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New Technologies, Digital Skills, and Occupational Mobility: Evidence from Ireland

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Abstract

This paper examines how skill mismatch, particularly in digital skills, constrains occupational mobility. Using worker transition data from the Irish Labour Force Survey and skill vectors from the ESCO database, we construct occupation-level mismatch measures and estimate their effect on worker flows in a framework combining matching and gravity models. Greater skill mismatch significantly reduces occupational mobility, with stronger constraints on transitions between digitally intensive occupations. We also document substantial heterogeneity in bilateral mobility costs and show that occupations that are easier to enter are harder to exit, creating bottlenecks. These findings highlight the importance of retraining policies, especially those supporting digital skill acquisition, to improve labour market adaptability.

JEL codes: J24, J62

Keywords: Occupational Mobility; Skill mismatch; Tasks; Mobility costs.

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Non-technical summary

Technological change is increasing the role of digital competencies across a range of jobs, which may widen skill gaps and influence the reallocation of workers across occupations. This paper examines the extent to which skill mismatch acts as a barrier to occupational mobility, with particular emphasis on digital skill mismatch.

To address this question, we combine worker transition data from the Irish Labour Force Survey covering 2007 to 2023 with occupation level skill profiles from the ESCO database. Occupations are represented as vectors of required skills, which allows the construction of a directional measure of mismatch between an origin and destination occupation pair. Skill mismatch is defined as the number of skills required in the destination occupation that are not required in the origin, reflecting the idea that missing skills raise the cost of entry while current skills no longer required in the destination occupation should not create a barrier to moving. The empirical analysis relates observed flows between occupations pairs to this mismatch measure using a gravity style specification. We distinguish between digital and non-digital skill mismatches to compare their relative importance.

We find a strong negative association between skill mismatch and occupational mobility. Transitions are less likely when the destination occupation requires skills that are absent from the origin occupation, and this relationship is substantially stronger for digital skills than for non-digital skills. The estimates imply that a one unit increase in digital skill mismatch (i.e., one additional skill required in destination occupation that is not required in origin occupation) is associated with circa 12% lower probability of occupation transition, compared with about 3% for non-digital skills mismatch, and the pattern is consistent across multiple robustness tests. These estimates – representing the marginal effect of each additional mismatched skill – demonstrate that digital skill mismatch exerts a considerably stronger effect on occupational mobility than non-digital skill mismatch, underscoring the importance of digital competencies in shaping occupational transitions.

Also, we find a strong negative relationship between entry and exit costs due to skill mismatch, i.e., occupations that are easier to enter for workers are relatively hard to exit (to different occupations), creating bottlenecks in the mobility network. Moreover, we find transitions into occupations requiring developer-level digital skills face substantially higher barriers than movements between roles requiring user- and practitioner-level digital skills, reflecting the greater learning costs associated with advanced digital competencies.

Overall, the paper provides evidence that skill differences, especially in digital competencies, are associated with observed patterns of occupational switching. The paper highlights where mobility constraints appear more pronounced across the occupation network. From a policy standpoint, there are two conclusions from this work. Firstly, retraining and upskilling efforts that target specific digital skill gaps potentially lead to greater benefits in terms of higher worker mobility. Second, employment supports aimed at occupations that are more susceptible to bottlenecks could yield broader economic benefits by improving labour market efficiency.

1. Introduction

The rapid pace of technological development is transforming labour markets around the world, creating new skill needs and disrupting old career paths (Autor et al., 2024). As occupations increasingly demand new competencies, workers must acquire new skills to remain employable; however, many workers struggle to transition into emerging roles due to skill mismatches (Neffke et al., 2024). Skill mismatch between occupations is particularly concerning in the context of the rapid development of digital technologies, which has widened skill gaps and contributed to labour market polarisation (Acemoglu et al., 2022). Skill mismatches can exacerbate labour market frictions by preventing workers from efficiently reallocating to new occupations, prolonging unemployment spells, and increasing inequality (Guvenen et al., 2020). These barriers are particularly concerning given empirical evidence showing that worker reallocation is often slow following structural shocks (Dix-Carneiro et al., 2023). While existing research acknowledges these challenges, there still remains a gap in our understanding about the quantitative importance of skill mismatch – particularly technological-skills mismatch – in shaping occupational mobility. This raises a critical question: to what extent does skill mismatch act as a barrier to occupational mobility in an increasingly digitalised economy? Understanding these dynamics is crucial for designing effective policies that support workers in navigating transitions and maintaining economic resilience, especially as the nature of work continues to evolve.

In this study, we quantify the importance of skill mismatch in occupational mobility, especially the role of digital skill mismatch. We adopt a task-based approach to measure skill requirements and mismatches, identified by differences in task requirements between occupations. We examine how skill mismatch affects workers' ability to navigate occupational transitions (Neffke et al., 2024; Cortes & Gallipoli, 2018). Understanding these occupational transition barriers is critical in light of evidence on increasing labour market polarisation (Autor & Dorn, 2003; Goos et al., 2014). Our analysis provides empirical evidence on which workers may be most exposed to technological change and are most likely to face challenges in securing new employment opportunities. It can also help inform the development of targeted retraining programs by identifying specific skill gaps that impede occupational mobility.

Central to the task-based approach is the notion that human capital is typically task-specific, and that skill transferability is higher between occupations with similar task requirements (Acemoglu & Autor, 2011; Autor & Dorn, 2013). Building on this, we examine how differences in required skills across occupations impact occupational mobility. Occupational transitions vary widely in the extent to which they require workers to shift their skill sets (Poletaev and Robinson, 2008; Gathmann and Schonberg, 2010). Put differently, not all job switches are alike; some involve minimal adjustments to existing tasks, while others demand a complete reorientation of new skills and responsibilities. Our empirical approach allows us to estimate these frictions between occupation pairs, conditional on the degree of skill overlap.

Our econometric approach draws from both the matching and gravity equation literatures. We develop an occupation choice model where, in each period, workers decide whether to remain in their current occupation or search for a new opportunity, weighing both the pecuniary and non-pecuniary benefits and costs of a move. Central to our model is the concept of skill mismatch between occupations, which is the source of the transition cost (similar to bilateral trade costs in trade literature). Our identification strategy primarily relies on worker flow data, effectively utilising information from both occupation switchers and stayers. By focusing on observed transitions, we can estimate the effect of skill-mismatch-related transition costs, while controlling for other market related factors.

