two years prior to the dismissal for each type of worker, after controlling by additional workers' characteristics at the point of displacement by interacting them with the displacement dummies, following equation (4). Black bars represent the corresponding 95% confidence intervals after clustering the standard errors at the match group level.

one standard deviation above (below) the mean remain very similar compared to the losses depicted in Figure 2.

For additional robustness, in columns (4) and (8) of Table 7 we provide estimates of the coefficients of equation (6) for the US and Norway, respectively. Here, instead of adding multiple interactions between the pre-displacement characteristics and the displacement dummies, we first residualize the pre-displacement knowledge specialization, and then we interact it with the displacement dummies. Regardless of the country, we find similar conclusions, with one standard deviation of pre-displacement knowledge specialization deepening the earnings losses of a displaced worker on average 3.2 percent per year in the US and by 2 percent per year in Norway.[42]

Finally, we consider whether the use of different definitions of displacement in the NLSY and the LEED could affect our estimates of the role of pre-displacement knowledge specialization on post-displacement earnings. If the effect of higher pre-displacement knowledge specialization is heterogeneous across workers and is correlated with the duration of unemployment after a displacement, it is possible that our LEED estimates are biased. The direction of this bias will depend on

[42] Appendix C.2, presents the results in this section when we instead use the JLS (1993) empirical strategy. Our main conclusions remain unchanged, although we find that the negative effect of one additional standard deviation of pre-displacement knowledge specialization is 0.4 to 0.8 percentage points weaker than the estimated effect using the matching strategy in the US and Norwegian samples, respectively.

whether this correlation is positive or negative. We test this in the NLSY, by changing the definition of displacement to the one in the LEED, as in the previous section. In this case, we estimate that one standard deviation of pre-displacement knowledge specialization deepens the earnings losses of a displaced worker by an average of 3.7 to 4.1 percentage points per year in the US, depending on the specification. These results are almost identical to our original estimates in columns (1) to (3) of Table 7. The similarity between both results suggests that the different definitions of displacement are unimportant for our estimated effects of higher pre-displacement specialization, even if they heavily affect our aggregate estimated losses in earnings post-displacement. Thus, we would expect a similar negative effect of higher pre-displacement specialization in Norway, compared to our current estimate, if we could define displacements similarly to how we do it for the NLSY.

# 7 Mechanisms

What is the mechanism through which higher pre-displacement knowledge specialization increases earnings losses after a displacement? This section proposes several mechanisms and analyzes their role in explaining why higher knowledge specialization leads to larger earnings losses post-displacement.

We divide these mechanisms into three different groups. First are mechanisms related to the change of jobs between pre- and post-displacement occupations, such as whether higher pre-displacement specialization increases the likelihood of changing industry, occupation, main skill (as in Poletaev and Robinson (2008)) or the distance (in a task sense) between the pre- and post-displacement jobs (as in Gathmann and Schönberg (2010)). Second are mechanisms related to the characteristics of the pre-displacement job. Here we rely on dimensions identified in previous work as relevant in explaining the patterns of employment and earnings in the last few decades, and test its relationship with the level of knowledge specialization. We evaluate mechanisms such as the pre-displacement occupation's routine, manual, or cognitive content, the complexity of its tasks, or the likelihood of the pre-displacement occupation (or its tasks) being offshored or automated. Third are mechanisms related to the quality and quantity of the worker's outside options. We propose a novel approach to measure an occupation's outside options based on its knowledge requirements, which allows us to estimate the number and quality of each worker's outside options at the point of displacement.

## 7.1 Pre-Displacement Knowledge Specialization and Industry, Occupation, Main Skill, and Distance Changes

We start by focusing on how pre-displacement knowledge specialization affects the likelihood of changing industry, occupation, main skill, or the distance between the pre-and post-displacement jobs. To determine whether a worker remains in the same industry or occupation as her previous job, we consider all the jobs held by the worker during the displacement year (post-displacement) and the year after the displacement. If any of the jobs during this period belong to the same industry or occupation group as the pre-displacement job, we classify that worker as returning to the same industry or occupation group. If none of the jobs held during this period belongs to the same industry or occupation group, we classify the worker as changing industry/occupation group. Classifications are the same for the NLSY and the LEED, apart from the fact that occupation groups are coarser in the LEED (see Figure B.2 in the appendix). However, we are less restrictive in the LEED and do not impose a timeline to define industry/occupation changes. Therefore, workers will change (remain) industries or occupations if their next job is in a different (same) industry or occupation, regardless of when they return to the labor market after the displacement.

To determine whether workers remain in the same skill group as in the pre-displacement job, we replicate the procedure followed by Poletaev and Robinson (2008). We first extract three principal components from the skill category of the O*NET. From there, each occupation is classified as being in skill portfolio one, two, or three based on which one of the skills has the largest value in the principal component. Then, we follow the same procedure as with industry and occupation changes to determine which workers return to jobs in the same or different skill group.

Finally, to define the distance between occupations we follow Gathmann and Schönberg (2010) and, for each pair of occupations, we calculate the angular distance between the knowledge importance categories. Since workers can potentially have more than one occupation in the displacement year and the year after it, we keep only the distance to the closest occupation within this time period.[43]

Using this procedure to classify job changes requires that we observe workers in a job within the first two years after the displacement takes place.[44] Moreover, it also requires that workers have valid (or non-missing) information on the occupation/industry of their jobs both pre- and post-displacement. These restrictions reduce our NLSY sample of displacements from 2,940 to 2,034 displacements, and the LEED sample of displacements from 21,079 to 16,790[45] (see Table 8 for details). Using the conditions above, around 46 percent of all displacements in the NLSY for which we observe industry and occupation pre- and post-displacement return to the same industry group, 52 percent of them return to the same occupation group, 34 percent return to the same industry and occupation group, and 66 percent return to jobs with the same main skill. We observe similar patterns in the LEED, with a somewhat higher probability of industry changes. In particular, only

[43]In the LEED the distance is determined by the first post-displacement job regardless of the timing of re-employment.

[44]We do not have this issue in the LEED. As long as workers return eventually to the labor market, we can potentially calculate the distance between jobs.

[45]Given the large decrease in the number of displacements we observe in the NLSY after we impose the conditions above, Table A.1 replicates the results shown in Table 7 but using only the sample of displacements for which we observe industry and occupation group pre- and post-displacement. We find very similar results compared to those in the previous section.

30 percent of workers stay in the same industry (compared to 46 percent in the NLSY), while 48 percent of workers return to the same occupation group (compared to 52 percent in the NLSY). That said, the changes in industry and occupation seem to preserve the main skill, since 68 percent return to jobs with the same main skill, a slightly larger fraction than in the NLSY (66 percent).

Our first exercise attempts to answer whether there is any relationship between the pre-displacement knowledge specialization and the probability of remaining in the same industry, occupation, or main skill. For that matter, we estimate a linear regression where the outcome is a dummy that takes the value of one if the worker remains in the same industry (or occupation, industry, and occupation, or main skill depending on the specification) and zero otherwise. Similarly, we include an additional specification that uses the distance between the pre- and post-displacement jobs as the outcome of interest. Our main explanatory variable is the pre-displacement level of knowledge specialization. We present three different specifications in Table 9. Column (1) does not include any additional covariates as controls. Column (2) adds the pre-displacement knowledge level as an additional control. Finally, column (3) adds all the covariates that we interact with the displacement dummies in equation (4) (i.e., age, gender, education, experience, tenure, unemployment rate, industry, and occupation group, at their values at the point of displacement).

The main takeaway of this exercise is displayed in column (3). Looking first at the NLSY results, we do not find any relationship between the pre-displacement knowledge specialization and the probability of remaining in the same industry, occupation, or main skill. Similarly, there is no correlation between pre-displacement knowledge specialization and the distance between the pre- and post-displacement occupations. Thus, conditional on covariates, workers are equally likely to remain in the same skill, industry, occupation, or both regardless of their pre-displacement knowledge specialization, and do not move to occupations closer or further away from their pre-displacement occupations. Moving to the LEED, the conclusions are somewhat different. Higher pre-displacement knowledge specialization is associated with a lower probability of remaining in the pre-displacement industry and occupation. A one standard deviation increase in knowledge specialization is associated with a 1.1 percent lower probability of returning to the same occupation (or a 2.1 percent lower probability of returning to the same industry). However, similar to the NLSY results, we do not find any significant association between workers finding jobs using the same main skill or the distance between the pre- and post-displacement occupations and knowledge specialization.

The limited association between pre-displacement knowledge specialization and the type of job transition suggests that the mechanism behind the negative effect of specialization on earnings is not an enhanced likelihood of moving further away or to a different industry, occupation, or skill. To confirm this, we extend our specifications from equation (5) by adding as additional controls the interaction between the displacement dummies and dummies for whether the worker remains in the same industry, occupation, skill group, and the distance between pre- and post-displacement occupations. If these industry, occupation, or skill changes are the drivers behind the effect on post-displacement earnings of greater knowledge specialization, the introduction of these controls interacted with the displacement dummies should make the coefficient of our variable of interest close to zero and insignificant.

The results are displayed in Table 10. In the NLSY, we find that one additional standard deviation of pre-displacement knowledge specialization increases the earnings losses after displacement by an average of 4.5 percentage points per year. Similarly, when looking at the LEED data, one additional standard deviation of pre-displacement knowledge specialization increases the earnings losses by an average of 1.6 percentage points per year. Both estimates are significant at the 1 percent level. These results are quite similar to our original results, displayed for convenience in columns (1) and (7) of Table 10.

In summary, the results of this section indicate that the larger earnings losses of workers with higher pre-displacement knowledge specialization are not driven by industry, occupation, or previous jobs' main skill changes nor by moves to jobs further away.[46] These results suggest that our measure of human capital specialization is not reflecting a human capital that is specific to the occupation, industry, or skill group, preserved if the worker stays and destroyed if she does not.

## 7.2 Knowledge Specialization Pre-Displacement vs. Other Characteristics of the Pre-Displacement Occupation

Our second group of mechanisms considers other dimensions of the pre-displacement occupation that could provide an explanation as to why further levels of specialization at displacement have a negative effect on the recovery path of earnings. Among the possibilities, we consider a) whether higher pre-displacement knowledge specialization is associated with jobs that are more likely to be automated or computerized; b) whether jobs with higher pre-displacement knowledge specialization are more likely to be offshored (or perform tasks that are more likely to be offshored); and c) whether more specialized jobs are more likely to be routine jobs or manual jobs.

All these aspects have been found in the literature to be relevant not only for the magnitude of the earnings losses of displaced workers but also to explain the employment and wage dynamics observed over the last few decades. For example, using Dutch micro-data with a direct measure of automation expenditures covering firms in all private non-financial industries over 2000-2016, Bessen et al. (2019) find that automation at the firm increases the probability of workers separating from their employers and decreases days worked, leading to a 5-year cumulative wage income loss

[46] While we find an increased likelihood of industry and occupational changes with higher pre-displacement knowledge specialization, we estimate similar negative effects of higher pre-displacement specialization for those who change their industry (or occupation) and those who do not. The opposite is true for the main skill and the distance changes. The negative effect of higher pre-displacement knowledge specialization increases in the distance of the move and when the worker changes the main skill, but we find no changes in the likelihood of moving further or changing the main skill based on the pre-displacement knowledge specialization.

of about 8 percent of one year's earnings for incumbent workers.[47] Furthermore, the decline in employment shares due to automation was concentrated in routine occupations (see Cortes et al. (2017)), which not only have seen an increase in the outflow rates but also a reduction in the inflows (see Cortes et al. (2020)). As a consequence, workers who were displaced from routine occupations become less likely to obtain a job in the same occupation, suffering significant losses if they are unable to switch to non-routine cognitive jobs (see Cortes et al. (2020)). Similarly, Kauhanen and Riukula (2019) and Blien et al. (2021) provide direct evidence of the effect of routinization on the earnings losses post-displacement. These papers find that Finnish, Swedish, and German workers displaced from routine-intensive occupations suffer larger earnings losses following an exogenous separation from their employer than displaced workers from non-routine occupations. Finally, offshoring not only increases the likelihood of job separation (see Geishecker (2008) and Munch (2010)), but also significantly increases earnings losses due to displacement. In particular, using Danish employer-employee matched data, Hummels et al. (2013) show that low-skill workers displaced due to offshoring shocks lose 21 percent of pre-displacement earnings while still showing significant losses 5 years after the initial displacement. In contrast, workers displaced due to other reasons see a 15 percent loss in the first year and almost entirely recover their losses after 5 years. The larger losses are partly attributed to the higher incidence of unemployment and industry switching among the workers displaced due to offshoring, suggesting worse labor market options in this case.

As in the previous section, we start by analyzing the relationship between the different mechanisms and pre-displacement knowledge specialization. We follow the same strategy and regress the covariate of interest (at its value at displacement) against the level of pre-displacement knowledge specialization. Table 11 presents three different specifications, identical to those described above for Table 9.

In panels (A) to (C), we analyze whether there's any association between pre-displacement knowledge specialization and three different measures representing the probability of the displacement occupation (or its tasks) being offshored and automated. For both the NLSY and the LEED we find a positive and significant association between knowledge specialization and the probability that the pre-displacement occupation could be offshored. In the NLSY, this relationship extends to tasks within an occupation. In particular, a one standard deviation increase in specialization is associated with being displaced from an occupation whose tasks are 19 percentage points more likely to be offshored. On the other hand, looking at the probability of being dismissed from an occupation with a higher likelihood of being automated, neither the NLSY nor the LEED results show any relationship between the pre-displacement occupation's knowledge specialization and the occupation's automation probability.

Panels (D) to (H) look at different dimensions of how routine, manual, cognitive, or complex an

[47] Unfortunately, their data have no information on either workers' occupation or workers' education.

occupation or its tasks are. In neither the NLSY nor the LEED we do find any association between the occupation's pre-displacement knowledge specialization and how routine or manual the tasks in an occupation are. On the other hand, the results for the NLSY and the LEED diverge when we consider the cognitive score and task complexity of the occupations. For the US, we find a strong positive association between the degree of knowledge specialization of the pre-displacement job and both, the degree of cognitive tasks it requires and the task complexity score of the occupation. However, neither of these two variables shows any association with the degree of specialization of the pre-displacement occupation in the LEED. The only variable that displays a positive association in Norway with pre-displacement knowledge specialization is the non-routine score of the occupation.

Why do our estimates from the NLSY and LEED differ across certain dimensions? First, as previously discussed, our definitions of displacement differ for the NLSY and the LEED. While we do not find a strong association between the effects of higher pre-displacement knowledge specialization on post-displacement earnings and our definition of displacement, it is possible that other dimensions of the pre-displacement occupation show a much stronger association with it, due to the sample selection created when changing the displacement definition. Second, our covariates measuring the routine, complexity, manual and cognitive scores of the occupations are based on the occupation's tasks of US workers[48] and are likely to better measure these concepts in US occupations. Finally, each sample focuses on a different time period, with only the NLSY covering decades in the 20th century. The routine, complexity, manual, and cognitive scores first introduced in Autor et al. (2003) were designed to understand the evolution of employment and wages in the US since 1960, and are more likely to be relevant for our NLSY sample.

In summary, workers displaced from occupations with higher pre-displacement knowledge specialization are significantly more likely to be displaced from occupations exposed to a higher risk of being offshored. Moreover, US workers dismissed from high-specialization occupations worked in occupations that required them to perform more complex and cognitive tasks, while their Norwegian counterparts worked occupations with a higher non-routine component. Neither country displays any association between specialization at displacement and the likelihood that the occupation will be automated, or the routine and manual scores of the pre-displacement occupations.

To understand whether the negative effect of pre-displacement specialization on the earnings losses of displaced workers is driven by these additional occupation characteristics, we rely on an extension of equation (5). Specifically, we add the interaction between the displacement dummies and the different covariates of interest, held constant at the point of displacement. We present the main results of this exercise in Table 12. In columns (2) and (3) (columns (6) and (7) for the Norwegian LEED), we add each type of mechanism one by one (variables related to the pre-displacement occupation being offshored or automated,[49] and variables related to the type and complexity of

[48]These score measures use as a starting point the DOT or O*NET.

[49]We do not include the likelihood that the occupation will be offshored due to the extremely high correlation of this variable with the variable measuring the likelihood that the occupation's tasks will be offshored. Including the

the occupation's tasks). Finally, in columns (4) and (8) (NLSY and LEED respectively), we add all types of mechanisms simultaneously. Our main interest is to understand whether the inclusion of any of the mechanisms makes the effect of pre-displacement specialization disappear. This would suggest that jobs with higher pre-displacement knowledge specialization see larger earnings losses because higher specialization is associated with some other dimension that drives the larger earnings losses and not because of the lack of diversification of the worker's knowledge.