We estimate the empirical matching-gravity equation using data on worker flows across ISCO-08 2-digit occupations from the Irish Labour Force Survey (LFS) from 2007 to 2023. To estimate the equation, we employ variables related to the mobility costs of occupational switches. Following the task-based approach (e.g. Autor et al., 2003, Acemoglu and Autor, 2011), we decompose occupations into vectors of specific skills applied to perform various tasks using data from European Skills, Competences, Qualifications and Occupations (ESCO).[1] Utilising these skill vectors, we construct our measures of skill mismatch between occupation pairs, capturing the degree of skill dissimilarity in the sets of tasks performed. An asymmetric measure of skill mismatch properly highlights the directional nature of skill gaps, where workers face greater barriers when moving into occupations that demand new skills not present in current roles. We first offer a general assessment of the costs of switching occupations given their specific skills, and thereafter concentrate on the necessary skills to meet the digital skill requirements of occupations. By concentrating on these skills, we aim to estimate the barriers that digital skills present to workers in an increasingly digitalised economy.

We find that differences in skill requirements significantly influence occupational mobility, with occupations requiring intensive digital skills imposing higher constraints than those intensive in non-digital skills. Using an asymmetric measure of skill dissimilarity, we estimate that a one-unit increase in skill mismatch – where a unit corresponds to an additional skill required in the destination occupation that is not required in the origin occupation – reduces the probability of occupational transitions by 11.66% for digital skills mismatch and 2.57% for non-digital skills mismatch. These results are robust to the inclusion of controls for vacancy rates and wages in the destination occupation. While higher vacancy rates encourage mobility, occupations with higher wages present barriers, likely due to the entry costs associated with these roles. Our analysis also reveals significant heterogeneity in bilateral mobility costs across occupation pairs due to heterogeneity in skill mismatch. Notably, we find a strong negative relationship between entry and exit costs due to skill mismatch, i.e., occupations that are easier to enter for workers are relatively hard to exit, creating bottlenecks in the mobility network. Furthermore, we find that labour market slack is

[1] ESCO is a European equivalent to O*NET. See https://esco.ec.europa.eu/en for more information.

associated with larger frictions in occupational mobility, conditional on controlling for demand in the destination occupation. These findings offer evidence for developing targeted strategies, such as retraining programs focused on digital skill acquisition and public job matching programs aimed at bottleneck occupations, to support occupational mobility and labour market resilience in the evolving period of technological change.

Our paper is related to a number of influential literatures, including those on the impact of technological change on the labour market and occupational mobility. Since Alan Kruger's seminal work on the effects of new digital technologies on workers (Kruger, 1993; Autor et al., 1998), a substantial body of literature has investigated the implications of automation technologies, artificial intelligence, and digital technologies on labour market outcomes. These outcomes include employment polarisation (Autor et al., 2003; Goos and Manning, 2007), aggregate employment (Autor, Dorn, and Hansen, 2015; Gregory, Salomons, and Zierahn, 2016), wages (Acemoglu et al., 2024), wage inequality (Webb, 2019), the demand for labour across cities (Beaudry, Doms and Lewis, 2006), and the demand for labour across firm (Dinlersoz and Wolf, 2018; Bessen et al., 2018). While these studies have significantly advanced our understanding of how technological change affects individual workers and firms, gaps remain in our understanding of how these factors affect mobility in the occupation network. Our paper adds to this growing literature by focusing on the barriers that differential skill requirements – and especially digital-skill requirements – present to occupational mobility.

Second, we contribute to the literature on human capital transferability and skill mismatch (Neffke et al., 2024; Addison et al., 2020; Guvenen et al., 2020; Perry et al., 2014; Leuven and Oosterbeek, 2011). This body of work highlights how the transferability of human capital between occupations is shaped by the similarity in skills required and tasks performed across jobs. Studies such as Poletaev and Robinson (2008) and Gathmann and Schonberg (2010) emphasise the importance of task-specific human capital and its implications in occupational transitions. Our work is most closely related to Cortes and Gallipoli (2018), and builds on their insights by explicitly measuring skill mismatch using skill vectors of occupations and its impact on occupational mobility. Third, we contribute to the labour market network analysis literature, which conceptualises the labour market as a set of interconnected occupations linked by the flow of workers (Schmutte, 2014; Neffke et al., 2017). These approaches have been used to model worker reallocations across industries and firms to study the distribution of skills, knowledge, and work activities across occupations (Neffke et al., 2024; del Rio-Chanona, 2021; Axtell et al., 2017). In this study, we integrate an asymmetric measure of skill mismatch into the occupational mobility network. This allows us to account for the directional and skill-specific frictions that shape observed flows, particularly in relation to digital competencies.

The remainder of the paper is organised as follows. In the next section, we develop a framework that draws on both the matching and gravity equation literatures to guide our econometric implementation. We describe our data in Section 3 and our results in Section 4, including a variety of extensions and robustness tests of our baseline regressions. Section 5 concludes with a summary of our main findings and their potential policy implications.

2. Estimation framework – When gravity meets matching

We combine the idea of a matching equation and a gravity equation to obtain an equation that relates the flows between occupations to a measure of "distance" between those occupations based on skill mismatch. The model considers a set of workers, denoted by l, $\{1,2,\ldots,L\}$, distributed across a finite set of occupations $\{1,2,\ldots,N\}$, each with a large number of employers. Workers vary in terms of observable characteristics such as education, gender, age, and initial occupation. Time is discrete in the model and is indexed by t. The flow from occupation i to occupation j is assumed to be given by a matching equation:

$$M_{\overrightarrow{ij}t} = e^{A}\left(v_{jt}N_{jt}\right)^{\beta}\left(f_{ijt}N_{it}\right)^{1-\beta}e^{\varepsilon_{ijt}}, \tag{1}$$

where $M_{\overrightarrow{ij}t}$ is the flow of workers from (or successful matches between) occupation i to occupation j, e^{A} is a matching efficiency parameter that incorporates a time-invariant specific measure of the ease of matching of a worker from occupation i with a job in occupation j, v_{jt} is the vacancy rate in occupation j, N_{it} is the total number of workers working in occupation i at time t, N_{jt} is the total number of workers in occupation j at time t, f_{ijt} is the fraction of workers in occupation i that choose to search for a job in occupation j, and ε_{ijt} is an i.i.d. lognormally distributed error term. Initially, we assume that an employed and an unemployed worker in occupation i has an equal chance of transitioning to an occupation j.

As noted, f_{ijt} is the fraction of workers in occupation i who search for a job in occupation j in time t. In period t, each worker chooses to move to a different occupation j or remain in the current occupation i in the next period to maximise their utility, which we assume is affected by both pecuniary (wages) and non-pecuniary benefits. We thus allow utility to reflect heterogeneous preferences for specific occupations. Moreover, switching occupations incurs worker-specific utility costs, with the costs varying across each occupation-pair. This switching cost could be related to the pecuniary component of utility, such as lower wages in a new job due to skill mismatch, or the non-pecuniary component, such as a need to relocate due to family reasons. For simplicity, we assume that a worker in occupation i is only able to search for a job in a single occupation in a given time period and we model this choice problem using a conditional logit framework.[2] For a given worker in occupation i, the utility of a job in occupation j is assumed to be:

[2] A richer structure would allow for a two-stage decision process. In the first stage, a worker in Occupation i would decide to search in another occupation or not to search (with the fall back option remaining in their current occupation). In the second stage, conditional on choosing to search, the worker would choose the best occupation to search. Of course, the worker would solve this decision problem backwards, first identifying the best alternative occupation conditional on search and then deciding to search or not. This could be modelled using a nested logit structure. We adopt the simpler

$$u_{\overrightarrow{ij}t} = \alpha \log W_{jt} - \gamma D_{\overrightarrow{ij}} + \tau_{jt} + \theta_{ijt}, \tag{2}$$

where $\log W_{jt}$ is the natural log of the wage in occupation j at time t, $D_{\overrightarrow{ij}}$ is a measure of the directional distance (or skill-mismatch between the two occupations at time t), τ_{jt} captures time-varying occupation-specific factors – such as institutional characteristics, prestige, and working conditions – that influence the attractiveness of occupation j to all workers. In this sense, τ_{jt} functions as a time-varying fixed effect that absorbs unobserved occupation level features influencing utility. θ_{ijt} is a random variable with an Extreme Value Type I (Gumbel) distribution. Using a standard result from the conditional logit model, the probability that a worker in occupation i chooses to search occupation j (i.e. $Y_{it} = j$) is then:

$$\Pr(Y_{it} = j|i) = \frac{e^{\left(\alpha \log W_{jt} - \gamma D_{\overrightarrow{ij}} + \tau_{jt}\right)}}{\sum_{q \in J} e^{\left(\alpha \log W_{qt} - \gamma D_{\overrightarrow{iq}} + \tau_{qt}\right)}}. \tag{3}$$

Aggregating over all workers in occupation i who choose to search occupation j, we assume that the fraction (f_{ijt}) of these workers who search occupation j is equal to the probability that an individual worker would search. We further note that the denominator in (3) is specific to occupation i at time t. We can therefore replace this term with a fixed effect that is specific to occupation i at time t and we can thus define the fraction of workers in occupation i that choose to search occupation j as:

$$f_{ijt} = e^{\left(\alpha \log W_{jt} - \gamma D_{\overrightarrow{ij}} + \tau_{jt}\right)} e^{\tau_{it}}. \tag{4}$$

where

$$e^{\tau_{it}} = \frac{1}{\sum_{q \in J} e^{\left(\alpha \log W_{qt} - \gamma D_{\overrightarrow{iq}} + \tau_{qt}\right)}}. \tag{5}$$

Substituting (4) into (1) and simplifying we obtain:

$$\begin{aligned} M_{\overrightarrow{ij}t} &= e^{A} e^{\tau_{it}} \left(v_{jt} N_{jt}\right)^{\beta} \left(W_{jt}^{\alpha} N_{it}\right)^{1-\beta} e^{\tau_{jt}} \left(e^{-\gamma D_{\overrightarrow{ij}}}\right)^{1-\beta} e^{\varepsilon_{ijt}} \\ &= e^{A} e^{\tau_{it}} \left(v_{jt} N_{jt}\right)^{\beta} \left(W_{jt}^{\alpha} N_{it}\right)^{1-\beta} e^{\tau_{jt}} e^{-\gamma(1-\beta) D_{\overrightarrow{ij}}} e^{\varepsilon_{ijt}} \end{aligned} \tag{6}$$

Taking advantage of the CRS assumption for the matching function, it is convenient to rewrite (6) as:

conditional logit structure to minimise complications. The choice model is conditional logit rather than multi-nominal logit as we focus on the attributes of the choices rather than the attributes of individual workers, although a worker's distance from an given alternative occupation can be viewed as a relation between an attribute of the worker (the skill requirements of their current occupation) and an attribute of the choice (the skill requirements of the alternative occupation).

$$m_{\overrightarrow{ij}t} = \frac{M_{\overrightarrow{ij}t}}{N_{it}} = e^{A} e^{\tau_{it}} {v_{jt}}^{\beta} W_{jt}^{\alpha(1-\beta)} \left(\frac{N_{jt}}{N_{it}}\right)^{\beta} e^{\tau_{jt}} e^{-\gamma(1-\beta)D_{\overrightarrow{ij}t}} e^{\varepsilon_{ijt}}, \tag{7}$$

where the left-hand side variable now has the convenient interpretation of a transition probability for a worker in occupation i transitioning to a job in occupation j. N_{jt}/N_{it} represents the relative size of the destination occupation j compared to the source occupation i.