Results are somewhat distinct for the NLSY and the LEED as we compare columns (4) and (8) in Table 12. In the NLSY adding the interaction between all of our mechanisms and the displacement dummies leaves our estimates on the effect of pre-displacement specialization on post-displacement earnings virtually unchanged.[50] A one standard deviation increase in pre-displacement specialization still significantly increases the earnings losses post-displacement by 3.9 percent. Differently, in the LEED, adding occupation characteristics reduces somewhat the point estimate on knowledge specialization. Furthermore, we lose statistical significance. While it is unclear how the occupation characteristics partially explain the role of knowledge specialization on post-displacement earnings losses, results from Table C.4 suggest that the degree of task complexity and routinization in the pre-displacement occupation may partially unravel the impact of knowledge specialization.

## 7.3 Pre-Displacement Knowledge Specialization and Lower Quality Outside Options

This section proposes a mechanism through which higher pre-displacement knowledge specialization increases the earnings losses of displaced workers. Our hypothesis is that knowledge-specialized occupations are more likely to be "dead ends" with a lower number and a lower quality of outside options. In this scenario, higher knowledge specialization jobs are occupations from which it is more difficult to transition to a different occupation that uses similar skills while also offering similar or higher average wages.

To test this hypothesis we propose two new measures of the quantity and quality of the available outside options for each occupation. To assess the number of outside options, for each (original) occupation we derive a set of possible occupations, based on the knowledge requirements in the original and target occupations. Specifically, we impose the condition that for all knowledge categories present in O*NET's data, the target occupation requires a level of knowledge importance in each category that is at most 1 unit larger than the knowledge importance of the original occupation in the same category. Thus, an occupation is a possible occupation from an origin occupation if the knowledge required to perform its tasks is similar or lower (in each knowledge category) compared to the requirements of the original occupation. For an origin occupation, we refer to its set of possible occupations as its *outside options*.

former instead of the latter leaves everything unchanged.

[50] Adding each group of mechanisms one by one results in identical conclusions.

Consequently, workers with skewed knowledge profiles are limited in where they can move, since most occupations may require knowledge in categories that are missing in the worker's current occupation. Notice that this restriction is binding even if the worker with a skewed knowledge profile has a high knowledge depth in the categories demanded by her current occupation. In fact, workers with lower depth but more diversified knowledge profiles may be in a better position to reposition themselves, since they may remain in similarly diversified occupations or move to jobs with differently skewed knowledge profiles, as long as the requirements are not very far from their original knowledge distribution. Furthermore, we can easily see that the definition of possible occupations implies that it is more likely that we observe moves from a diversified occupation to a specialized one than the other way around. This asymmetry distinguishes our measure from common measures of occupational transitions, such as the distance between jobs or whether workers remain in the same skill, industry, or occupation. These dimensions, commonly used in understanding the heterogeneity in earnings losses across workers, implicitly classify the transition between two very different occupations as equivalent to the symmetric change.

Once we define the set of outside options for each origin occupation, we calculate the share of total possible employment for each origin occupation using data from the OEWS in the case of the NLSY, and directly from the LEED for our Norwegian sample. For instance, if an origin occupation has ten occupations as its outside options, we sum the share of employment in these ten occupations and assign it to the origin occupation as the share of possible employment. Following the example above, psychologists have 4 occupations in their set of outside options, representing 0.2 percent of the total employment, while education administrators have 63 occupations in their set of outside options, representing 23 percent of the total employment.

While the above steps allow us to calculate the share of total employment available as an outside option for each occupation, they do not speak to whether those outside options are better than, similar to, or worse than the current occupation. To do this, we define a measure of the quality of an occupation's outside options. To calculate it, for each origin occupation we average the average hourly wages[51] of each occupation in its set of outside options, weighing each occupation's average hourly wages by the relative shares of total employment within the set of outside options. Then, we subtract the average hourly wage of the origin occupation from the weighted average wage in the set of outside options.

This allows us to compute a measure of the quality of the outside options for each origin occupation. For an origin occupation, if most possible occupations have lower hourly earnings, most of its outside options will be undesirable and our variable will be negative. On the other hand, if an occupation has a set of possible occupations with similar or higher average annual earnings, its outside options will be more robust, and our measure will be zero or positive. For instance, the difference in average annual earnings/hourly wages between education administrators and their set

[51] Using annual earnings results in almost identical results.

of outside options is larger than that of psychologists and their set of outside options, even if the former occupation has significantly more outside options. (On average education administrators make 90,000 dollars per year, and the average annual earnings of their outside options are 35,000 dollars. In the case of psychologists, annual average earnings are 78,000 dollars, while the average annual earnings of their outside options are 58,000 dollars.)

Combining the information on the quality and quantity of each occupation's outside options with our NLSY (LEED) sample, we find that displaced workers have on average outside options in jobs that represent 13 (12) percent of the total employment (this includes the share of total employment in their own pre-displacement occupation, which on average represents 1 percent of the total employment). This ranges from a minimum of 0.07 (0.02) percent to 45 (45) percent, depending on the pre-displacement occupation. However, despite the relatively low share of employment in their outside options, displaced workers take jobs in occupations in their set of possible options at a much higher rate. Fifty-one (51) percent of displacements take a post-displacement job in an occupation within the set of outside options of the pre-displacement occupation; 32 (40) percent of displacements return to the exact same SOC (STYRK-08) occupation after displacement, while the remaining 18 (11) percent return to one of the occupations within the set of outside options that is not their pre-displacement occupation. On average, the average annual earnings (or hourly wages) of the set of possible occupations are 26 percentage points lower compared to the average annual earnings in the pre-displacement occupation in the NLSY. Here we do see a significant difference with the LEED, where we see on average no difference in compensation. However, even in the NLSY this gap does not necessarily imply that workers take jobs in lower-paying occupations after displacement. The median difference in average annual earnings between the pre-and post-displacement occupations is approximately zero in the NLSY, and about - 2 percentage points in the LEED.

To test the relevance of the worker's outside options in explaining the negative effect of specialization on post-displacement earnings, we start by looking at the relationship between specialization and the share of employment in possible occupations and the difference in wages between the pre-displacement occupation and its set of possible occupations. Table 13 shows the main results. Looking at column (3) of panel (a), where we use the NLSY and add all additional control variables detailed above, we find that one additional standard deviation of pre-displacement specialization is associated with a 3 percentage point decrease in the share of total employment in a possible occupation. Workers with one standard deviation higher pre-displacement knowledge specialization are 16 percentage points less likely to be displaced from an occupation with above-average outside possible opportunities (column (3) in panel (b)).

Regarding the quality of the outside options, as shown in column (3) of panel (c), higher pre-displacement specialization is associated with a 5 percentage point larger negative difference between the average hourly earnings of the pre-displacement occupation and the average hourly earnings in the set of possible occupations. This results in workers with one standard deviation higher specialization being 11 percentage points more likely to be displaced from an occupation that has a negative difference between its average wage and the average wages in the set of its possible occupations (panel (d)). In summary, not only do US workers with higher pre-displacement specialization have a much more limited amount of jobs (and employment) where they can transfer their previous knowledge, but also within this set of jobs, average wages are much lower compared to the average wage of the pre-displacement occupation.

On the other hand, our results for the LEED, shown in column (6), show no relationship between the occupations' outside options and the pre-displacement knowledge specialization. One additional standard deviation of pre-displacement specialization is associated with a not statistically significant 0.8 percentage point decrease in the share of total employment in possible occupations. Similarly, the relationship between pre-displacement specialization and the likelihood of being displaced from an occupation with above-average outside opportunities is 5 times smaller in the LEED (-3 pp) than in the NLSY and not statistically significant. We also find no results on the association between knowledge specialization and the quality of the outside options. While a sharp contrast with the NLSY, these results are not surprising, given that there is no average difference in hourly compensation between the pre-displacement occupation and the set of possible occupations.

How do the amount and quality of the outside options affect the earnings losses after a displacement? Is the lack of quality outside options behind the negative effect of pre-displacement specialization in the earnings losses of displaced workers? To answer these two questions we rely again upon the empirical specification in equation 5. As before, we extend it by including the interaction between the displacement dummies and two dummies capturing the amount and quality of these outside options. The first dummy takes a value of one if the worker is displaced from an occupation with an above-average share of total employment in her set of outside options, and zero if the share of total employment in her set of outside options is below average.[52] The second dummy takes the value of one if the difference between the pre-displacement occupation's hourly wages and the average hourly wage of the set of possible occupations is positive or zero, and zero otherwise.

We present the results in Table 14, which follows an identical structure to that of Tables 10 and 12. Looking at the NLSY results in column (3) we find that both the amount and quality of the outside options have a positive impact on re-employment wages. Workers displaced from occupations with an above-average share of employment in their outside options have earnings losses that are approximately 5 percentage points smaller than workers displaced from occupations with a below-average share of employment in their outside options. Even more important is the quality of these options. Workers displaced from an occupation that has lower average earnings than the

[52]We define this average based on the average share of employment in outside options at the point of displacement of all displaced workers in our sample, and not based on workers currently employed.

(employment-weighted) average earnings of its outside options see earnings losses 10 percentage points smaller than workers facing the opposite scenario.

Furthermore, once we account for the amount and quality of the pre-displacement occupation's outside options, we find that pre-displacement specialization does not affect anymore the earnings losses after displacement (Table 14, the first row of column (4)). Compared to our original results (in column (1)), the coefficient of the impact of one additional standard deviation of pre-displacement specialization on post-displacement earnings is reduced by almost 50 percent (from -0.037 to -0.019), and it is no longer significantly different from zero. This result suggests that, at least for the US, workers in occupations with higher pre-displacement human capital specialization find themselves at a "dead end." They face a more limited amount of available employment to which they can transfer their human capital, and those jobs where they could easily transfer their knowledge are of a lower quality, compared to their pre-displacement occupations.

Our Norwegian results, however, present a different conclusion. We find that accounting for the quality and quantity of the workers' outside options has a negligible impact on our estimate of the effect of specialization on re-employment earnings (from -0.016 to -0.014). Thus, in the Norwegian case, it does not seem that the mechanism through which higher pre-displacement knowledge specialization affects the earnings losses post-displacement is the quantity and quality of the outside options. As shown above, the differences in the distribution of the quality of the outside options between the US and Norway are likely to explain the differences in our results in this section. The average displaced Norwegian worker faces similar quality outside options (relative to the pre-displacement occupation) and the quality of these outside options does not vary significantly with the occupation's specialization. This is not the case for the US, where the quality of the occupation's outside options of the average worker is significantly worse (relative to the pre-displacement occupation) and varies significantly with the pre-displacement specialization.

Finally, to try to understand whether the definition of displacement that we impose in the LEED could be behind the differential relevance of the outside options between the LEED and NLSY results, we again replicate the LEED definition of displacement in the NLSY data. Thus, we keep only workers within the group of displacements that would have been identified as displaced under the LEED definition and rerun our estimates in Table 12. Accounting for the quality and quantity of the outside options results in a coefficient of -0.020 for pre-displacement knowledge specialization. This is the same estimate we recover for our complete sample and translates to an identical percentage decrease (approx. 50 percent) from the original estimate of the effect of pre-displacement specialization on earnings (-0.037) than the one we recovered in the complete sample. Therefore, it seems very unlikely that the difference we find between the NLSY and LEED results is driven by the different displacement definitions used in each sample.

# 8 Conclusion

This paper proposes an alternative way of measuring the specialization of human capital. Workers possess human capital in different knowledge domains, and the specialization of this human capital is determined based on the distribution of the occupation's knowledge requirements. Starting from O*NET's indicators of the knowledge required to perform the occupation's tasks, we define this specialization as the degree of concentration of an occupation's knowledge across the different categories used in the entire economy.

We provide a comprehensive description of the relationship between knowledge specialization and other worker characteristics and document a positive association between earnings and specialization in the labor market. Furthermore, our analysis of the earnings losses of displaced workers suggests that higher specialization pre-displacement decreases post-displacement earnings over a prolonged period of time. We find this to be true across different time periods and in different countries. We argue that, in the US, specialization affects the earnings losses post-displacement because it reduces the quantity and quality of the worker's outside options. Workers with higher knowledge specialization have significantly fewer jobs they can move to, and these jobs tend to be lower paid relative to their pre-displacement occupation. However, this is not the case for Norway, where the routine intensity and offshore probability of the pre-displacement occupation are the only dimensions that explain part of the negative effect of specialization on re-employment earnings.

The advantage of our definition of human capital specialization is that it does not impose an arbitrary (even if reasonable) dimension that determines the re-usability of human capital. The human capital in this paper is not specific to "something" (3-digit occupation, industry, main skill, etc.), but it is simply more or less specific, based on the skewness of the knowledge distribution relative to the rest of the labor market. Our measure is agnostic about the domain that determines human capital specialization but focuses on determining the idiosyncrasy of its distribution.

One additional advantage of thinking about human capital specialization in this way is that it allows us to add richness to the results in the literature. We find that previous efforts that set a dimension for the specialization of human capital are still reasonably predictive of the earnings losses even when considering our measure of human capital. However, we also find that our approach adds an extra layer to this work, showing how neither of those dimensions is sufficient to determine at what level the human capital is specific.

Similarly, defining human capital specialization in this broader way allows us to focus on workers' *ex-ante* characteristics, based on their job characteristics pre-displacement. The decision of whether workers stay in the same industry, occupation, or skill depends, among other things, on the expected earnings of that choice post-displacement, introducing potential endogeneity bias. These concerns do not affect our *ex-ante* measure.[53] This is something useful from a policy perspective and could

[53]One could argue that the decision of taking a job with a knowledge profile that is more or less specific is also

help inform decisions on UI or job training of displaced workers.

Our measures of the quantity and quality of the outside options are an extension of our original decisions in the paper. If workers have knowledge in certain domains, then job mobility should be determined by the similarity of the knowledge distribution across all these domains. This helps us connect nicely the importance of specialization in determining the quantity and quality and outside options, since more specific profiles will tend to be more "separated" from a majority of other jobs in the economy. After a displacement, these profiles can still move between jobs, but either they find a similarly idiosyncratic profile, or they will be forced to move "down" to a more general job that uses less knowledge in aggregate. On the other hand, as in Poletaev and Robinson (2008), thinking about outside options in this way is likely to present some challenges when studying occupational mobility within a career path, where workers transition between seemingly "unrelated" occupations moving up the ladder.

In combination, our results on the effect of higher knowledge specialization on earnings, both pre- and post-displacement open the door for future research analyzing workers' decisions on what jobs to take in the labor market from the beginning of their careers. We document how further specialization could be associated with increased earnings volatility over the lifetime. Previous work has emphasized the role of occupational mobility in smoothing the earnings volatility of occupations. Here, we highlight the opposite side of this coin: the earnings volatility created via involuntary occupational mobility for higher specialization levels.

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a function of the expected future earnings path, which itself will depend on the possibility of losing the current job with a more specific knowledge profile. While this is true, we see this as one extra step back in the decision chain in that it happens prior to displacement, and not after the displacement has taken place.

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# Tables

**Table 2:** Knowledge Specialization and Level: Relationship with Earnings, Education, and Task Content

| | CPS | | LEED | |
|---|---|---|---|---|
| | Specialization | Level | Specialization | Level |
| Less than HS | -0.165*** | -0.020 | -0.094* | -0.028** |
| | [0.049] | [0.020] | [0.055] | [0.013] |
| Some College | 0.054** | 0.043*** | -0.061 | 0.040*** |
| | [0.024] | [0.012] | [0.045] | [0.014] |
| College | -0.040 | 0.056*** | -0.093 | 0.064*** |
| | [0.076] | [0.016] | [0.098] | [0.022] |
| Post-College | -0.152 | 0.055** | -0.181 | 0.028 |
| | [0.109] | [0.024] | [0.112] | [0.031] |
| Cognitive Score | 0.122 | 0.143*** | -0.021 | 0.087* |
| | [0.096] | [0.032] | [0.198] | [0.045] |
| Routine Score | 0.016 | -0.118*** | 0.013 | -0.129*** |
| | [0.077] | [0.024] | [0.219] | [0.041] |
| Manual Score | 0.145 | -0.048* | -0.295 | -0.103** |
| | [0.154] | [0.027] | [0.261] | [0.045] |
| Task Complexity | 1.384* | 1.069*** | 0.374 | 0.642*** |
| | [0.738] | [0.271] | [0.552] | [0.242] |
| Task Offshorability | 0.364*** | -0.032 | 0.245*** | -0.060*** |
| | [0.083] | [0.032] | [0.072] | [0.017] |
| Pr(Automation) | 1.110*** | -0.093 | 0.133 | -0.089 |
| | [0.321] | [0.117] | [0.333] | [0.097] |
| Constant | -1.593*** | 6.034*** | -0.564 | 6.040*** |
| | [0.522] | [0.193] | [0.465] | [0.160] |
| Controls | Yes | Yes | Yes | Yes |
| N | 196,644 | 196,644 | 4,097,939 | 4,097,939 |

**Note:** This table displays a linear regression for *Knowledge Specification* and *Knowledge Level* against other measures of worker and task characteristics across occupations. We use two samples CPS (columns (1) and (2)) and LEED (columns (3) and (4)). Controls include the worker's age and log(annual earnings). Scores on routine, cognitive, and manual are obtained from Acemoglu and Autor (2011). Measures on task complexity are from Caines et al. (2017). Probability of automation is from Frey and Osborne (2017). Results for the CPS are weighted by ASECWT.