Given that there are zero flows across multiple occupation pairs in the data, we use the Poisson Pseudo Maximum Likelihood (PPML) estimator to estimate the matching function (Yotov et al., 2016; Santos Silva and Tenreyro, 2006). As detailed data on covariates is not available, we also include fixed effects for the destination occupation to control for unobserved heterogeneity in job characteristics and occupation attractiveness. Therefore, our reduced form regression takes the form of the following gravity equation:

$$m_{\overrightarrow{ij}t} = \exp\left(A + \tau_{it} + \tau_{jt} + \beta log v_{jt} + \alpha(1-\beta)\log W_{jt} + \beta\log\left(\frac{N_{jt}}{N_{it}}\right) \right. \\ \left. - \gamma(1-\beta)D_{\overrightarrow{ij}}\right) e^{\varepsilon_{ijt}} \tag{8}$$

Given that detailed data on vacancy rates and average wages in the destination occupation are available only from 2019 onwards, we estimate the baseline specification over the full sample period from 2007–2023 without including them explicitly. Nonetheless, destination-occupation fixed effects in the full-sample specification capture time-invariant differences in occupation attractiveness, which may partly reflect these factors. Consequently, the estimated effect of skill mismatch is identified from within-origin and within-destination variation in transition probabilities across occupation pairs over time. For the 2019–2023 sub-period, we additionally include observed vacancy and wage variables directly in the regression, allowing us to assess their role more explicitly.

2.1 Measuring the skill-distance between occupations as skill mismatch

As our baseline measure of mismatch, we use a simple asymmetric measure of distance between occupations based on the number of skills that are not part of the skill set of the source occupation, but are a required part of the skill set in the destination occupation. We can think of our (asymmetric) distance measure as being determined by the (asymmetric) skill mismatch between the occupations.

We illustrate the basis for this distance measure with an example that assumes that there are 10 skills in total in the economy. We consider two occupations, labelled occupation i and occupation j. The required skills in a given occupation are represented by a vector, where the skills are indexed from 1 to 10, and a 1 at kth position ($k = 1$ to 10) indicating that that skill is required in the occupation. We assume the following two occupational skill vectors in our example:

Skill	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Occupation i	0	1	1	1	1	0	1	0	1	1
Occupation j	0	0	1	0	1	0	1	1	0	1

Note first that the Euclidean distance between the two occupational skill vectors is $\sqrt{4}$, where 4 is the total number of skills that differ between the occupations. However, the Euclidean distance is not a good measure of directional distance between the two vectors, as we want to allow the "cost" of moving occupations to depend on the direction of the move. We also want to allow for "free disposal," as not needing a skill that you do need in your present occupation should not be a barrier to moving. In calculating the asymmetric distance measure, we thus focus on those skills that are currently not needed in your present occupation (identified by a 0) but are needed in the destination occupation (indicated by a 1). For a move from occupation i to occupation j the distance, $D_{\overrightarrow{ij}}$, is 1; similarly, for a move from occupation j to occupation i the distance, $D_{\overrightarrow{ji}}$, is 3. Note that the Euclidean distance is given by: $\sqrt{D_{\overrightarrow{ij}} + D_{\overrightarrow{ji}}} = \sqrt{1+3} = \sqrt{4}$. The reason is that the differences taken from each direction exhaust the total differences between the elements of the vectors that determine the Euclidean distance. Therefore, we focus on the asymmetric distance between occupations, which is defined as follows:

$$D_{\overrightarrow{ij}} = \sum_{k=1}^{n} \max\left(0, O_{jk} - O_{ik}\right), \tag{9}$$

where O_{jk} is a dummy variable that takes on a value of 1 if skill k is required in occupation j and O_{ik} is a dummy variable that takes on the value of 1 if skill k is required in occupation i and the total number of skills is given by n.

2.2 Distinguishing skill type

Our skill mismatch measure thus far assumed that there is no differential effect on distance based on the skill-type in the destination occupation (say, a difference between digital and non-digital skills). Occupations can be usefully thought of as having two broad types of skill requirements – digital skills and non-digital skills. In this paper, digital skills are those skills that relate to any competencies and activities required to use, develop, manage, or integrate digital technologies across various domains. These digital skills range from basic digital literacy (e.g., using Excel) to advanced technical competencies (e.g., programming, AI, 3D-printing), where many of these skills support or enable automation (e.g., Robotics, Machine Learning). Whereas non-digital skills comprise any of the remaining skills required for the occupation.

Examining the impact of digitalisation on occupational mobility has become imperative in the wake of rapid technological shifts and increasing adoption of new technologies. As economies pivot towards new technologies, the ability of the workforce to effectively adopt and use new technologies emerges as a requirement for a stable labour market and broader economic competitiveness (Neffke et al., 2024). Thus, distinguishing between digital and non-digital skills provides useful insight into skill mismatches and barriers to workers' mobility due to specific skills. To capture these differences, we extend our skill mismatch measure by decomposing total skill mismatch into two distinct components:

$$D_{\overrightarrow{ij}} = D_{\overrightarrow{ij}}^{D} + D_{\overrightarrow{ij}}^{N} \tag{10}$$

where $D_{\overrightarrow{ij}}^{D}$ is the digital skill mismatch between occupation i and j, $D_{\overrightarrow{ij}}^{N}$ is the skill mismatch between occupation i and j due to non-digital skills. For each skill-type, we compute the asymmetric distance described in equation (9). Substituting these back in the baseline gravity equation (8) and allowing for a differential effect of digital and non-digital skills, we obtain the following specification:

$$m_{\overrightarrow{ij}t} = \exp\left(A + \tau_{it} + \tau_{jt} + \beta \log v_{jt} + \alpha(1-\beta)\log W_{jt} + \beta \log\left(\frac{N_{jt}}{N_{it}}\right) - \gamma_D(1 - \beta)D_{\overrightarrow{ij}}^{D} - \gamma_N(1-\beta)D_{\overrightarrow{ij}}^{N}\right) e^{\varepsilon_{ijt}} \tag{11}$$

3. Data

3.1 Occupation mobility rates

Our estimation approach relies on observing aggregate flows across occupations. We use the Irish Labour Force Survey (I-LFS) microdata to measure the flows of workers across occupations. I-LFS is a quarterly survey of approximately 30,000 households by the Central Statistics Office of Ireland, and is the main source of labour statistics in Ireland. I-LFS provides detailed information on respondents' occupation, gender, sex, educational attainment, and other characteristics. The I-LFS follows a rotating sampling structure, which means respondents are included in the survey for up to five consecutive quarters, with one-fifth of the sample being replaced each quarter. Given this sampling design, a maximum of 80% of respondents are potentially matched across consecutive quarters. In practice, the proportion of respondents that are matched could be lower due to the fact that the I-LFS is an address-based survey.[3] In 2016, modifications were made to the sampling procedure to select the target population; however, there was no change in the survey methodology.[4] The key advantage of I-LFS lies in its explicit design to represent the entire Irish population at any given time. As a result, the occupational flows derived from this dataset accurately reflect the actual labour market dynamics.

[3] See https://www.cso.ie/en/methods/labourmarket/labourforcesurvey/ for more detail on the construction of the I-LFS data.
[4] See ucd.ie/issda/data/lfs for more information on sampling procedure.

A key benefit of I-LFS is that it follows the International Standard Classification of Occupations (ISCO)-08 coding techniques to accurately define an occupation. These standardised coding techniques allow us to measure the flows according to international standards. The I-LFS started following the ISCO-08 coding structure from the year 2007 onwards. Therefore, to take advantage of the standardised occupation coding, we use the data from 2007 until the end of 2023 for our empirical analysis. Our sample is restricted to respondents aged 15 to 74 years and who are not in the Armed Forces related occupations. We focus on the flows between occupations at the ISCO-08 2-digit level. A higher level (1-digit level) creates occupation groups that are too coarse, whereas more detailed occupation groups (3-digit level) result in aggregation that is too fine-grained to capture substantial flows of workers between each occupation pair (Cortes and Gallipoli, 2018).[5] Table A.1 in the appendix provides the list of the occupations included in our analysis. We first construct the quarterly flows of workers at 2-digit level using the data of respondents who are observed across consecutive quarters. A respondent is defined as a switcher from occupation i to occupation j if the respondent was employed in occupation i at time $t-1$ and employed in occupation j at quarter t. We aggregate the flows of workers at the annual level to obtain our measure of flows $M_{\vec{ij}t}$, which is then used to compute $m_{\vec{ij}t}$ according to equation (7).

The transition patterns reveal that a large share of workers remain within the same occupation over time, indicating limited overall occupational mobility (Figure A.1 presents the aggregate transition probability between occupations over the period 2007-2023). However, mobility differs substantially across occupations, for example, Labourers in Mining, Construction, Manufacturing and Transport occupation exhibit the highest transition rates out of their occupation, with circa 30% of workers moving to a different occupation. In contrast, occupations such as Teaching Professionals and Business and Administration Professionals experience the lowest transitions rates of 3-5% approximately. More broadly, the data suggest that occupational mobility tends to higher in relatively lower skill occupations, whereas higher skill professional occupations display lower mobility over time.

3.2 Occupations skill dissimilarity

To develop our measure of skill mismatch between occupation pairs, we draw on previous literature and employ a task-based approach, which characterises occupations using a vector of skill or task characteristics (Autor et. al., 2024; Webb, 2019; Feltan et al., 2021; Acemoglu & Restrepo, 2018; *inter alia*). We use the European Skills, Competences, Qualifications, and Occupations (ESCO) classification to construct a vector of skill content of occupations.[6] Developed and maintained by the European Commission, ESCO is designed to align with the European labour market and serves as the European counterpart to the US based O*NET system. ESCO provides detailed information on the skills required for each occupation,

[5] See ISCO-08 document to obtain more information on the occupation structure.
[6] We use the ESCO version v1.2.0 released in may 2024.

structured according to the ISCO-08 occupation classification. It categorises occupational skill requirements along two broad dimensions: the skills utilised by workers in a specific occupation and the education and knowledge required by that role. The skill vector is further categorised at various levels of aggregation. For a given occupation i, we focus on the vector of skill characteristics $O_{i_n} = (s_1, .., s_n)$, at the ESCO 3-digit skill level, where $n = 404$ represents the number of required skills at the 3-digit level of granularity.

ESCO provides binary information that means whether a particular skill k is required in that occupation i or not. Using the vector of skill requirements for each occupation, we construct our measure of asymmetric distance for total skill mismatch, $D_{\overrightarrow{ij}}$, as well as for digital and non-digital skill mismatches, $D_{\overrightarrow{ij}}^{D}$ and $D_{\overrightarrow{ij}}^{N}$, respectively. Panel A in Table 1 provides summary statistics for the total-, digital-, and non-digital asymmetric skill mismatch, and Panel B presents examples of asymmetric skill mismatch for three selected occupation pairs – Information and Communications Technology Professionals, General and Keyboard Clerks, Science and Engineering Professionals – highlighting variations in skill distance across different occupational transitions.

4. Results

This section investigates the quantitative importance of skill mismatches in skill content across occupations in shaping occupational mobility patterns. We employ the PPML estimator to estimate the models in equations (8) and (11). Table 2 reports the results for the effect of skill mismatch on the occupation transition probability. Columns (1) and (2) show the results for the total skill mismatch and skill mismatches disaggregated by skill-type between digital and non-digital skills, computed according to an asymmetric distance measure, respectively. Columns (3) and (4) include vacancy rate and average wage as controls (from 2019 to 2023 only). Specifications in all columns include the natural log of the relative size between the source and destination occupations, as defined in equation (7). Additionally, across all specifications, we control for source-time and destination-time fixed effects. Robust standard errors are clustered at the source-destination pair.

Column (1) records the significant effect of the baseline measure of skill mismatch on occupation transition probability. The coefficient estimate of -0.034 indicates that a unit increase in the skill mismatch between occupation pairs is associated with approximately a 3.34% decrease in the transition probability, where a unit corresponds to a skill required in the destination occupation that is not required in the origin occupation, with the skill mismatch measure having a mean of 73.6. Column (2) models the heterogeneity in skill mismatch based on skill type, decomposing total mismatch into digital and non-digital mismatches. Both digital and non-digital skill mismatches significantly decrease the probability of occupational transition, with one additional mismatched digital skill associated with an 11.66% decrease and one additional mismatched non-digital skill associated with a 2.57% decrease in transition probability. As our mismatch measures are constructed as raw counts of mismatched skills, the estimated coefficients represent the marginal effect of one additional mismatched skill in each domain. This result suggests that disaggregating the skill mismatch by skill-type reveals that digital skill mismatch exerts a stronger marginal effect on occupational transitions than non-digital skill mismatch, underscoring the importance of digital competencies in shaping occupational mobility patterns.