**Table 3:** Detailed Occupation Summary Statistics. CPS 1990-2019

| | | | | | | Average Percentile | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | Knowledge | | Share | | | Score | | | Probability | | Task |
| Occupation Name | Emp | Spec | Level | Male | College | Earn | Rout | Cogn | Man | Autom | Offshr | Complex |
| Accountants and Auditors | 1.37 | 2.92 | 6.41 | 0.40 | 0.70 | 64 | 71 | 56 | 19 | 87 | 100 | 74 |
| Bookkeeping, Accounting, and Auditing Clerks | 1.28 | 2.09 | 6.23 | 0.07 | 0.16 | 37 | 92 | 75 | 34 | 97 | 96 | 45 |
| Customer Service Representatives | 0.71 | 1.77 | 6.23 | 0.30 | 0.26 | 40 | 90 | 72 | 24 | 52 | 92 | 51 |
| Psychologists | 0.18 | 1.59 | 6.91 | 0.34 | 0.94 | 64 | 4 | 87 | 100 | 4 | 46 | 100 |
| Computer Systems Analysts | 0.99 | 1.41 | 6.28 | 0.70 | 0.64 | 75 | | | | 4 | | 90 |
| Stock Clerks and Order Fillers | 0.60 | 1.41 | 4.67 | 0.55 | 0.10 | 34 | 55 | 17 | 41 | 56 | 68 | 8 |
| Human Resources Workers | 0.55 | 1.26 | 6.77 | 0.30 | 0.53 | 62 | 15 | 63 | 48 | 96 | 84 | 78 |
| Receptionists and Information Clerks | 0.73 | 1.11 | 6.20 | 0.05 | 0.13 | 29 | 48 | 25 | 37 | 92 | 64 | 24 |
| Automotive Service Technicians and Mechanics | 0.64 | 0.90 | 5.75 | 0.99 | 0.04 | 50 | 72 | 36 | 92 | 53 | 4 | 48 |
| First-Line Supervisors of Office Workers | 0.92 | 0.86 | 6.61 | 0.29 | 0.30 | 54 | 48 | 97 | 57 | 8 | 43 | 55 |
| Secretaries and Administrative Assistants | 2.65 | 0.85 | 6.51 | 0.02 | 0.15 | 38 | 66 | 41 | 14 | 83 | 63 | 33 |
| Maids and Housekeeping Cleaners | 0.86 | 0.82 | 5.58 | 0.10 | 0.05 | 18 | 61 | 4 | 42 | 60 | 86 | 4 |
| Inspectors, Testers, Sorters, Samplers, and Weighers | 0.62 | 0.78 | 5.51 | 0.57 | 0.11 | 47 | 83 | 24 | 72 | 97 | 56 | |
| Miscellaneous Assemblers and Fabricators | 0.78 | 0.75 | 4.93 | 0.57 | 0.05 | 39 | 100 | 60 | 93 | 96 | 41 | |
| Financial Managers | 0.83 | 0.69 | 6.86 | 0.45 | 0.60 | 73 | 51 | 67 | 43 | 25 | 75 | 97 |
| Hairdressers, Hairstylists, and Cosmetologists | 0.57 | 0.65 | 6.09 | 0.08 | 0.05 | 26 | 53 | 36 | 58 | 29 | 12 | 12 |
| First-Line Supervisors of Retail Sales Workers | 3.64 | 0.64 | 6.66 | 0.62 | 0.28 | 55 | 30 | 52 | 30 | 40 | 23 | 59 |
| Lawyers | 0.86 | 0.48 | 6.88 | 0.69 | 0.98 | 82 | 29 | 94 | 68 | 16 | 86 | 96 |
| Sales Representatives, Wholesale and Manufacturing | 1.13 | 0.33 | 6.42 | 0.75 | 0.42 | 66 | 8 | 10 | 51 | 63 | 87 | |
| Office and Administrative Support Workers | 0.63 | 0.22 | 6.35 | 0.13 | 0.18 | 36 | 71 | 45 | 10 | 92 | 78 | 17 |
| Medical Assistants | 0.51 | 0.21 | 6.90 | 0.26 | 0.58 | 68 | 22 | 100 | 64 | 4 | 16 | 92 |
| Designers | 0.57 | 0.20 | 6.61 | 0.44 | 0.50 | 54 | 25 | 51 | 13 | 24 | 80 | 53 |
| Cashiers | 1.18 | 0.19 | 6.07 | 0.19 | 0.09 | 19 | 94 | 77 | 66 | 95 | 68 | 12 |
| Other Teachers and Instructors | 0.54 | 0.15 | 6.78 | 0.34 | 0.56 | 45 | 13 | 74 | 77 | 30 | 68 | 66 |
| First-Line Supervisors of Production Workers | 0.89 | 0.09 | 6.33 | 0.82 | 0.13 | 61 | 75 | 93 | 56 | 12 | 28 | 52 |
| Real Estate Brokers and Sales Agents | 0.58 | 0.09 | 6.83 | 0.44 | 0.45 | 55 | 4 | 47 | 30 | 78 | 60 | 56 |
| Carpenters | 1.02 | 0.01 | 6.27 | 0.98 | 0.07 | 48 | 63 | 12 | 81 | 62 | 30 | 29 |
| Social Workers | 0.68 | -0.01 | 6.99 | 0.23 | 0.72 | 52 | 14 | 61 | 87 | 12 | 52 | 73 |
| Electricians | 0.63 | -0.02 | 6.26 | 0.98 | 0.07 | 62 | 52 | 20 | 88 | 31 | 4 | 49 |
| Driver/Sales Workers and Truck Drivers | 2.33 | -0.11 | 6.03 | 0.95 | 0.05 | 49 | 83 | 20 | 96 | 68 | 32 | 14 |
| Laborers and Freight, Stock, and Material Movers | 1.28 | -0.12 | 5.14 | 0.77 | 0.05 | 33 | 79 | 38 | 68 | 74 | 13 | 12 |
| Waiters and Waitresses | 0.70 | -0.14 | 6.06 | 0.22 | 0.13 | 20 | 38 | 17 | 47 | 87 | 35 | 4 |
| Registered Nurses | 2.13 | -0.15 | 6.81 | 0.08 | 0.55 | 62 | | | | | | 93 |
| Chief Executives | 0.74 | -0.26 | 7.02 | 0.73 | 0.70 | 84 | 45 | 96 | 60 | 12 | 86 | 100 |
| Medical and Health Services Managers | 0.98 | -0.27 | 6.62 | 0.10 | 0.08 | 27 | 68 | 44 | 54 | 43 | 8 | 36 |
| Advertising and Promotions Managers | 0.75 | -0.35 | 6.95 | 0.59 | 0.65 | 76 | 15 | 70 | 35 | 19 | 72 | 76 |
| Office Clerks, General | 0.62 | -0.41 | 6.69 | 0.22 | 0.27 | 45 | 34 | 12 | 22 | 90 | 46 | 32 |
| Building Cleaning Workers | 1.43 | -0.51 | 5.58 | 0.65 | 0.05 | 29 | 58 | 4 | 38 | 57 | 56 | 4 |
| Physicians and Surgeons | 0.61 | -0.54 | 7.08 | 0.67 | 0.97 | 82 | 26 | 71 | 76 | 4 | 17 | 100 |
| Retail Salespersons | 1.31 | -0.54 | 6.41 | 0.55 | 0.25 | 39 | 27 | 32 | 37 | 81 | 17 | 40 |
| Teacher Assistants | 0.80 | -0.54 | 6.41 | 0.05 | 0.20 | 20 | 8 | 28 | 50 | 52 | 75 | 25 |
| Postsecondary Teachers, General | 0.84 | -0.61 | 7.07 | 0.53 | 0.93 | 59 | 6 | 94 | 52 | 15 | 78 | 89 |
| Production Workers, All Other | 0.88 | -0.63 | 6.32 | 0.70 | 0.05 | 43 | 34 | 12 | 22 | | 46 | |
| Preschool and Kindergarten Teachers | 0.49 | -0.64 | 6.66 | 0.02 | 0.56 | 33 | 10 | 60 | 60 | 19 | 39 | 46 |
| Childcare Workers | 0.74 | -0.71 | 6.18 | 0.03 | 0.14 | 16 | 4 | 28 | 68 | 26 | 60 | 38 |
| Detectives and Criminal Investigators | 0.56 | -0.77 | 7.04 | 0.87 | 0.35 | 66 | 76 | 69 | 84 | 46 | 20 | 66 |
| Education Administrators | 0.71 | -0.89 | 7.08 | 0.36 | 0.79 | 69 | 4 | 100 | 92 | 5 | 46 | 79 |
| Elementary and Middle School Teachers | 2.19 | -0.94 | 6.90 | 0.17 | 0.91 | 55 | 19 | 89 | 84 | 21 | 43 | 63 |
| Managers, All Other | 5.08 | -1.13 | 6.95 | 0.65 | 0.44 | 72 | 39 | 79 | 4 | 33 | 90 | 80 |
| Food Service Managers | 0.83 | -1.15 | 6.75 | 0.54 | 0.26 | 49 | 60 | 88 | 53 | 26 | 16 | 79 |
| First-Line Supervisors of Construction Workers | 0.66 | -1.22 | 6.61 | 0.98 | 0.11 | 64 | 54 | 68 | 42 | 33 | 12 | 58 |
| Nursing, Psychiatric, and Home Health Aides | 0.67 | -1.31 | 6.36 | 0.10 | 0.09 | 24 | 49 | 24 | 27 | 48 | 24 | 33 |
| Chefs and Head Cooks | 1.17 | -1.38 | 6.75 | 0.50 | 0.06 | 24 | 91 | 86 | 80 | 28 | 59 | 20 |
| Farmers, Ranchers, and Other Agricultural Managers | 0.95 | -1.53 | 6.88 | 0.79 | 0.19 | 47 | | | | 18 | | |
| Secondary School Teachers | 1.14 | -1.70 | 7.00 | 0.43 | 0.92 | 61 | 11 | 72 | 100 | 7 | 35 | 69 |
| Construction Laborers | 0.64 | -1.74 | 6.52 | 0.96 | 0.07 | 39 | 79 | 16 | 72 | 77 | 40 | 20 |

*Note:* Knowledge specialization in column (3) is normalized to have zero mean and standard deviation of one within the CPS sample. Percentiles are calculated for each sample year. Earnings are calculated as the product of weekly earnings times the usual weeks worked per year. The data on routine, manual, and cognitive scores and offshore probability are taken from Acemoglu and Autor (2011). Task complexity and offshore probability are taken from Caines et al. (2017). Automation probability is taken from Frey and Osborne (2017).

**Table 4:** Relationship between Knowledge Specialization and Earnings

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| B: CPS. Dependent Variable: Log of Weekly Earnings × Weeks Worked Last Year | | | | | | |
| $\beta$sp | 0.097*** | 0.061*** | 0.043*** | 0.026*** | 0.024*** | 0.018*** |
| | [0.020] | [0.013] | [0.011] | [0.006] | [0.005] | [0.005] |
| Controls | $knw_i$ | All | All | All | All | All |
| Occ & Task Measures | No | No | All | No | No | All |
| Fixed Effects | All | All | All | All | All | All |
| Individual FE | No | No | No | Yes | Yes | Yes |
| $N$ | 226,344 | 226,344 | 196,643 | 204,534 | 204,534 | 167,854 |
| C: NLSY. Dependent Variable: Log of Total Annual Earnings | | | | | | |
| $\beta$sp | 0.090*** | 0.062*** | 0.037*** | 0.029*** | 0.025*** | 0.016*** |
| | [0.018] | [0.011] | [0.010] | [0.009] | [0.006] | [0.005] |
| Controls | $knw_i$ | All | All | All | All | All |
| Occ & Task Measures | No | No | All | No | No | All |
| Fixed Effects | All | All | All | All | All | All |
| Individual FE | No | No | No | Yes | Yes | Yes |
| $N$ | 186,235 | 181,186 | 159,232 | 185,146 | 185,146 | 157905 |
| D: LEED. Dependent Variable: Log of Total Annual Earnings | | | | | | |
| $\beta$sp | 0.071*** | 0.013* | 0.009 | 0.022*** | 0.022*** | 0.000 |
| | [0.026] | [0.008] | [0.009] | [0.006] | [0.006] | [0.007] |
| Controls | $knw_i$ | All | All | All | All | All |
| Occ & Task Measures | No | No | All | No | No | All |
| Fixed Effects | All | All | All | All | All | All |
| Individual FE | No | No | No | Yes | Yes | Yes |
| $N$ | 5,538,842 | 5,529,836 | 4,090,568 | 5,458,451 | 5,449,910 | 4,005,946 |

*Note:* This table displays the estimated coefficients of knowledge specialization from different specifications where the outcome is the log of annual earnings. Fixed Effects *All*: All specifications in the CPS add state by year, education by year, and gender by year fixed effects. All specifications in the NLSY include education by year and gender by year fixed effects. Controls $knw_i$: Only adds as an additional control the knowledge level of the occupation. Controls *All*: Adds as additional controls industry and occupation group fixed effects, experience and tenure (NLSY and LEED), marital status, immigration status, the field of degree, English knowledge, and occupation prestige score (CPS). Specifications in columns (1), (2), and (3) do not include individual fixed effects, while those in columns (4), (5), and (6) include them. Standard errors are clustered at the SOC occupation level in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 5:** Summary Statistics Displacement Matches

| NLSY | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Number of job-year-worker matches | | | | | | | |
| | | | Percentiles | | | | | | |
| Matched Covs | Displacements | Mean | 1st | 5th | 25th | Median | 75th | 95th | 99th |
| 7 | 20 | 10.4 | 4 | 4 | 8 | 10 | 13.5 | 17 | 19 |
| 8 | 148 | 5.9 | 1 | 1 | 2 | 4 | 7.5 | 16 | 19 |
| 9 | 416 | 3.8 | 1 | 1 | 1.5 | 3 | 5 | 10 | 14 |
| 10 | 881 | 2.8 | 1 | 1 | 1 | 2 | 4 | 8 | 12 |
| 11 | 973 | 2.2 | 1 | 1 | 1 | 2 | 3 | 6 | 9 |
| 12 | 426 | 1.5 | 1 | 1 | 1 | 1 | 2 | 4 | 6 |
| 13 | 74 | 1.2 | 1 | 1 | 1 | 1 | 1 | 2 | 3 |
| 14 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Total | 2,940 | 2.7 | 1 | 1 | 1 | 2 | 3 | 8 | 15 |

| LEED | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Number of job-year-worker matches | | | | | | | |
| | | | Percentiles | | | | | | |
| Matched Covs | Displacements | Mean | 1st | 5th | 25th | Median | 75th | 95th | 99th |
| 7 | 66 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 7 |
| 8 | 409 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 4 |
| 9 | 1,007 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 4 |
| 10 | 1,831 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |
| 11 | 2,687 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 6 |
| 12 | 3,307 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |
| 13 | 3,188 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |
| 14 | 2,630 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 6 |
| 15 | 1,946 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |
| 16 | 1,358 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 5 |
| 17 | 943 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |
| 18 | 711 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 5 |
| 19 | 550 | 2 | 1 | 1 | 1 | 1 | 1 | 4 | 10 |
| 20 | 294 | 2 | 1 | 1 | 1 | 1 | 2 | 5 | 10 |
| 21 | 134 | 1 | 1 | 1 | 1 | 1 | 2 | 3 | 6 |
| 22 | 18 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 2 |
| Total | 21,079 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 5 |

*Note:* This table displays summary statistics from the matching process in the NLSY and LEED. An example to interpret the numbers of the table: 973 displacements match in a maximum of 11 covariates with their best control matches. The median displacement within this group has 2 best matches (unique individual-year observations) in the control sample, while the average number of matches within this group is 2.2.

**Table 6:** Displacement Effects

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | Earnings | Hours | Wages | Earnings | Hours | Wages |
| $\delta_{-5}$ | -0.009 | -0.023* | 0.014 | -0.019*** | -0.048*** | 0.030*** |
| | [0.015] | [0.012] | [0.009] | [0.007] | [0.007] | [0.007] |
| $\delta_{-4}$ | -0.014 | -0.034*** | 0.020** | -0.033*** | -0.071*** | 0.038*** |
| | [0.014] | [0.011] | [0.008] | [0.005] | [0.005] | [0.005] |
| $\delta_{-3}$ | -0.022* | -0.025** | 0.003 | -0.036*** | -0.061*** | 0.024*** |
| | [0.012] | [0.010] | [0.006] | [0.004] | [0.005] | [0.004] |
| $\delta_{-2}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta_{-1}$ | -0.026*** | -0.004 | -0.022*** | -0.008*** | 0.029*** | -0.037*** |
| | [0.009] | [0.006] | [0.006] | [0.003] | [0.003] | [0.003] |
| $\delta_0$ | -0.251*** | -0.189*** | -0.063*** | -0.747*** | -0.632*** | -0.107*** |
| | [0.018] | [0.014] | [0.010] | [0.007] | [0.007] | [0.008] |
| $\delta_1$ | -0.400*** | -0.282*** | -0.118*** | -0.810*** | -0.620*** | -0.174*** |
| | [0.022] | [0.017] | [0.011] | [0.012] | [0.009] | [0.009] |
| $\delta_2$ | -0.255*** | -0.136*** | -0.119*** | -0.455*** | -0.381*** | -0.071*** |
| | [0.020] | [0.015] | [0.012] | [0.009] | [0.008] | [0.007] |
| $\delta_3$ | -0.220*** | -0.117*** | -0.103*** | -0.314*** | -0.256*** | -0.056*** |
| | [0.020] | [0.015] | [0.012] | [0.009] | [0.007] | [0.007] |
| $\delta_4$ | -0.168*** | -0.083*** | -0.085*** | -0.273*** | -0.228*** | -0.045*** |
| | [0.019] | [0.014] | [0.012] | [0.009] | [0.007] | [0.007] |
| $\delta_5$ | -0.163*** | -0.086*** | -0.077*** | -0.254*** | -0.201*** | -0.052*** |
| | [0.020] | [0.014] | [0.012] | [0.009] | [0.007] | [0.007] |
| $\delta_6$ | -0.131*** | -0.065*** | -0.066*** | | | |
| | [0.020] | [0.015] | [0.013] | | | |
| $\delta_7$ | -0.120*** | -0.052*** | -0.068*** | | | |
| | [0.021] | [0.015] | [0.013] | | | |
| $N$ | 90,299 | 90,299 | 90,299 | 421,224 | 421,224 | 421,224 |
| Displacements | 2,879 | 2,879 | 2,879 | 21,015 | 21,015 | 21,015 |

*Note:* This table presents the estimated coefficients from equation (2)), using the matching identification strategy and the control group described in Section 4.1. Columns (1), (2), and (3) show the results for the NLSY, while columns (4), (5), and (6) present the estimated coefficients for the LEED. We set the baseline period two years prior to the displacement event. Each coefficient captures the difference in earnings/hours worked/wages (in log points) in that period between the treatment and control groups relative to two years before the dismissal. In columns (1) and (4) the outcome variable is the log of total annual earnings. In columns (2) and (5) the outcome variable is the log of total annual hours worked. In columns (3) and (6) the outcome variable is the log of the average annual hourly wages. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 7:** Displacement Effects of Knowledge Specialization on Earnings

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Pre}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta^{sp}_{Post}$ | -0.036*** | -0.042*** | -0.037** | -0.032* | -0.025*** | -0.028*** | -0.016*** | -0.019*** |
| | [0.012] | [0.013] | [0.018] | [0.019] | [0.005] | [0.005] | [0.006] | [0.006] |
| $\delta^{knw}_{Post}$ | | -0.042* | -0.043 | | | -0.025*** | 0.002 | |
| | | [0.023] | [0.029] | | | [0.009] | [0.011] | |
| $\delta^{female}_{Post}$ | | | -0.035 | | | | 0.026** | |
| | | | [0.030] | | | | [0.012] | |
| $\delta^{exp}_{Post}$ | | | 0.054 | | | | 0.007 | |
| | | | [0.051] | | | | [0.025] | |
| $\delta^{age}_{Post}$ | | | -0.005* | | | | 0.001** | |
| | | | [0.003] | | | | [0.001] | |
| $\delta^{college}_{Post}$ | | | 0.082** | | | | -0.001 | |
| | | | [0.038] | | | | [0.015] | |
| $\delta^{UR}_{Post}$ | | | -0.014** | | | | 0.016** | |
| | | | [0.007] | | | | [0.007] | |
| $\delta^{tenure}_{Post}$ | | | -0.052** | | | | -0.056*** | |
| | | | [0.022] | | | | [0.015] | |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | None | $knw_{i,0}$ | All | None |
| $N$ | 84,635 | 84,635 | 82,897 | 82,897 | 421,224 | 421,224 | 420,245 | 420,245 |
| Displacements | 2,690 | 2,690 | 2,624 | 2,624 | 21,015 | 21,015 | 21,001 | 21,001 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. In columns (1) and (5) we display the estimated $\delta^{sp}_{Post}$ from equation (5) without including any interaction between the pre-displacement covariates (other than specialization) and the displacement dummies. In columns (2) and (6) we display the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between the pre-displacement knowledge level and the displacement dummies. In columns (3) and (7) we present the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between all the pre-displacement covariates of interest and the displacement dummies. (The $\delta^{ind/occ=w}_{Post}$ for each industry and occupation group are included in the estimation but not shown in the table.) Finally, in columns (4) and (8) we present the estimated $\delta^{sp}_{Post}$ from equation (6). Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 8:** Summary Statistics Industry/Occupation Changes

| | | | | |
|---|---|---|---|---|
| **Displacements** | | | | |
| | NLSY | | LEED | |
| | Total | Post D Ind & Occ Info | Total | Post D Ind & Occ Info |
| Total | 2940 | 2061 | 21,079 | 16,790 |
| Pre D Ind & Occ Info | 2687 | 2034 | 21,079 | 16,790 |
| **Industry, Occupation & Main Skill Changes (Shares)** | | | | |
| | Same Industry | Same Occupation | Same Ind & Occ | Same Main Skill |
| NLSY | 0.46 | 0.52 | 0.34 | 0.66 |
| LEED | 0.30 | 0.48 | 0.20 | 0.68 |

*Note:* This table displays summary statistics from the availability of industry and occupation data pre- and post-displacement, and the share of workers whose post-displacement job is in the same industry, occupation, industry and occupation, and main skill as their last pre-displacement job.

**Table 9:** Role of Knowledge Specialization on
Industry/Occupation/Skill/Distance Changes Post Displacement

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | A: Reemployment Same Industry | | | |
| $\beta_{sp}$ | -0.026** | -0.032*** | -0.012 | -0.033*** | -0.035*** | -0.021*** |
| | [0.011] | [0.012] | [0.015] | [0.003] | [0.003] | [0.004] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,022 | 2,022 | 2,013 | 17,687 | 17,687 | 17,019 |
| | | | B: Reemployment Same Occupation | | | |
| $\beta_{sp}$ | 0.021* | 0.020* | 0.020 | -0.014*** | -0.015*** | -0.011** |
| | [0.011] | [0.011] | [0.015] | [0.004] | [0.004] | [0.005] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,080 | 2,080 | 2,027 | 16,780 | 16,780 | 16,137 |
| | | | C: Reemployment Same Industry & Occupation | | | |
| $\beta_{sp}$ | -0.029*** | -0.039*** | -0.018 | -0.038*** | -0.041*** | -0.025*** |
| | [0.010] | [0.011] | [0.014] | [0.003] | [0.003] | [0.004] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,060 | 2,060 | 2,025 | 17,523 | 17,523 | 16,856 |
| | | | D: Reemployment Same Main Skill | | | |
| $\beta_{sp}$ | 0.005 | 0.002 | 0.006 | 0.002 | -0.000 | -0.001 |
| | [0.010] | [0.011] | [0.015] | [0.004] | [0.004] | [0.004] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,080 | 2,080 | 2,027 | 16,210 | 16,210 | 15,585 |
| | | | E: Distance of the Move (Task's Similarity) | | | |
| $\beta_{sp}$ | 0.005*** | 0.002 | 0.003 | 0.001*** | 0.000 | 0.001 |
| | [0.002] | [0.002] | [0.002] | [0.001] | [0.001] | [0.001] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,000 | 2,000 | 1,948 | 16,341 | 16,341 | 15,717 |

*Note:* This table displays the estimated coefficients of the association between pre-displacement knowledge specialization and the probability that the worker will remain in the same industry (panel (a)), occupation (panel (b)), industry and occupation (panel (c)), and main skill group (panel (d)) after displacement. Panel (e) displays the relationship between pre-displacement knowledge specialization and the distance (in the task sense) between the pre- and post-displacement occupations. In panels (a) to (d), the outcome variable is a dummy taking the value of 1 if the worker remains in the same industry, occupation, both or main skill (respectively) and zero otherwise. In panel (e) the outcome variable is the distance between the pre- and post-displacement occupations. Controls *None*: No additional controls added to the regression. Controls $knw_i$: Only adds as an additional control the knowledge level of the pre-displacement occupation. Controls *All*: Adds as additional controls the worker's gender, the pre-displacement knowledge level, experience, age, unemployment rate, tenure, as well as industry and occupation group fixed effects based on the pre-displacement occupation. Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 10:** Displacement Effects of Knowledge Specialization on Earnings.
Conditional on Changing Industry, Occupation, Skill and Distance Between Pre- and Post-Displacement Occupations

| | NLSY | | | | | | LEED | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\delta^{sp}_{Post}$ | -0.047*** | -0.043** | -0.047*** | -0.049*** | -0.049*** | -0.045** | -0.014** | -0.016** | -0.013*** | -0.014*** | -0.016*** | -0.014*** |
| | [0.018] | [0.019] | [0.018] | [0.018] | [0.018] | [0.019] | [0.007] | [0.006] | [0.007] | [0.007] | [0.007] | [0.005] |
| $\delta^{Distance}_{Post}$ | | -0.615*** | | | | -0.436 | | -0.658*** | | | | -0.615*** |
| | | [0.196] | | | | [0.275] | | [0.085] | | | | [0.113] |
| $\delta^{Same\_Ind}_{Post}$ | | | 0.066*** | | | 0.032 | | | 0.087*** | | | 0.065 |
| | | | [0.026] | | | [0.030] | | | [0.012] | | | [0.013] |
| $\delta^{Same\_Occ}_{Post}$ | | | | 0.073*** | | 0.013 | | | | 0.049*** | | -0.012 |
| | | | | [0.026] | | [0.036] | | | | [0.012] | | [0.015] |
| $\delta^{Same\_Skill}_{Post}$ | | | | | 0.058** | 0.012 | | | | | 0.041*** | -0.013 |
| | | | | | [0.028] | [0.032] | | | | | [0.013] | [0.015] |
| Disp. Controls | All | All | All | All | All | All | All | All | All | All | All | All |
| $N$ | 61,657 | 58,975 | 60,374 | 61,501 | 61,501 | 57,701 | 362,907 | 339,852 | 362,872 | 344,357 | 332,901 | 332,746 |
| Displacements | 1,998 | 1,918 | 1,982 | 1,996 | 1,996 | 1,903 | 17,645 | 16,514 | 17,643 | 16,736 | 16,168 | 16,160 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in the table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year for whom we observe industry and occupation pre- and post-displacement. Columns (1) to (6) show the results for the NLSY, while columns (7) to (12) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (7) replicate the results in columns (3) and (7) of Table A.1. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5), after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 11:** Relationship between Knowledge Specialization Pre-Displacement & Other Mechanisms

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| A: Pre-Displacement Pr of Automation | | | | | | |
| $\beta_{sp}$ | 0.102*** | 0.058** | 0.007 | 0.007 | -0.018 | 0.011 |
| | [0.027] | [0.028] | [0.026] | [0.031] | [0.020] | [0.014] |
| B: Pre-Displacement Pr of Occupation Offshorability | | | | | | |
| $\beta_{sp}$ | 0.269** | 0.364*** | 0.125 | 0.177*** | 0.201*** | 0.097** |
| | [0.119] | [0.094] | [0.080] | [0.059] | [0.077] | [0.042] |
| C: Pre-Displacement Pr of Task Offshorability | | | | | | |
| $\beta_{sp}$ | 0.459*** | 0.476*** | 0.187** | 0.138 | 0.114 | 0.031 |
| | [0.078] | [0.079] | [0.076] | [0.176] | [0.164] | [0.092] |
| D: Pre-Displacement Task Complexity | | | | | | |
| $\beta_{sp}$ | 0.004 | 0.035*** | 0.026*** | 0.011 | 0.026*** | 0.005 |
| | [0.017] | [0.012] | [0.009] | [0.014] | [0.009] | [0.006] |
| E: Pre-Displacement Occupation Routine Index | | | | | | |
| $\beta_{sp}$ | 0.143** | -0.005 | -0.013 | -0.084 | -0.158** | -0.043 |
| | [0.066] | [0.071] | [0.079] | [0.115] | [0.068] | [0.042] |
| F: Pre-Displacement Occupation Non-Routine Index | | | | | | |
| $\beta_{sp}$ | -0.212*** | -0.173** | 0.025 | -0.001 | -0.004 | 0.094*** |
| | [0.063] | [0.068] | [0.065] | [0.041] | [0.042] | [0.024] |
| G: Pre-Displacement Occupation Manual Index | | | | | | |
| $\beta_{sp}$ | -0.044 | -0.180** | 0.029 | -0.182*** | -0.222*** | -0.005 |
| | [0.122] | [0.087] | [0.085] | [0.037] | [0.038] | [0.023] |
| H: Pre-Displacement Occupation Cognitive Index | | | | | | |
| $\beta_{sp}$ | 0.070 | 0.198*** | 0.179*** | 0.080 | 0.123 | 0.042 |
| | [0.082] | [0.067] | [0.063] | [0.067] | [0.096] | [0.033] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |

*Note:* This table displays the estimated coefficients of the association between pre-displacement knowledge specialization and the outcome variable (fixed at its pre-displacement value) shown in the panel's name. Controls *None*: No additional controls added to the regression. Controls $knw_i$: Only adds as an additional control the knowledge level of the pre-displacement occupation. Controls *All*: Adds as additional controls the worker's gender, the pre-displacement knowledge level, experience, age, unemployment rate, tenure, as well as industry and occupation group fixed effects based on the pre-displacement occupation. Standard errors clustered at the SOC occupation level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 12:** Displacement Effects of Knowledge Specialization on Earnings. Mechanisms

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Post}$ | -0.037** | -0.038** | -0.035* | -0.039** | -0.016** | -0.013** | -0.010 | -0.010 |
| | [0.018] | [0.019] | [0.021] | [0.020] | [0.006] | [0.006] | [0.007] | [0.007] |
| $\delta^{Pr(Autom)}_{Post}$ | | 0.042 | | 0.005 | | 0.033 | | 0.018 |
| | | [0.055] | | [0.071] | | [0.028] | | [0.034] |
| $\delta^{Pr(Task-Offs)}_{Post}$ | | 0.014 | | 0.023 | | -0.005 | | -0.003 |
| | | [0.017] | | [0.020] | | [0.008] | | [0.010] |
| $\delta^{Task-Complex}_{Post}$ | | | 0.117 | 0.212 | | | -0.064 | -0.074 |
| | | | [0.210] | [0.223] | | | [0.074] | [0.080] |
| $\delta^{Routine}_{Post}$ | | | 0.027 | 0.025 | | | 0.013 | 0.008 |
| | | | [0.025] | [0.027] | | | [0.012] | [0.013] |
| $\delta^{Non-Routine}_{Post}$ | | | -0.037 | -0.032 | | | 0.002 | -0.003 |
| | | | [0.036] | [0.037] | | | [0.014] | [0.015] |
| $\delta^{Manual}_{Post}$ | | | 0.014 | 0.018 | | | -0.009 | -0.015 |
| | | | [0.026] | [0.026] | | | [0.020] | [0.020] |
| $\delta^{Cognitive}_{Post}$ | | | -0.037 | -0.040 | | | 0.012 | 0.014 |
| | | | [0.028] | [0.031] | | | [0.017] | [0.017] |
| Disp. Controls | All | All | All | All | All | All | All | All |
| $N$ | 82,897 | 74,803 | 70,627 | 70,443 | 420,245 | 420,543 | 395,472 | 394,872 |
| Displacements | 2,624 | 2,389 | 2,249 | 2,241 | 20,885 | 20,786 | 20,783 | 20,783 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (5) replicate the results in columns (3) and (7) of Table 7. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5) after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table 13:** Role of Knowledge Specialization in Possible Changes and Avg Diff in Wages of Possible Changes

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| A: Share of Possible Employment | | | | | | |
| $\beta_{sp}$ | -0.040*** | -0.029*** | -0.031*** | -0.011 | -0.004 | -0.008 |
| | [0.006] | [0.005] | [0.006] | [0.020] | [0.014] | [0.011] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,747 | 2,747 | 2,674 | 21,011 | 21,011 | 21,092 |
| B: Above Average Share of Possible Employment | | | | | | |
| $\beta_{sp}$ | -0.194*** | -0.123*** | -0.163*** | -0.060 | -0.020 | -0.031 |
| | [0.035] | [0.033] | [0.037] | [0.098] | [0.070] | [0.045] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,747 | 2,747 | 2,674 | 21,011 | 21,011 | 21,092 |
| C: Avg Diff in Wages in Possible Occs | | | | | | |
| $\beta_{sp}$ | 0.017 | -0.023 | -0.048*** | -0.024 | -0.031 | -0.010 |
| | [0.027] | [0.020] | [0.014] | [0.015] | [0.021] | [0.007] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,724 | 2,724 | 2,653 | 21,011 | 21,011 | 21,092 |
| D: Positive Avg Diff in Wages in Possible Occs | | | | | | |
| $\beta_{sp}$ | -0.034 | -0.079*** | -0.113*** | -0.006 | -0.013 | 0.039 |
| | [0.028] | [0.025] | [0.032] | [0.068] | [0.074] | [0.031] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 2,724 | 2,724 | 2,653 | 21,011 | 21,011 | 21,092 |