In columns (3) and (4), we report the results with the additional labour market control variables – vacancy rate and log wage in the destination occupation, which are labour market factors that influence an individual's decision to change occupations.[7] The effects of skill mismatch remain similar to those in columns (1) and (2), with digital skill mismatch presenting a stronger negative effect on occupational mobility than non-digital mismatches. The effect of vacancy rate is positive across all specifications, indicating that when more job opportunities are available, there is an increase in occupational mobility. This result is expected as the prior literature on economic downturn suggests that mobility declined in periods of low economic activity and increased in periods of better economic activity (Modestino et al., 2020). Additionally, the effect of relative occupation size is positive on occupation mobility, indicating workers are more likely to transition into larger occupations. Interestingly, we find a negative effect of the wage variable on the mobility. The findings are contrary to the classical Roy model, which argues that workers choose the job in which they gain the highest wages (Taber and Vejlin, 2020). Potential reasons for the negative effect could be that occupations that provide higher wages in general are more technical and require new skills or involve higher entry costs (Blair et al., 2021; Autor and Thompson, 2025). This creates a barrier for workers who lack the required skills, which could deter mobility. Notwithstanding that, all else equal, higher wages should make an occupation attractive.

Our findings highlight two critical aspects of the labour market. First, the significance of digital skills in the working of labour markets, especially related to job polarisation and new technologies. Prior literature has highlighted how technological advancements disproportionately affect middle-skill occupations, leading to bifurcation in job opportunities (see, for example, Acemoglu and Restrepo, (2020); Goos et al., (2014); Michaels et al., (2014); Autor and Dorn, (2013)). The stronger negative effect of digital skills mismatch underscores the pivotal role of technological competencies in job transitions. The results resonate with that literature in a way that reveals how an higher demand for skills has raised the transition costs by requiring additional efforts from workers to acquire technological proficiency to remain competitive. As a result, the social costs associated with frictions in labour markets also increase due to technological advancements. Second, the significant effect of the asymmetric distance measure highlights the importance of task-specific human capital. The findings show that the cost of transitioning is not uniform and depends on the direction of

[7] We estimate the baseline specification on the restricted 2019–2023 sample, and it produces coefficients very similar to the main results columns (3) and (4) in Table 2, suggesting that the additional controls do not drive the main findings.

the move, increasing with the requirement to develop new skills (Gathmann and Schonberg, 2010). This contrasts with symmetric distance measures, which implicitly assume that the cost of moving between two occupations is identical in both directions. It underscores the importance of targeted training programs that address specific skill gaps to enhance mobility and reduce mismatches.

4.1. Occupations entry and exit costs

There exists heterogeneity in bilateral mobility costs across occupation pairs due to heterogeneity in skill mismatch. To better understand the role of specific occupations in the mobility network we collapse the estimated bilateral coefficients from columns (2) of Table 2, interpreted as measure of bilateral transition costs, by source and destination occupations to obtain average entry and exit costs due to digital and non-digital skill mismatch for each occupation. Importantly, these costs capture only the component of occupational transitions attributable to skill mismatch, as time-invariant occupation-specific preferences and amenities are absorbed by the fixed effects in the regression framework. Panels A and B in Figure 1 show the average cost estimates for each occupation, both as a source and a destination, due to digital and non-digital skill mismatch.[8] Higher cost for source occupation suggests workers in that occupation face greater difficulty transitioning to other occupations due to digital skill mismatch, i.e., higher exit costs. Conversely, a higher cost for a destination occupation implies it is less accessible from other occupations in digital mismatch terms, i.e., higher entry costs.

The figure shows a strong negative relation between average mobility costs when an occupation is a source compared to when it is a destination. This implies that occupations that are difficult to leave tend to be easy to enter, and conversely, occupations that are hard to enter tend to be easier to leave. Specifically, occupations with low entry costs and high exit costs – such as Cleaners and Helpers and Food preparation assistants – are those that require generic or broadly applicable skills. As a result, these roles are relatively accessible within the occupational network, drawing in workers from a wide range of backgrounds. However, workers in these occupations find it difficult to transition out, as the skills acquired are not transferable or sufficiently applicable to occupations that demand more advanced competencies. This asymmetry creates a form of occupational bottleneck, where certain roles act as absorbing states. On the other hand, difficult to enter and easy to leave occupations such as Science and Engineering Professionals and ICT Professionals may function as gateways within the occupation network, offering strong potential for mobility once entry barriers are overcome.

[8] Figures B.1 and B.2 present the average bilateral mobility costs for each occupation pair, thereby offering a granular depiction of how distinct dimensions of skill mismatch shape the structure of occupational mobility across the labour market.

These findings have important implications for policymakers as they highlight the need to identify and monitor bottleneck occupations where workers may face long term immobility due to a lack of skills. The findings also point to the importance of targeted reskilling policies, particularly for workers in occupations with high exit costs and limited skill transferability, especially those involving digital skills. Additionally, the asymmetric structure of mobility costs suggests that policies aimed at increasing mobility must account not just for entry barriers into high skill occupations, but also for hidden barriers to exit from easily accessible roles.

4.2. Dynamic skill mismatch

Until now, our estimations have employed a static measure of skill mismatch, $D_{\overrightarrow{ij}}$, where the degree of mismatch between the occupations remains constant over time. However, in reality, occupational skill requirements evolve as new technologies emerge and certain skills become obsolete (Braxton and Taska, 2023). Deming and Noray (2020) find that most occupations experience changes in skill requirements within the same occupation over a decade, with the largest shifts occurring in STEM-related occupations. This dynamic nature of skill demand implies that the degree of mismatch between occupations is not fixed but rather fluctuates over time. However, our static measure does not capture these temporal variations in occupational skill content. The existing literature on skill mismatch has predominantly relied on a static measure (e.g. Cortes and Gallipoli, 2018; Neffke et al., 2024; Gathmann and Schonberg, 2010), largely due to data limitations in tracking occupational skill changes over time. To address this gap, we construct a dynamic skill mismatch measure $D_{\overrightarrow{ij}t}$, which incorporates changes in skill requirements across occupations and over time. Specifically, we allow the set of required skills in each occupation to update annually, reflecting the continuous adaptation of occupations to technological advancements.