*Note:* This table displays the estimated coefficients of the association between pre-displacement knowledge specialization and the pre-displacement occupation's share of employment in possible occupations (panel (a)), whether the pre-displacement occupation's share of employment in possible occupations is above the mean (panel (b)), the difference in average wages between the pre-displacement occupation and its set of possible occupations (panel (c)), and whether the difference in average wages between the pre-displacement occupation and its set of possible occupations is positive or negative (panel (d)). Controls *None*: No additional controls added to the regression. Controls $knw_i$: Only adds as an additional control the knowledge level of the pre-displacement occupation. Controls *All*: Adds as additional controls the worker's gender, the pre-displacement knowledge level, experience, age, unemployment rate, tenure, as well as industry and occupation group fixed effects based on the the pre-displacement occupation. Standard errors clustered at the SOC occupation level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

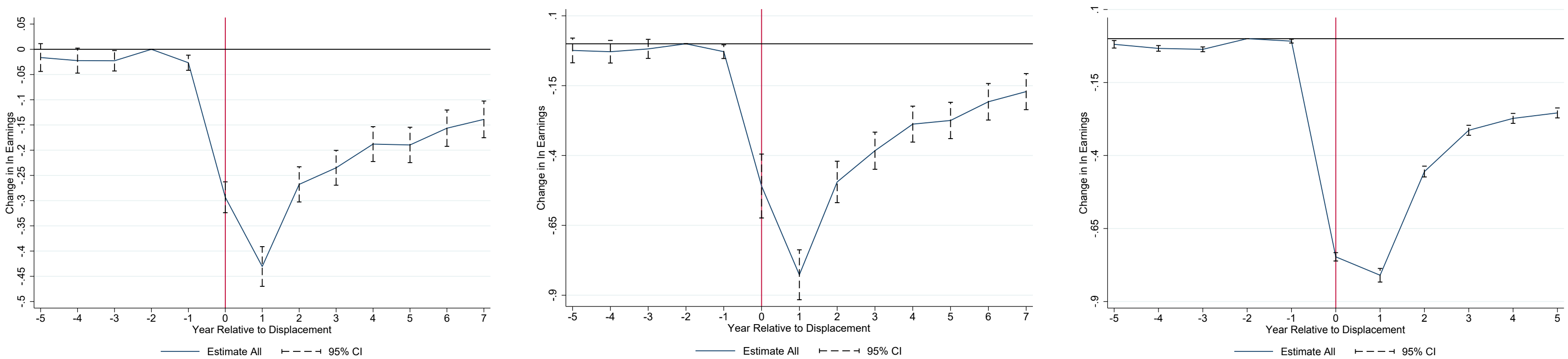
**Table 14:** Displacement Effects of Knowledge Specialization on Earnings. Conditional on Amount and Quality of Outside Offers

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Post}$ | -0.037** | -0.033* | -0.031 | -0.019 | -0.016** | -0.016** | -0.015** | -0.014** |
| | [0.018] | [0.018] | [0.019] | [0.020] | [0.006] | [0.006] | [0.006] | [0.006] |
| $\delta^{Above\_Avg\_Possible}_{Post}$ | | 0.028 | | 0.049* | | 0.014 | | 0.020 |
| | | [0.023] | | [0.025] | | [0.014] | | [0.014] |
| $\delta^{Positive\_Avg\_Diff}_{Post}$ | | | 0.082** | 0.097** | | | -0.040*** | -0.040*** |
| | | | [0.040] | [0.041] | | | [0.014] | [0.014] |
| Disp. Controls | All | All | All | All | All | All | All | All |
| $N$ | 82,897 | 78,727 | 78,112 | 78,112 | 420,245 | 420,167 | 420,167 | 410,889 |
| Displacements | 2,624 | 2,624 | 2,606 | 2,606 | 21,001 | 20,997 | 20,997 | 20,539 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (5) replicate the results in columns (3) and (7) of Table 7. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5) after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

# A Appendix

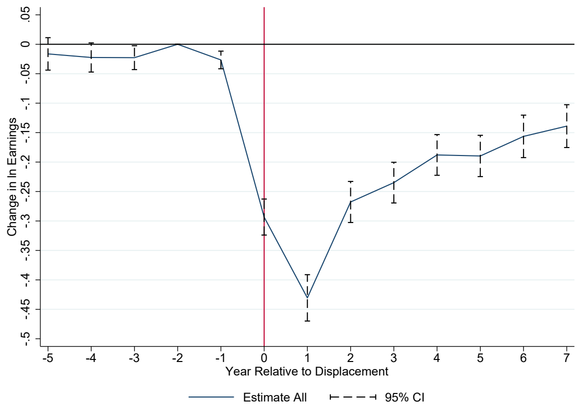
**Figure A.1:** Displacement Effects on Earnings
Alternative Definition of Displacement in NLSY



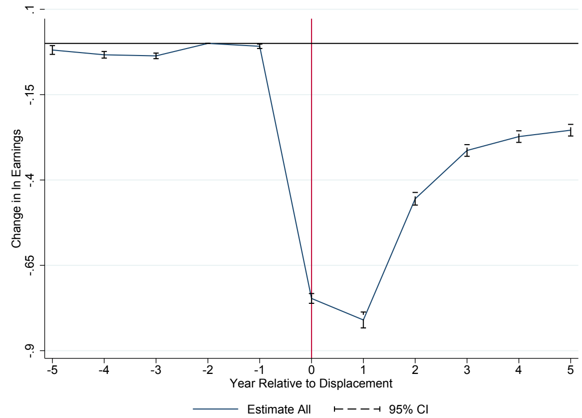

(a) NLSY. Original Definition of Displacement (b) NLSY. LEED's Definition of Displacement (c) LEED

*Note:* This figure presents the estimated earnings losses from displacement, where the outcome of interest is the log of total annual earnings. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the matching empirical strategy outlined in the text and the control group described in Section 4.1. The value on the y-axis captures the difference in earnings in the period relative to the difference between treatment and control during the year prior to the dismissal. Panels (a) and (b) use data from the NLSY and panel (c) uses data from the LEED. Panel (a) uses our original definition of displacement in the NLSY. Panels (b) and (c) use the LEED definition of displacement. Black bars represent the corresponding 95% confidence intervals after clustering the standard errors at the match group level.

**Figure A.2:** Displacement Effects on Earnings




(a) NLSY




(b) LEED

*Note:* This figure presents the estimated earnings losses from displacement, where the outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the identification strategy proposed by Jacobson et al. (1993) and combine it with the control group generated by the matching strategy, described in Section 4.1. The value on the y-axis captures the difference in earnings in the period relative to two years before the dismissal. Black bars represent the corresponding 95% confidence intervals after clustering the standard errors at the match group level.

**Table A.1:** Displacement Effects of Knowledge Specialization on Earnings. Sample Conditional on Industry & Occupation Pre- and Post-Displacement

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Pre}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta^{sp}_{Post}$ | -0.034*** | -0.043*** | -0.047*** | -0.049*** | -0.026*** | -0.030*** | -0.014*** | -0.019*** |
| | [0.013] | [0.013] | [0.018] | [0.019] | [0.006] | [0.006] | [0.006] | [0.007] |
| $\delta^{knw}_{Post}$ | | -0.047** | -0.058** | | | -0.030*** | 0.004 | |
| | | [0.023] | [0.028] | | | [0.009] | [0.012] | |
| $\delta^{female}_{Post}$ | | | -0.008 | | | | 0.030** | |
| | | | [0.029] | | | | [0.013] | |
| $\delta^{exp}_{Post}$ | | | 0.028 | | | | 0.019 | |
| | | | [0.048] | | | | [0.027] | |
| $\delta^{age}_{Post}$ | | | -0.005* | | | | 0.001 | |
| | | | [0.003] | | | | [0.001] | |
| $\delta^{college}_{Post}$ | | | 0.011 | | | | -0.003 | |
| | | | [0.038] | | | | [0.016] | |
| $\delta^{UR}_{Postnur}$ | | | -0.012 | | | | 0.020*** | |
| | | | [0.008] | | | | [0.008] | |
| $\delta^{tenure}_{Post}$ | | | -0.039* | | | | -0.049*** | |
| | | | [0.023] | | | | [0.016] | |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | None | $knw_{i,0}$ | All | None |
| $N$ | 62,999 | 62,999 | 61,657 | 61,657 | 363,845 | 363,845 | 362,907 | 362,907 |
| Displacements | 2,047 | 2,047 | 1,998 | 1,998 | 17,656 | 17,656 | 17,645 | 17,645 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year for whom we observe industry and occupation pre- and post-displacement. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. In columns (1) and (5) we display the estimated $\delta^{sp}_{Post}$ from equation (5) without including any interaction between the pre-displacement covariates (other than specialization) and the displacement dummies. In columns (2) and (6) we display the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between the pre-displacement knowledge level and the displacement dummies. In columns (3) and (7) we present the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between all the pre-displacement covariates of interest and the displacement dummies. (The $\delta^{ind/occ=w}_{Post}$ for each industry and occupation group are included in the estimation but not shown in the table.) Finally, in columns (4) and (8) we present the estimated $\delta^{sp}_{Post}$ from equation (6). Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

# B Detailed Summary Statistics: Knowledge Specialization

In this appendix, we provide detailed summary statistics of the relationship between knowledge specialization and different common covariates.[54] Figure B.1 shows the relationship between knowledge specialization/level and age, annual earnings, education, the occupation's routine, manual and cognitive score, as well as the occupation's offshoring/automation probability and task complexity. Looking first at panel (a) we observe a clear positive relationship between age and knowledge level as well as a negative relationship between age and knowledge specialization. Similarly, we see that the knowledge level is increasing in the annual earnings percentile (panel (b)) and the education level (panel (c)). Interestingly, the relationship between knowledge specialization and earnings/education is not linear but takes an inverted U-shape. For annual earnings, it reaches its maximum between the 30th and 40th percentile, while for education it peaks for workers with more than high school but less than a completed college education. Panels (d) to (h) consider the relationship between our variables of interest and other dimensions related to an occupation's types of tasks.

For panels (d) to (f), we rely on the data from Acemoglu and Autor (2011) and consider the routine, manual and cognitive scores of the occupations in our sample, as well as the likelihood that the occupation will be offshored. Looking first at panel (d) we see a positive relationship between knowledge specialization and the routine score of the occupation, while the opposite is true for the knowledge level. However, we still find significant variation across the distribution of the routine score, with occupations with similar routine scores presenting vastly different levels of knowledge specialization. Panels (e) and (f) show how occupations that have higher levels of knowledge specialization are not necessarily more manual or less cognitive. The level of knowledge specialization shows a slightly decreasing pattern over the distribution of the manual score and a non-linear relationship with the cognitive score. Finally, when looking at the likelihood that the occupation will be offshored (not shown in figure B.1), we do not see any clear association between the occupation's knowledge specialization and the probability that the occupation will be offshored.

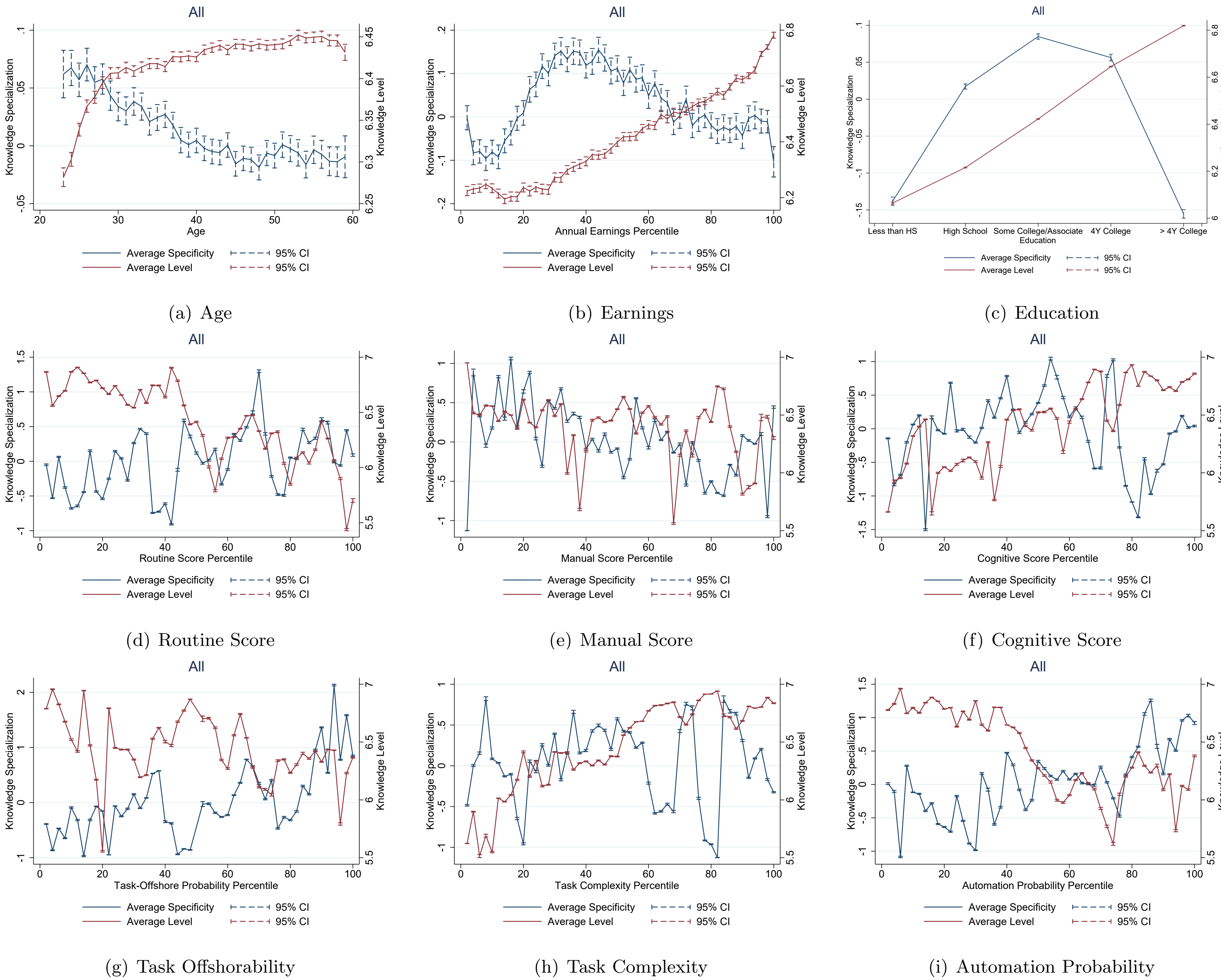
Next, we turn to Caines et al. (2017) and use their data on the complexity of an occupation's tasks and the likelihood that the tasks of an occupation will be offshored. In panel (h) we do not find any clear relationship between the knowledge specialization of the occupation and the complexity of its tasks. However, we observe a clear positive relationship between the knowledge level required in an occupation and the complexity of its tasks, a finding in line with our expectations. When looking at the likelihood that the tasks of an occupation will be offshored in panel (g), we observe no clear relationship between the knowledge specialization of the occupation and the probability that the occupation's tasks will be offshored, although jobs over the 95th percentile of task-offshorability

[54] Section D.1 presents equivalent summary statistics for our alternative definition of knowledge specialization and compares it with our preferred measure. We find that regardless of the measure chosen, the main patterns remain identical.

show large average knowledge specialization values.

Finally, we also use the data from Frey and Osborne (2017) on the probability that the occupation will be automated. Occupations that are more likely to be automated show larger levels of knowledge specialization, especially for large values of the automation probability. However, we still find a large degree of heterogeneity in the bottom 80 percentiles of the distribution, with occupations with similar automation probabilities having vastly different degrees of knowledge specialization.

**Figure B.1:** Summary Statistics I: Knowledge Specialization & Level




(a) Age

(b) Earnings

(c) Education

(d) Routine Score

(e) Manual Score

(f) Cognitive Score

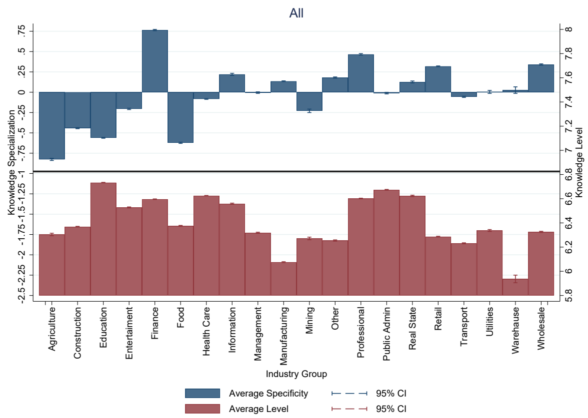
(g) Task Offshorability

(h) Task Complexity

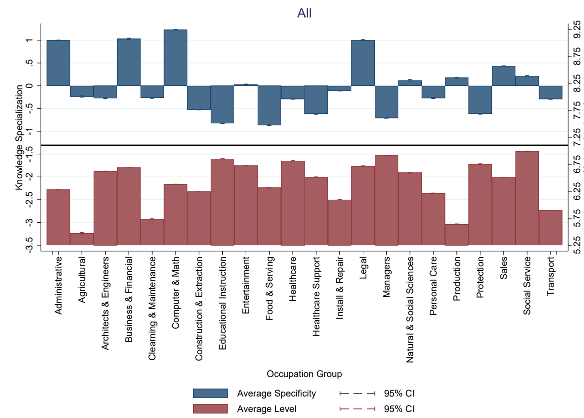
(i) Automation Probability

*Note:* Bars represent the corresponding 95% confidence intervals for the mean at that point.

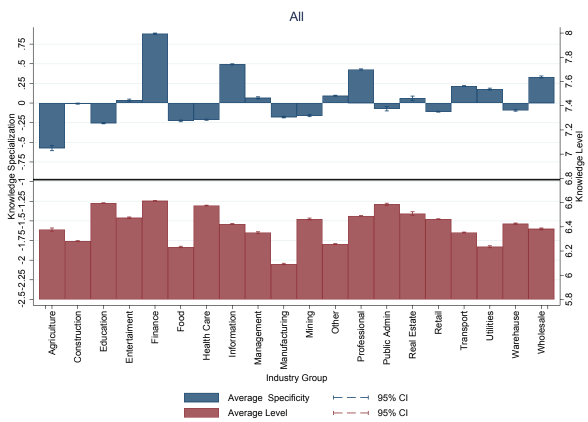
**Figure B.2:** Summary Statistics II: Knowledge Specialization & Level



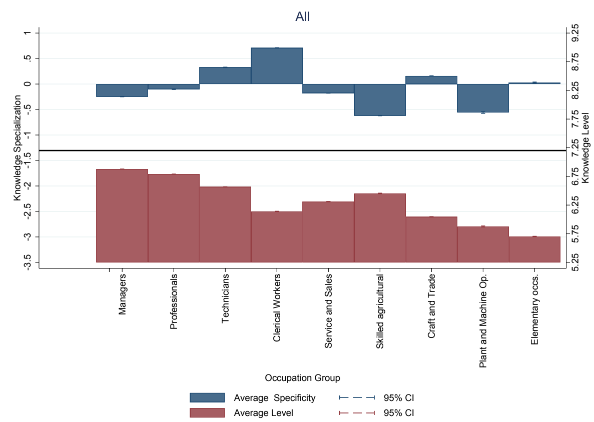

(a) CPS: Industry Group




(b) CPS: Occupation Group




(c) LEED: Industry Group




(d) LEED: Occupation Group

*Note:* Bars represent the corresponding 95% confidence intervals for the mean of the group.

# C Empirical Strategy II

## C.1 Empirical Strategy: JLS (1993)

For additional robustness, we propose a second empirical strategy that follows the ideas in Jacobson et al. (1993). For our treatment group, we focus only on the first displacement and keep observations from 5 years prior to the displacement event to 7 years post-displacement (5 years post-displacement in the LEED data). We define our control group sample using a similar approach to our definition of the treatment group. We select observations for our control group based on: a) no involuntary job loss in that year, b) by the end of the year[55] the individual must have at least 104 weeks of prior tenure in the job; c) the individual is at least 25 years old at year-end;[56] and d) the individual worked at least 25 hours (20 hours in the LEED) per week, on average, in that job for the duration of the job. Finally, we focus on individuals with positive earnings, dropping observations where total annual earnings are equal to zero.

In the NLSY, this results in an estimation sample that, conditional on having non-zero earnings contains 120,000 observations, with 21,500 observations from the treatment group and 98,500 observations in the control group. We have an average of 7.4 observations per worker in the displaced group, and an average of 9.2 observations per worker in the control group. The LEED grants us a much larger sample size. We have over 2.4 million observations with positive earnings, with 165,537 observations in the treatment group, and 2.3 million observations in the control group. On average, each worker in the treatment group is observed 8.7 times, v.s. 12.7 times for workers in the control group.

For our empirical strategy we rely upon Jacobson et al. (1993), and estimate equation (2'):

$$Y_{it} = \sum_{k=-5}^{k=7} \delta_k D_{it}^k + \boldsymbol{\beta X_{it}} + \alpha_i + \gamma_t + \epsilon_{it} \tag{2'}$$

where $\alpha_i$ are individual fixed effects, $\gamma_t$ are year fixed effects, and $\boldsymbol{X_{it}}$ is a vector of individual controls including non-parametric controls by age, education, and the interactions of education with time fixed effects, and, for the NLSY, education with NLSY round, NLSY round with time fixed effects, and NLSY round with time fixed effects and education.[57] $D_{it}^k$ are dummy variables around the displacement event. For instance, for an individual displaced in 1999, $D_{i,1999}^0 = 1$ and all other $D_{i,1999}^j$ will be zero. That same individual in 2004 will have $D_{i,2004}^5 = 1$ and all other $D_{i,2004}^j = 0$. If an individual is never displaced but satisfies the conditions above, all the dummies around the displacement event will be equal to zero. The dependent variable $Y_{it}$ will represent any measure of interest to be analyzed around the displacement event (i.e., real annual earnings or hours, hourly

[55] In the case of the LEED, by the survey date

[56] Individuals must also be younger than 57 years old in the LEED

[57] Our baseline controls are slightly different in the Norwegian LEED, since we have no control for either race or NLSY round. Apart from that, all other controls are the same.

wages, etc.)

The use of the specification on equation (2') renders the control group irrelevant in order to identify the $\delta^k$ parameters associated with the time periods around the displacement event. On the other hand, the introduction of a control group is crucial to identify the effects on the outcome of all the control variables (i.e., age, education, NLSY group, etc.) as well as the macroeconomic conditions captured by the year-fixed effects, since they represent more than 3/4 of the total number of observations available. To interpret the estimated $\delta^k$ coefficients as the earnings effect of job displacement requires that, conditional on individual fixed effects and all the other control variables, the control group's earnings define the counterfactual earnings of displaced workers in the absence of job displacement. The use of equation (2') to estimate the earnings losses of displaced workers implies that even if workers are displaced based on some unobserved (constant) characteristic and/or their earnings differ based on some unobserved covariate, this will not bias our results. One of the concerns arises if firms choose which worker to displace based on poor past performance during a short time span before the displacement. Situations as such would generate a bias in the estimated results, whose relevance would depend on the structure of the error term.

As with the matching empirical strategy, to account for the heterogeneity in earnings losses for different types of workers, we extend the main model in equation (2').[58] On top of the dummy variables ($D^k$) representing the periods around the displacement event, we also include the interaction of these dummies with the value of knowledge specialization and the knowledge level in the pre-displacement job. Therefore, we augment equation (2') to:

$$Y_{it} = \sum_{k=-5}^{k=7} \delta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k^{sp} D_{it}^k spec_{i0} + \sum_{k=-5}^{k=7} \delta_k^{kw} D_{it}^k knw_{i0} + \boldsymbol{\beta X_{it}} + \alpha_i + \gamma_t + \epsilon_{it} \tag{3'}$$

where $spec_{i0}$ and $knw_{i0}$ are the knowledge specialization and knowledge level of the pre-displacement occupations and are held constant for all periods in the estimation.

Changing the empirical strategy does not solve one of the main concerns of the matching design: the fact that knowledge specialization at displacement is strongly correlated with other worker characteristics at displacement, which are unaccounted for in equation (3'). We replicate here the alternative solutions we proposed in Section 4.1. First, we interact the displacement dummies with additional pre-displacement controls that prior work has identified as relevant in explaining the heterogeneity of earnings losses post-displacement.This results in the following estimation equation:

$$Y_{it} = \sum_{k=-5}^{k=7} \delta_k D_{it}^k + \sum_{k=-5}^{k=7} \delta_k^{sp} D_{it}^k spec_{i0} + \sum_{w \in W} \Big[ \sum_{k=-5}^{k=7} \delta_k^W D_{it}^k w_{i0} \Big] + \boldsymbol{\beta X_{it}} + \alpha_i + \gamma_t + \epsilon_{it} \tag{4'}$$

[58]Our extension of the model is akin to that introduced in Jacobson et al. (1993).

where each $w_{i0}$ is one of the worker/occupation/economy characteristics at displacement.

To deal with the large standard errors generated in the period-by-period estimation and gain statistical power, we replicate our strategy in section 4.1 and rely on a transformation of equation (4'). Equation (5') replaces the dummies around the displacement event interacted with the pre-displacement characteristics of the job by two different dummies, $D_{it}^{Pre}$ and $D^{Post}$. $D_{it}^{Pre}$ takes the value of one for all the periods prior to the displacement event (i.e., $k \in [-5, -1]$) and zero otherwise, while $D_{it}^{Post}$ takes the value of one in all the periods after the displacement takes place, including the year of the displacement (i.e., $k \in [0, -7]$), and zero otherwise:

$$Y_{it} = \sum_{k=-5}^{k=7} \delta_k D_{it}^k + \sum_{k=Pre}^{k=Post} \delta_k^{sp} D_{it}^k spec_{i0} + \sum_{k=Pre}^{k=Post} \delta_k^{kw} D_{it}^k knw_{i0} + \boldsymbol{\beta X_{it}} + \alpha_i + \gamma_t + \epsilon_{it} \tag{5'}$$

Second, we residualize the knowledge specialization variable following the procedure described in the main text. Then, we interact the residualized specialization with the displacement dummies:

$$Y_{it} = \sum_{k=-5}^{k=7} \delta_k D_{it}^k + \sum_{k=Pre}^{k=Post} \delta_k^{sp} D_{it}^k uspec_{i0} + \boldsymbol{\beta X_{it}} + \alpha_i + \gamma_t + \epsilon_{it} \tag{6'}$$

where $uspec_{i0}$ is the residualized knowledge specialization measure of the displaced individuals at the point of displacement.

In summary, our two identification strategies differ in a number of ways. First, the control group is completely different in each strategy. Our first choice, the matching design, focuses on defining the control group at the point of displacement and maintains the same individuals as a control for a specific worker for the entirety of the sample. Matched workers can be younger than 25 in the pre-displacement periods, work any amount of hours, and have any job tenure during any of the periods other than the matched period. On the other hand, in this appendix we use a replica of Jacobson et al. (1993), where workers in the control group always have at least two years of job tenure, work at least 25 hours per week on average during the year, are 25 years old or older and never suffer a displacement. Using this method, when comparing treatment and control five years prior to the displacement, we are essentially comparing workers who will be displaced in 5 years, and may be working full-time or part-time, with any job tenure, and could be younger than 25, to workers that are more established in their jobs, are older, and working regularly. This issue arises because this strategy does not "match" displaced workers with control workers around displacement and follows them over time, but sets a series of baseline conditions that units in the control group need to satisfy always, but treated workers do not.

The second largest difference arises in the identification of the $\delta_k$ coefficients. In the method proposed in this appendix, by adding individual fixed effects to our specification, our estimation of the $\delta_k$ coefficients is just a comparison between the current and baseline period for the earnings (or wages or hours) of the displaced worker, conditional on her age, education, year of the observation and NLSY group. The effects on earnings of these covariates are mostly determined by the control group since they represent over 80 percent of the observations. However, when we use the matching strategy the $\eta_k$ coefficients are identified from the difference in earnings between the treated and the control individuals within the match, relative to the difference in the baseline period (i.e., the year prior to displacement), conditional on age, gender, education, year fixed effects, and NLSY group.

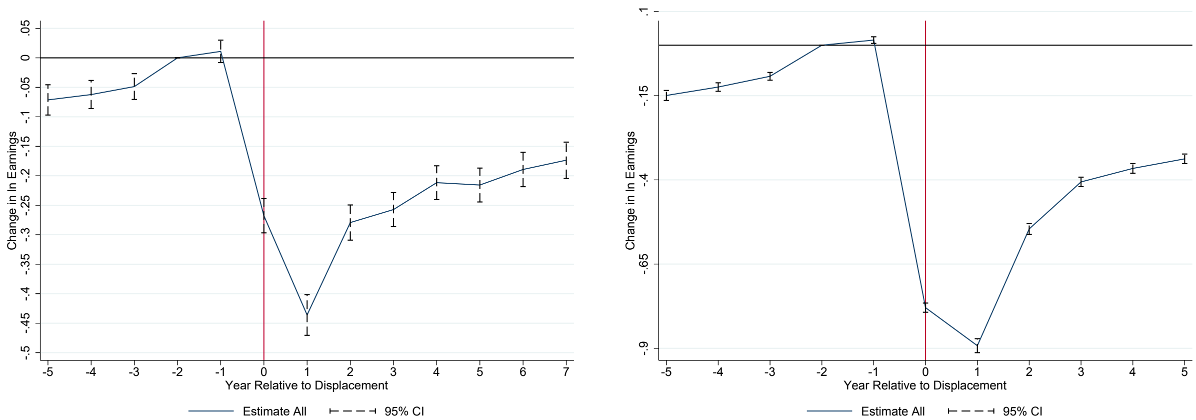
### C.2 Earnings Losses of Displaced Workers: JLS (1993)

We estimate the effects of displacement on earnings using equation (2'). The results are shown in Figure C.1. Panel (a) shows the estimated $\delta^k$ coefficients for the NLSY. Compared to two years prior to the displacement event, we do not see any significant difference in total earnings in the year before the worker is displaced. This is followed by a large drop in annual earnings that reaches 24 percent in the displacement year (period 0),[59], 36 percent during the first full year after displacement (period 1) and recovers at a constant pace to levels around 16 percent 7 years after the displacement event. In panel (b) we present equivalent estimates using the LEED data. As in the main text, the earnings losses are significantly larger in our Norwegian data, reaching 59 percent in the first year of unemployment,[60] and recovering to a level 30 percent below the pre-displacement earnings five years post-displacement.

However, in both panels, when looking at years 3 to 5 prior to the dismissal, we observe annual earnings that are significantly lower compared to the last two years prior to the displacement, casting doubt on whether the estimated post-displacement coefficients reflect the counterfactual path of earnings that would have taken placed in the absence of a dismissal. This is a limitation of our implementation of the Jacobson et al. (1993) empirical strategy. It arises because of the differences between the treatment and control groups in periods far from the displacement event. While the former group does not need to satisfy any conditions on hours worked, age, or tenure 3 to 5 years prior to displacement (or post-displacement), each observation of the control group has at least two years of job tenure, is 25 years old or older, and works 25 hours per week or more. Therefore, the JLS (1993) empirical strategy only offers a valid estimate of the causal effect of displacement under the assumption that the working history of displaced workers would have evolved similarly to that of the control group post-displacement in the absence of the dismissal, even if the earnings and working patterns in the years prior to the displacement are significantly different across groups. This assumption is difficult to justify, and it is not required when using the matching empirical strategy, since we do not observe differences in earnings pre-displacement

[59] $(\exp(-0.27) - 1)$=-0.236
[60] $(\exp(-0.89) - 1)$=-0.589

**Figure C.1:** Displacement Effects on Earnings. JLS (1993)




(a) NLSY (b) LEED

*Note:* This figure presents the estimated earnings losses from displacement, where the outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the JLS (1993) empirical strategy and use the control group described in Section C.1. The value on the y-axis captures the difference in earnings in the period relative to the baseline period, two years before the dismissal, following equation (2'). Black bars represent the corresponding 95% confidence intervals.

between treatment and control in our matching strategy.

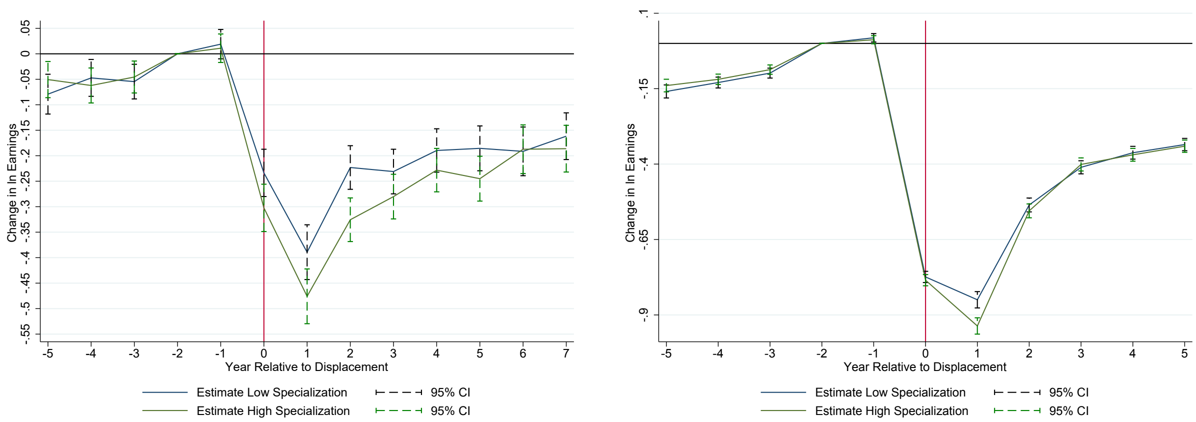
Interestingly, the lack of individual fixed effects in equation (2) plays a very limited role in the difference between both sets of estimates. We can see this by adding individual fixed effects to our estimation in the matching sample. In this case, as with the JLS (1993) method, the identification of the $\eta_k$ arises through the earnings comparison across periods within displaced individuals, while the control group helps determine the age, education, year, and NLSY round effects. We present the results in Figure A.2 in the appendix. We find coefficients that are extremely similar to those of Figure 1, with very small and mostly insignificant differences in earnings prior to displacement.