To construct the alternative dynamic mismatch measure, we utilise online job vacancy data from Cedefop and Eurostat's Skills OVATE.[9] This dataset collects and aggregates comprehensive data for millions of online job postings across thousands of sources, extracting key characteristics from free text job postings such as occupation, location, year, and required skills. Each job posting is classified using the ISCO-08 classification system, with data reported monthly and pooled annually to avoid duplication. Skill requirements in job postings are categorised according to the ESCO skill dictionary at 3-digit level, allowing us to systematically track occupational skill requirements over time. We extract the set of required skills for each occupation in each year (as discussed in section 3.2) to compute the dynamic asymmetric distance between occupations as defined in equation (9). By allowing skill requirements to change over time, this measure accounts for both new skill adoption and potential obsolescence in both source and destination occupations. To gauge the extent of these dynamics, we compute the correlation between the dynamic mismatch measure for each year

[9] See https://www.cedefop.europa.eu/en/tools/skills-online-vacancies for more details on this data source

and the baseline static measure. The correlation is high and stable over time – around 0.94 for digital skills and 0.9 for non-digital skills – suggesting that the relative skill distance between occupations changes moderately over the sample period. A caveat of the online job postings data is that the data is available from 2018. As a result, we estimate the specifications in equations (8) and (11) using the dynamic mismatch measure for the post-2017 period.

Table 3 reports the results for the effect of dynamic skill mismatch on occupational mobility. Consistent with our previous findings, the coefficient on our asymmetric distance measure shows a negative effect on occupational mobility. The results closely follow the pattern observed in Table 2, reinforcing the robustness of our findings. Column (1) of Table 3 shows that the total mismatch is associated with 4.11% decline in occupational mobility. When disaggregating by skill type, we find that a one unit increase in digital skill mismatch significantly reduces the probability of occupational transition by 12.19%, while non-digital skills mismatch decreases mobility by only 2.96%. These results highlight the particularly restrictive nature of digital skill mismatches, further underscoring the role of technological adaptation in shaping labour market transitions.

4.3. Accounting for Employment Levels

The results in Table 2 imply that skill mismatch is negatively associated with occupational mobility, while making a strong assumption that both employed and unemployed occupation i workers have an equal chance of transitioning to occupation j. However, it is not obvious ex ante which group will have the higher transition probability. Unemployed workers have more time to search and to make up any skill deficiencies required for the new occupation; on the other hand, it might be easier to acquire new skills when currently employed and to signal productivity to a prospective employer. To explore this, we interact the skill mismatch measure with the unemployment rate in the source occupation. When the unemployment rate is high, workers may become less selective, potentially expanding their search to more dissimilar occupations. A positive interaction between skill distance and the unemployment rate would reflect adaptive behaviour, suggesting that the mismatch becomes less binding under slack. Alternatively, unemployed workers may face greater constraints, such as limited access to retraining, making transitions to distant occupations more difficult, implying that slack exacerbates the skill mismatch barrier, resulting in a negative coefficient on the interaction term.

Understanding how the effect of skill mismatch varies with employment status has direct implications for the design of labour-market policies, particularly in the context of accelerating technological change. If mismatch becomes more binding when unemployment is high, this will imply that unemployed workers are pushed out of their occupations but are constrained in their ability to switch fields – possibly due to lack of training or prior experience. Here, upskilling and retraining programs become crucial, particularly those that offer modular, occupation-specific training tailored to distant but growing occupations. For employed workers, if skill mismatch deters transitions due to opportunity costs or risk aversion, policies that promote on-the-job training or encourage proactive reskilling can help pre-empt displacement.

Table 4 presents the estimation results, which incorporate the unemployment rate in the source occupation. The unemployment rate in the source occupation is positively and significantly associated with transition probabilities in the full sample (columns (1) and (2)). This suggests that occupations with a larger number of unemployed workers tend to exhibit higher outflows. The interaction terms reveal important differences by skill type. The negative coefficient on the interaction between unemployment and digital skill mismatch indicates that the adverse effect of digital skill gaps on occupational transitions becomes more pronounced as unemployment in the source occupation rises. In contrast, the positive interaction between unemployment and non-digital skill mismatch implies that the effect of non-digital skill gaps on mobility weakens under higher unemployment. When we add additional labour market controls (columns (3) and (4)), the coefficient on the unemployment rate turns negative, indicating that – conditional on destination demand – higher unemployment is associated with lower transition probability. Importantly, the sign of interaction terms remains consistent, reinforcing the interpretation that digital skill mismatches constitute a binding constraint on occupational mobility, and that this constraint intensifies in periods of labour market slack when workers face greater competition and fewer opportunities to acquire or signal advance competencies.

These findings reflect the underlying trade-off between search effort and employability. While unemployed workers may devote more time to job search or invest in acquiring new skills, they may also face greater barriers to transition. The negative coefficient suggests that higher unemployment may be associated with deeper frictions, such as skill mismatches or weaker productivity signalling. The findings are consistent with the idea that mobility is often higher in thriving segments of the economy, where matching frictions are lower and search costs are reduced (Bhuller et al., 2023). The interaction results suggest that these frictions are particularly pronounced for digital skill gaps, where heightened competition and stricter screening reduce opportunities for workers to transition into roles for which they do not fully meet digital skill requirements. s. It is reasonable to assume that the rapid pace of technological change necessitates constant on-the-job acquisition of digital skills at the knowledge frontier – learning opportunities that remain largely inaccessible to unemployed workers. Non-digital gaps may be easier to overcome, possibly because they rely more on general skills or shorter adjustment periods. This asymmetry underlines the need for targeted upskilling initiatives that differentiate between the nature of the skills in short supply.

5. Robustness and Exploring heterogeneity

5.1 Expertise measure

In our baseline estimations (Table 2), the measure of skill mismatch, $D_{\vec{\imath}\vec{\jmath}}$, provides valuable insights into the mismatch across occupations; however, it assumes all skills and knowledge are homogeneous within and across occupations. Human capital is task specific and not all skills are equally important (Gathmann and Schonberg, 2010). Consequently, relying solely on a measure that assumes homogeneous relevance of skills may overlook important differences in the significance of skills. To address this, we construct an expertise-adjusted asymmetric skill mismatch measure that weights skills by their relative importance. Specifically, to construct an expertise of a skill within an occupation, we draw on the approach proposed by Autor and Thompson (2025), who developed a language-based measure of task expertise. This measure quantifies the level of expertise associated with each task based on linguistic features of task descriptions.