## C.3 Knowledge Specialization Pre-Displacement and Earnings Losses: JLS (1993)

Figure C.2 plots the estimated earnings losses of a worker one standard deviation above the mean (high specialization) and those of a worker one standard deviation below the mean (low specialization), using the JLS (1993) empirical strategy described in equation (3').

The estimates of the effect of pre-displacement knowledge specialization on post-displacement earnings using the JLS (1993) empirical strategy are slightly more muted compared to the ones we present in the main text. However, the patterns and conclusions we derived in the main text still apply here in both the NLSY and the LEED data. Note that while we observe significantly lower earnings in the treatment group 3 to 5 years prior to displacement using this empirical strategy,

**Figure C.2:** Displacement Effects of Knowledge Specialization on Earnings. JLS (1993)




(a) NLSY

(b) LEED

*Note:* This figure presents the estimated earnings losses from displacement for workers with high vs. low knowledge specialization pre-displacement. Low (High) knowledge specialization: Estimated earnings losses of a worker with knowledge specialization pre-displacement one standard deviation below (above) the median. The outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the JLS (1993) empirical strategy and use the control group described in Section C.1. The value on the y-axis captures the difference in earnings in the period relative to the baseline period, two years before the dismissal for each type of worker, following equation (3'). Black bars represent the corresponding 95% confidence intervals.

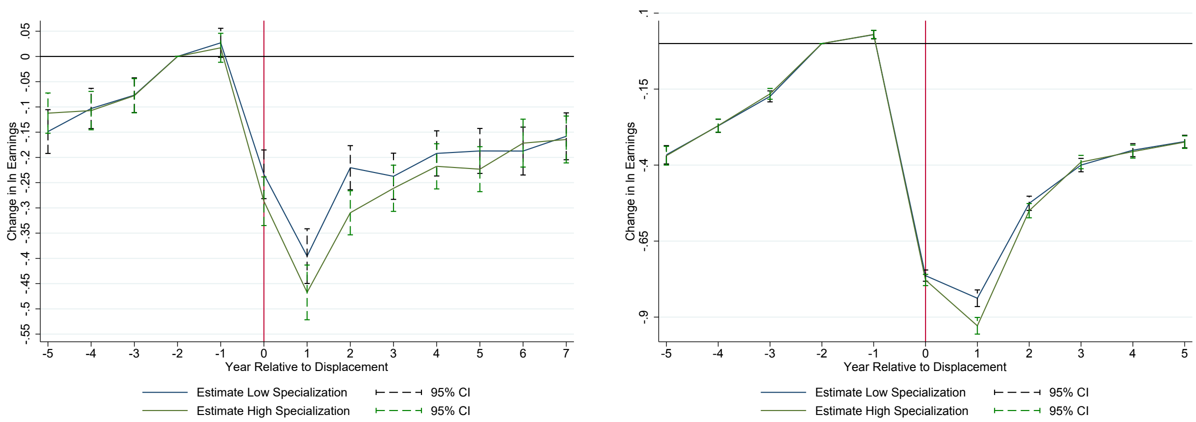
we do not see any further differences for workers with lower or higher pre-displacement knowledge specialization.

Figure C.3, plots the estimated earnings losses of a high- vs. low-specialization worker, after controlling for the interaction between additional covariates at the point of displacement and the displacement dummies, following equation (4'). As in the results included in the main text, adding these additional controls does not change the negative effect of higher pre-displacement knowledge specialization on post-displacement earnings, even if the estimated coefficients under JLS (1993) are slightly more muted than the ones from our matching strategy.

We wrap up this section with Table C.2, which presents results equivalent to those in Table 7, but instead uses the JLS (1993) empirical strategy. We find that an additional standard deviation of pre-displacement knowledge specialization increases the earnings losses post-displacement by approximately 2.9 percentage points in the US data and by 1.2 percentage points in the Norwegian data. As with the results in the main text, whether we add additional controls or residualize our measure of pre-displacement specialization does not change our conclusions.

In summary, we find that the use of the JLS (1993) empirical strategy poses some challenges if the objective is estimating the causal effect of displacement on earnings. However, despite those challenges, we find it similarly reliable in estimating the effect of higher pre-displacement knowledge specialization on re-employment earnings. Our JLS (1993) estimates of the negative impact of

**Figure C.3:** Displacement Effects of Knowledge Specialization on Earnings




(a) NLSY (b) LEED

*Note:* This figure presents the estimated earnings losses from displacement for workers with high vs. low knowledge specialization pre-displacement. Low (High) knowledge specialization: Estimated earnings losses of a worker with knowledge specialization pre-displacement one standard deviation below (above) the median. The outcome of interest is the log of total annual earnings. Panel (a) uses the NLSY sample and panel (b) uses the LEED sample. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Each value of the x-axis represents the year, relative to the displacement year (period 0). We set the baseline period two years prior to the displacement event. We follow the JLS (1993) empirical strategy and use the control group described in Section C.1. The value on the y-axis captures the difference in earnings in the period relative to the baseline period, two years before the dismissal for each type of worker, after controlling by additional workers' characteristics at the point of displacement by interacting them with the displacement dummies, following equation (4'). Black bars represent the corresponding 95% confidence intervals.

higher pre-displacement knowledge specialization on post-displacement earnings are consistent with those from the matching design, but the magnitudes decrease by around 0.4 to 0.8 percentage points per year (2.9 vs. 3.7 in the NLSY and 1.2 vs. 1.6 in Norway).

## C.4 Mechanisms: JLS (1993)

Here, we test the same set of mechanisms introduced in the main text, to see whether the estimated effects of higher pre-displacement specialization arise due to the correlation of this variable with the different covariates we propose.

Starting with the set of mechanisms related to how workers change between pre-and post-displacement jobs, Table C.3 displays the estimated impact of one additional standard deviation of pre-displacement knowledge specialization on the post-displacement earnings, after controlling for industry, occupation and main skill changes, and by the distance between the pre-and post-displacement occupations.[61] As with the results in Table 10, we find no evidence of these mechanisms being behind the larger losses associated with higher levels of pre-displacement knowledge

[61] To estimate the coefficients in Table C.3 we extend equation (5') by adding the interaction between dummies capturing whether the worker changes or remains in the same industry, occupation, or skill and the displacement dummies, and a continuous variable measuring the distance between pre- and post-displacement occupations and the displacement dummies.

specialization, since their inclusion leaves our estimate of higher pre-displacement knowledge specialization on post-displacement earnings unchanged.[62]

Moving to the second set of mechanisms, those related to the characteristics of the pre-displacement occupation (i.e., its automatability, offshorability, task complexity, routine, manual and cognitive scores), we present the results in Table C.4. Our conclusions for the NLSY remain identical when compared to those from the results in Table 12. Controlling for other occupation characteristics at the point of displacement (automation/offshoring likelihood, task complexity, cognitive, routine scores, etc.) does not impact our estimate of the effect of higher pre-displacement specialization on re-employment earnings.[63]

Similar to our main results in the paper, the Norwegian results using the JLS(1993) strategy show a slight decrease in the estimated effect of higher pre-displacement knowledge specialization on re-employment earnings once we account for additional occupation characteristics. While the change is small (from -1.2 percentage points to -0.8 percentage points), it is enough to make our estimate insignificantly different from zero. Our results suggest that the routine intensity of the occupation and the complexity of the occupation's tasks pick up part of the negative effect of specialization having a small but positive impact on post-displacement earnings.

Finally, we replicate the results in the main text in regard to the pre-displacement knowledge specialization and its relationship with the quantity and quality of the occupation's outside options. The results are displayed in Table C.5.

Our estimates using the JLS (1993) empirical strategy provide the same conclusion as the ones displayed in the main text. In our US data, the quantity and quality of the outside options is an important mechanism through which higher levels of pre-displacement knowledge specialization negatively affect the earnings losses post-displacement. Furthermore, for the NLSY, the JLS (1993) empirical strategy enhances the relevance of the quality and quantity of the outside options in explaining the negative effects of pre-displacement knowledge specialization on post-displacement earnings. Once we account for this, the negative effect of higher pre-displacement specialization on the earnings losses of displaced workers is reduced by 66 percent and becomes insignificant.

In the LEED, we still find no clear relationship between higher pre-displacement knowledge specialization and the quantity and quality of outside options. This suggests that, at least in the Norwegian case, higher specialization does not necessarily translate into "dead end" occupations for which there are no good outside options, the same conclusion we derived in the main text.

In summary, whether we use the JLS (1993) or the matching strategy shown in the main text,

[62] For the ease of comparison, we present the results without controlling for any of these mechanisms in columns (1) for the NLSY and (7) for Norway. Note that these two results differ from those in column (3) of Table C.2. The reason is that we restrict the sample to displacements where we observe the pre- and post-displacement industry and occupation so that within Table C.3 the results are easily comparable.

[63] For the ease of comparison, we present the results without controlling for any of these mechanisms in columns (1) for the NLSY and (4) for Norway.

our conclusions for both the NLSY and the LEED remain identical. Workers with higher pre-displacement knowledge specialization see significantly larger earnings losses. These additional losses cannot be explained by how workers move between pre- and post-displacement jobs (i.e., whether they stay in the same industry, occupation, or main skill and the distance between jobs).

In Norway, the negative effect of knowledge specialization on post-displacement earnings is partially picked up by the routine intensity of the pre-displacement occupation and its likelihood of being offshored. This is not the case for the US, where these mechanisms are irrelevant in explaining the negative effect of pre-displacement specialization on re-employment earnings. On the other hand, US workers with highly specific human capital see larger losses because the quality and quantity of their outside options are significantly lower. This is not true for Norwegian workers, for whom we find no connection between knowledge specialization at displacement and the workers' outside options.

However, even if our conclusions remain unchanged, the use of the JLS (1993) identification strategy results in estimates that are slightly smaller (in absolute value) by around 0.4 to 0.8 percentage points, compared to the results using the matching empirical strategy.

## Additional Tables

**Table C.1:** Displacement Effects. JLS (1993)

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | Earnings | Hours | Wages | Earnings | Hours | Wages |
| $\delta_{-5}$ | -0.071*** | -0.065*** | -0.007 | –0.149*** | -0.172*** | 0.027*** |
| | [0.013] | [0.011] | [0.007] | [0.008] | [0.006] | [0.006] |
| $\delta_{-4}$ | -0.062*** | -0.059*** | -0.003 | -0.124*** | -0.154*** | 0.032*** |
| | [0.012] | [0.010] | [0.006] | [0.006] | [0.005] | [0.005] |
| $\delta_{-3}$ | -0.049*** | -0.043*** | -0.006 | -0.092*** | -0.114*** | 0.023*** |
| | [0.011] | [0.009] | [0.006] | [0.006] | [0.005] | [0.004] |
| $\delta_{-2}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta_{-1}$ | 0.011 | 0.029** | -0.018*** | 0.015*** | 0.106*** | -0.089*** |
| | [0.010] | [0.008] | [0.006] | [0.005] | [0.004] | [0.004] |
| $\delta_0$ | -0.268*** | -0.184*** | -0.084*** | -0.779*** | -0.626*** | -0.144*** |
| | [0.015] | [0.013] | [0.007] | [0.007] | [0.006] | [0.007] |
| $\delta_1$ | -0.436*** | -0.307*** | -0.129*** | -0.892*** | -0.665*** | -0.210*** |
| | [0.018] | [0.015] | [0.007] | [0.011] | [0.008] | [0.008] |
| $\delta_2$ | -0.279*** | -0.157*** | -0.122*** | -0.546*** | -0.439*** | -0.101*** |
| | [0.015] | [0.013] | [0.007] | [0.008] | [0.007] | [0.006] |
| $\delta_3$ | -0.257*** | -0.140*** | -0.118*** | -0.406*** | -0.319*** | -0.083*** |
| | [0.015] | [0.012] | [0.007] | [0.007] | [0.006] | [0.006] |
| $\delta_4$ | -0.212*** | -0.105*** | -0.107*** | -0.366*** | -0.291*** | -0.071*** |
| | [0.015] | [0.012] | [0.007] | [0.007] | [0.006] | [0.006] |
| $\delta_5$ | -0.216*** | -0.113*** | -0.103*** | -0.337*** | -0.262*** | -0.072*** |
| | [0.015] | [0.012] | [0.007] | [0.007] | [0.006] | [0.006] |
| $\delta_6$ | -0.189*** | -0.091*** | -0.098*** | | | |
| | [0.015] | [0.013] | [0.008] | | | |
| $\delta_7$ | -0.174*** | -0.083*** | -0.091*** | | | |
| | [0.016] | [0.013] | [0.009] | | | |
| $N$ | 118,113 | 118,113 | 118,113 | 2,488,584 | 2,488,584 | 2,488,584 |
| Displacements | 2,818 | 2,818 | 2,818 | 20,442 | 20,442 | 20,442 |

*Note:* This table presents the estimated coefficients from equation (2'), using the Jacobson et al. (1993) identification strategy and the control group described in Section C.1. Columns (1), (2), and (3) show the results for the NLSY, while columns (4), (5), and (6) present the estimated coefficients for the LEED. We set the baseline period two years prior to the displacement event. Each coefficient captures the difference in earnings/hours worked/wages (in log points) in that period relative to two years before the dismissal. In columns (1) and (4) the outcome variable is the log of total annual earnings. In columns (2) and (5) the outcome variable is the log of total annual hours worked. In columns (3) and (6) the outcome variable is the log of the average annual hourly wages. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table C.2:** Displacement Effects of Knowledge Specialization on Earnings. JLS (1993)

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Pre}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta^{sp}_{Post}$ | -0.025*** | -0.028*** | -0.029*** | -0.021** | -0.012*** | -0.011*** | -0.011*** | -0.012*** |
| | [0.008] | [0.008] | [0.011] | [0.011] | [0.004] | [0.004] | [0.004] | [0.004] |
| $\delta^{knw}_{Post}$ | | -0.016 | -0.009 | | | 0.008 | 0.015* | |
| | | [0.013] | [0.017] | | | [0.006] | [0.008] | |
| $\delta^{female}_{Post}$ | | | -0.072*** | | | | -0.012 | |
| | | | [0.019] | | | | [0.008] | |
| $\delta^{exp}_{Post}$ | | | -0.127*** | | | | -0.266*** | |
| | | | [0.036] | | | | [0.018] | |
| $\delta^{age}_{Post}$ | | | 0.006*** | | | | 0.003*** | |
| | | | [0.002] | | | | [0.000] | |
| $\delta^{college}_{Post}$ | | | 0.073*** | | | | -0.027*** | |
| | | | [0.022] | | | | [0.010] | |
| $\delta^{UR}_{Post}$ | | | -0.019*** | | | | -0.065*** | |
| | | | [0.005] | | | | [0.005] | |
| $\delta^{tenure}_{Post}$ | | | -0.146*** | | | | -0.228*** | |
| | | | [0.014] | | | | [0.011] | |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | None | $knw_{i,0}$ | All | None |
| $N$ | 116,659 | 116,659 | 116,226 | 116,226 | 2,488,584 | 2,488,584 | 2,487,936 | 2,487,936 |
| Displacements | 2,635 | 2,635 | 2,573 | 2,573 | 20,442 | 20,442 | 20,259 | 20,259 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the JLS (1993) identification strategy and the control group described in Section C.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. In columns (1) and (5) we display the estimated $\delta^{sp}_{Post}$ from equation (5') without including any interaction between the pre-displacement covariates (other than specialization) and the displacement dummies. In columns (2) and (6) we display the estimated $\delta^{sp}_{Post}$ from equation (5') including the interaction between the pre-displacement knowledge level and the displacement dummies. In columns (3) and (7) we present the estimated $\delta^{sp}_{Post}$ from equation (5') including the interaction between all the pre-displacement covariates of interest and the displacement dummies. (The $\delta^{ind/occ=w}_{Post}$ for each industry and occupation group are included in the estimation but not shown in the table.) Finally, in columns (4) and (8) we present the estimated $\delta^{sp}_{Post}$ from equation (6'). Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table C.3:** Displacement Effects of Knowledge Specialization on Earnings. JLS (1993)
Conditional on Changing Industry, Occupation, Skill and Distance Between Pre- and Post-Displacement Occupations

| | NLSY | | | | | | LEED | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\delta^{sp}_{Post}$ | -0.037*** | -0.041*** | -0.039*** | -0.038*** | -0.039*** | -0.046*** | -0.011** | -0.013*** | -0.008* | -0.010** | -0.013*** | -0.010** |
| | [0.011] | [0.012] | [0.011] | [0.011] | [0.011] | [0.012] | [0.005] | [0.005] | [0.005] | [0.005] | [0.005] | [0.005] |
| $\delta^{Distance}_{Post}$ | | -0.558*** | | | | -0.180 | | -0.589*** | | | | -0.546*** |
| | | [0.117] | | | | [0.159] | | [0.058] | | | | [0.079] |
| $\delta^{Same\_Ind}_{Post}$ | | | 0.111*** | | | 0.082*** | | | 0.086*** | | | 0.067*** |
| | | | [0.016] | | | [0.019] | | | [0.009] | | | [0.010] |
| $\delta^{Same\_Occ}_{Post}$ | | | | 0.079*** | | 0.018 | | | | 0.045*** | | -0.017 |
| | | | | [0.016] | | [0.022] | | | | [0.008] | | [0.011] |
| $\delta^{Same\_Skill}_{Post}$ | | | | | 0.078*** | 0.037** | | | | | 0.041*** | -0.004 |
| | | | | | [0.017] | [0.019] | | | | | [0.009] | [0.011] |
| Disp. Controls | All | All | All | All | All | All | All | All | All | All | All | All |
| $N$ | 112,195 | 111,536 | 112,064 | 112,178 | 112,178 | 111,414 | 2,471,271 | 2,460,445 | 148,208 | 140,909 | 2,459,295 | 135,708 |
| Displacements | 1,967 | 1,887 | 1,951 | 1,965 | 1,965 | 1,872 | 17,033 | 15,729 | 17,031 | 16,149 | 15,597 | 15,528 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section C.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in the table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year for whom we observe industry and occupation pre- and post-displacement. Columns (1) to (6) show the results for the NLSY, while columns (7) to (12) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (7) replicate the results in columns (3) and (7) of Table C.2. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5') after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table C.4:** Displacement Effects of Knowledge Specialization on Earnings. JLS (1993). Mechanisms

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Post}$ | -0.029*** | -0.032*** | -0.028** | -0.031** | -0.011*** | -0.007 | -0.007 | -0.008* |
| | [0.011] | [0.012] | [0.013] | [0.013] | [0.004] | [0.005] | [0.005] | [0.005] |
| $\delta^{Pr(Autom)}_{Post}$ | | 0.017 | | -0.004 | | 0.027 | | 0.025 |
| | | [0.034] | | [0.045] | | [0.020] | | [0.024] |
| $\delta^{Pr(Task-Offs)}_{Post}$ | | 0.014 | | 0.013 | | -0.003 | | 0.002 |
| | | [0.011] | | [0.013] | | [0.005] | | [0.006] |
| $\delta^{Task-Complex}_{Post}$ | | | 0.244* | 0.286** | | | 0.073 | 0.087* |
| | | | [0.133] | [0.139] | | | [0.045] | [0.047] |
| $\delta^{Routine}_{Post}$ | | | 0.041*** | 0.039** | | | 0.023** | 0.020** |
| | | | [0.016] | [0.017] | | | [0.009] | [0.010] |
| $\delta^{Non-Routine}_{Post}$ | | | -0.036* | -0.034 | | | 0.014 | 0.019 |
| | | | [0.021] | [0.022] | | | [0.015] | [0.016] |
| $\delta^{Manual}_{Post}$ | | | -0.001 | -0.001 | | | -0.009 | -0.006 |
| | | | [0.015] | [0.015] | | | [0.015] | [0.015] |
| $\delta^{Cognitive}_{Post}$ | | | -0.037** | -0.037* | | | 0.012 | 0.011 |
| | | | [0.018] | [0.019] | | | [0.013] | [0.013] |
| Disp. Controls | All | All | All | All | All | All | All | All |
| $N$ | 116,226 | 114,562 | 113,449 | 113,381 | 2,487,936 | 2,463,063 | 2,462,035 | 2,462,035 |
| Displacements | 2,573 | 2,347 | 2,210 | 2,202 | 19,507 | 19,026 | 19,026 | 19,026 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section C.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (5) replicate the results in columns (3) and (7) of Table C.2. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5') after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

**Table C.5:** Displacement Effects of Knowledge Specialization on Earnings. JLS (1993) Conditional on Amount and Quality of Outside Offers

| | NLSY | | | | LEED | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta^{sp}_{Post}$ | -0.029*** | -0.025** | -0.020 | -0.010 | -0.011*** | -0.011*** | -0.010** | -0.010** |
| | [0.011] | [0.012] | [0.012] | [0.013] | [0.004] | [0.004] | [0.004] | [0.004] |
| $\delta^{Above\_Avg\_Possible}_{Post}$ | | 0.026 | | 0.046** | | 0.006 | | 0.010 |
| | | [0.022] | | [0.023] | | [0.010] | | [0.010] |
| $\delta^{Positive\_Avg\_Diff}_{Post}$ | | | 0.093*** | 0.108*** | | | -0.030*** | -0.031*** |
| | | | [0.030] | [0.030] | | | [0.010] | [0.010] |
| Disp. Controls | All | All | All | All | All | All | All | All |
| $N$ | 116,659 | 116,226 | 116,114 | 116,114 | 2,487,936 | 2,487,423 | 2,487,423 | 2,487,423 |
| Displacements | 2,573 | 2,573 | 2,555 | 2,555 | 20,192 | 20,192 | 20,192 | 20,192 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section C.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. Columns (1) to (4) show the results for the NLSY, while columns (5) to (8) present the estimated coefficients for the LEED. To simplify the comparison of results, columns (1) and (5) replicate the results in columns (3) and (7) of Table C.2. In all other columns, we display the estimated $\delta^{sp}_{Post}$ from equation (5') after including the interaction between the pre-displacement variables (at their values at displacement) shown in the table and the displacement dummies. Robust standard errors are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

# D Alternative measures of Knowledge Specialization

**Table D.1:** Correlation between Alternative Measures of Knowledge Specialization

| | Spec Original | HHI |
|---|---|---|
| A: CPS | | |
| Spec Original | 1.000 | |
| HHI | 0.971 | 1.000 |
| B: NLSY | | |
| | Spec Original | HHI |
| Spec Original | 1.000 | |
| HHI | 0.974 | 1.000 |

*Note:* This table shows the correlation between our preferred measure of knowledge specialization, used throughout the text, and a second alternative measure of knowledge specialization, for the CPS 1990-2019 and the NLSY79&97 for the years 1986 to 2019. $HHI$ calculates knowledge specialization as the HHI of the occupation's knowledge over all the knowledge categories.

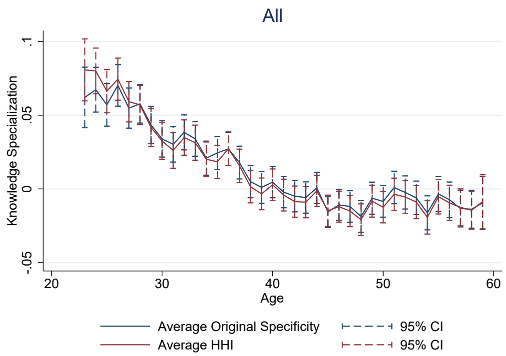
## D.1 Summary Statistics

**Table D.2:** Relationship between Knowledge Specialization and Earnings. Alternative Measures

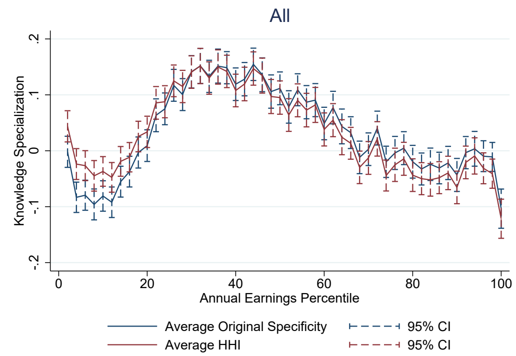
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Spec Original | | HHI | |
| CPS. Dependent Variable: Log of Weekly Earnings × Weeks Worked Last Year | | | | |
| $\beta_{sp}$ | 0.046*** | 0.018*** | 0.041*** | 0.014*** |
| | [0.012] | [0.005] | [0.011] | [0.005] |
| Controls | All | All | All | All |
| Occ & Task Measures | All | All | All | All |
| Fixed Effects | All | All | All | All |
| Individual FE | No | Yes | No | Yes |
| $N$ | 196,643 | 167,854 | 196,643 | 167,854 |
| NLSY. Dependent Variable: Log of Total Annual Earnings | | | | |
| $\beta_{sp}$ | 0.037*** | 0.016*** | 0.032*** | 0.013** |
| | [0.010] | [0.005] | [0.010] | [0.006] |
| Controls | All | All | All | All |
| Occ & Task Measures | All | All | All | All |
| Fixed Effects | All | All | All | All |
| Individual FE | No | Yes | No | Yes |
| $N$ | 159,232 | 157,905 | 159,232 | 157,905 |

*Note:* This table displays the estimated coefficients of knowledge specialization from different specifications where the outcome is the log of annual earnings. Columns (1) and (2) replicate our original results in Table 4, while columns (3) and (4) use the same specifications but replace our original measure of knowledge specialization with the $HHI$. Fixed Effects *All*: All specifications in the CPS add state by year, education by year, and gender by year fixed effects. All specifications in the NLSY include education by year and gender by year fixed effects. Controls *All*: Adds as additional controls industry and occupation group fixed effects, experience and tenure (NLSY and LEED), marital status, immigration status, the field of degree, English knowledge, and occupation prestige score (CPS). Specifications in columns (1) and (3) do not include individual fixed effects, while those in columns (2) and (4) include them. Standard errors are clustered at the SOC occupation level in brackets. p-value: * 0.10 ** 0.05, *** 0.01.

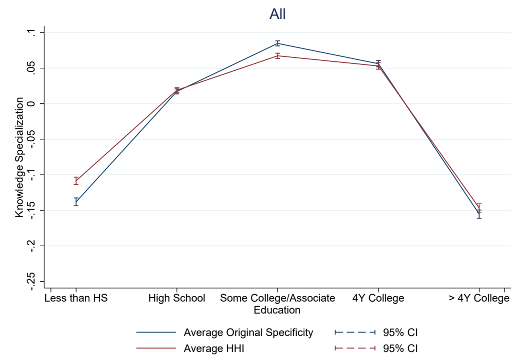
**Figure D.1:** Summary Statistics I: Alternative Measures of Knowledge Specialization



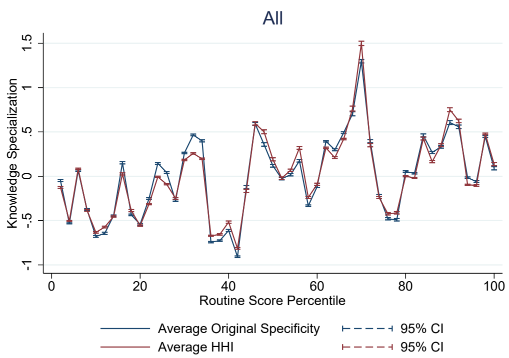

(a) Age



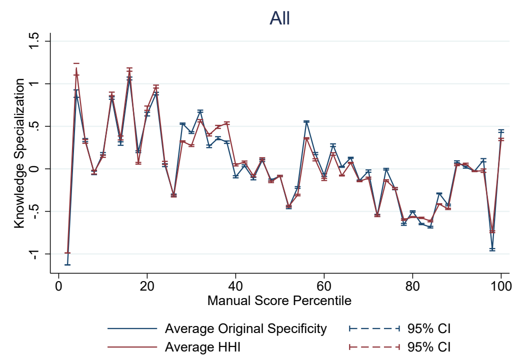

(b) Earnings



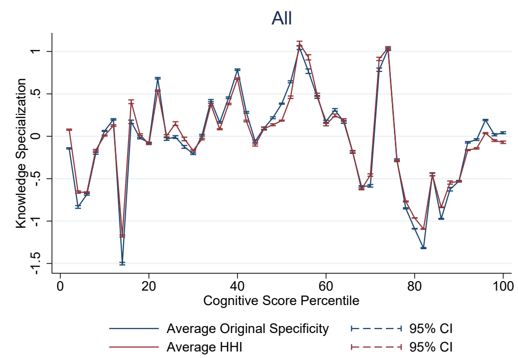

(c) Education



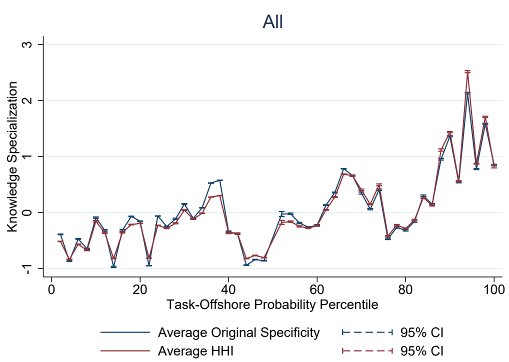

(d) Routine Score



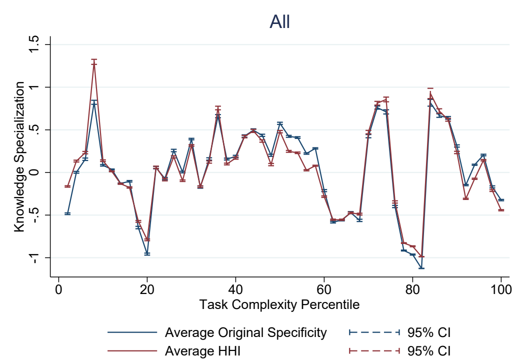

(e) Manual Score



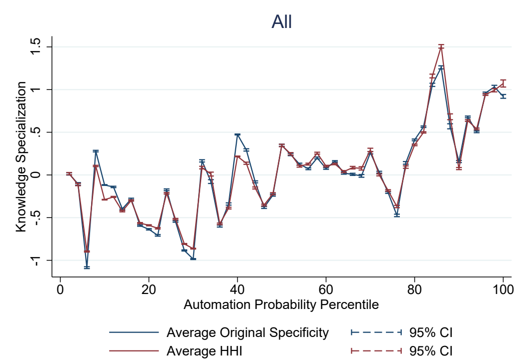

(f) Cognitive Score




(g) Task Offshorability




(h) Task Complexity




(i) Automation Probability

*Note:* Bars represent the corresponding 95% confidence intervals for the mean at that point.

## D.2 Displacement Effects of Knowledge Specialization on Earnings

**Table D.3:** Displacement Effects of Knowledge Specialization on Earnings. Alternative Measures

| | NLSY | | | LEED | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Knowledge Specialization Measure: Spec Original | | | | | | |
| $\delta^{sp}_{Pre}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta^{sp}_{Post}$ | -0.036*** | -0.042*** | -0.037** | -0.025*** | -0.028*** | -0.016*** |
| | [0.012] | [0.013] | [0.018] | [0.005] | [0.005] | [0.006] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 84,635 | 84,635 | 82,897 | 421,224 | 421,224 | 420,245 |
| Displacements | 2,690 | 2,690 | 2,624 | 21,015 | 21,015 | 21,001 |
| Knowledge Specialization Measure: HHI | | | | | | |
| $\delta^{sp}_{Pre}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [.] | [.] | [.] | [.] | [.] | [.] |
| $\delta^{sp}_{Post}$ | -0.033*** | -0.040*** | -0.032** | -0.019*** | -0.028*** | -0.015* |
| | [0.012] | [0.013] | [0.017] | [0.006] | [0.006] | [0.008] |
| Disp. Ctrls | None | $knw_{i,0}$ | All | None | $knw_{i,0}$ | All |
| $N$ | 84,635 | 84,635 | 82,897 | 421,224 | 421,224 | 420,245 |
| Displacements | 2,690 | 2,690 | 2,624 | 21,015 | 21,015 | 21,001 |

*Note:* The coefficients $\delta^{sp}_{Post}$ in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one additional standard deviation in pre-displacement knowledge specialization, using the matching identification strategy and the control group described in Section 4.1. Similarly, the remaining $\delta^{W}_{Post}$ coefficients in this table present the estimated effect (in log points) on annual post-displacement earnings of an increase of one unit in pre-displacement variable $W$. We restrict the estimation to individuals in our sample with positive annual earnings during that year. ALL columns show the results for the NLSY. Columns (1) to (3) replicate the results of Table 7 using our original measure of knowledge specialization. Columns (4) to (6) use the same specifications but replace our original measure of knowledge specialization with the $HHI$. In columns (1) and (4) we display the estimated $\delta^{sp}_{Post}$ from equation (5) without including any interaction between the pre-displacement covariates (other than specialization) and the displacement dummies. In columns (2) and (5) we display the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between the pre-displacement knowledge level and the displacement dummies. In columns (3) and (6) we present the estimated $\delta^{sp}_{Post}$ from equation (5) including the interaction between all the pre-displacement covariates of interest and the displacement dummies. (The $\delta^{ind/occ=w}_{Post}$ for each industry and occupation group are included in the estimation but not shown in the table.) Standard errors clustered at the match level are shown in brackets. p-value: * 0.10 ** 0.05, *** 0.01.