To construct the expertise-adjusted skill mismatch measure, we first develop task level expertise score following Autor and Thompson (2025). This method is rooted in the Efficient Coding Hypothesis (Barlow, 1961), which posits that expert vocabulary emerges in professional domains as a means of effectively communicating complex ideas. In contrast, commonplace words are those that are used more often when the idea is communicated to a non-specialist audience across multiple domains.

According to Autor and Thompson (2025), occupations involving a higher use of expert language are more resistant to technology substitution because they rely on tacit knowledge and specialised communication that current technological systems struggle to replicate. To quantify this, we compute the expertise level of each task using the text of task descriptions from the ESCO database. Each word in the task description is assigned an expertise score using data from SUBTLEX, a corpus of English word frequencies. Words with low frequency and low entropy (i.e., strongly associated with a specific domain) are classified as more expert. To ensure robustness, the measure is corrected for semantic outliers using the Dale-Chall readability index, which identifies words familiar to the general population. We then winsorise words deemed too simple according to the Dale-Chall index to avoid misclassifying them as experts, and lemmatise and drop the stop words. Then, the final task-level expertise score is computed as the average expertise score of the remaining words in the task description. We then use these task level expertise scores in the asymmetric mismatch measure by weighting each skill in an occupation according to its expertise level. This yields an expertise-adjusted skill mismatch measure that allows for testing whether transitions between occupations are more constrained when the skills mismatch is more cognitively specialised.

Table 5 reports the results on the effect of expertise-adjusted skill mismatch on occupational mobility. As this measure reweights missing skills by their associated expertise levels, its units differ from the baseline count-based mismatch measure; therefore, the coefficient magnitudes are not directly comparable to those reported in Table 2. Nevertheless, the coefficient estimates confirm our baseline findings, with even stronger coefficients than those obtained using the unadjusted measure. Column (1) shows that expertise-adjusted skill mismatch is associated 6.76% decline in the probability of transition, a larger effect than observed in Table 2. We also find stronger negative effects when disaggregating the mismatch by skill type. As shown in column (2), expertise-adjusted digital and non-digital skill mismatches are associated with a 22.35% and 5.15% decline in occupation mobility. These results suggest that the absence of specialised skills poses a greater barrier to occupational mobility than the absence of lower expertise skills.

5.2 By groups

Up to now, we have focused our empirical analysis on the effect of skill mismatch at the aggregate labour market level. However, the effects of skill mismatch could vary across all worker groups. Guvenen et al. (2020) show that older workers are less likely to change occupation relative to younger cohorts, and the effects of skill mismatch differ conditional on education qualification. Using a network of occupations, Knicker et al. (2024) find different transition patterns across gender and age groups. Deming (2023) shows that the labour market outcomes differ between college-educated and non-college-educated cohorts. Differences in worker characteristics, such as gender, age, or education, may lead to varying levels of sensitivity to skill mismatch.

To explore these potential differences, we extend our analysis by examining the heterogeneity in effects across different groups based on gender, age, and education level. Each group is divided into two categories: gender – male and female; education – college educated (bachelor's degree or higher) and non-college-educated (high school or lower); and age – above 35 years and below 35 years. We modify our baseline specification (equations (8) and (11)) by interacting the skill mismatch measure with the proportion of each demographic group in the source occupation. Specifically, we run separate regressions where we interact the mismatch measure with the share of male workers, the share of college educated workers, and the share of workers aged over 35 in the source occupation. This approach allows us to test whether the probability of occupational transition varies depending on the demographic composition of the origin occupation. The results are presented in Table 6.

Male versus Female. Columns (1) and (2) present the results by gender composition of the source occupation. In both specifications, the coefficient on the interaction term between the proportion of male workers and skill mismatch is small and statistically insignificant. This suggests that the sensitivity of occupational mobility to mismatch does not differ systematically between male and female dominated occupations. We also find a negative and statistically significant coefficient on the proportion of male workers in the source occupation, suggesting that male dominated occupations exhibit lower occupational mobility compared to female dominated. A potential explanation could be that male dominated occupations are more specialised or may have fewer alternative occupations, thereby limiting mobility

(Brussevich, 2018). More broadly, these results suggest that gender composition does not significantly alter the extent to which skill mismatch constrains occupational mobility.

College graduates. Another critical dimension is the education level of the workers. We segregate our sample into two groups: individuals who acquired third-level of education or higher, i.e. the college-educated cohort, and those who did not attend college, i.e. non-college-educated cohort. Columns (3) and (4) present the results. The interaction term between the proportion of college educated workers and total skill mismatch is insignificant in column (3). However, when mismatch is disaggregated by skill type, the interaction coefficient is positive for digital skill mismatch and negative for non-digital skill mismatch. This implies that educated workers are better able to overcome skill mismatches in digital skills, potentially due to broader and more transferable skill sets, greater adaptability to new roles, and better access to a professional network that reflects productivity ability. Alternatively, higher education may enhance the ability to learn and adapt to new digital tasks, reducing the effective cost of digital skill adjustment. The coefficient on the proportion of college educated workers is negative in both specifications, which may reflect several mechanisms. For example, highly educated jobs may be more desirable, offer high wages, or have better career progression, which reduces mobility to other occupations. In addition, many high skill occupations are highly specialised, limiting the number of closely related alternative occupations (Forsythe, 2019; Hämäläinen, 2019). Overall, the results indicate that college educated workers are less mobile on average, but when they do move, they face fewer barriers from digital skill mismatch compared to their less educated counterparts.

Younger versus Older workers. Finally, we examine heterogeneity by age, dividing the sample between workers aged 35 or below (younger cohort) and above 35 (older cohort). Columns (5) and (6) present the results. In both specifications, the coefficients on the proportion of younger workers and the interaction between the proportion of younger workers and skill mismatch are statistically insignificant. This indicates no systematic difference in either baseline mobility or mismatch sensitivity between younger and older worker cohorts. The absence of statistically significant results may reflect several potential offsetting mechanisms at play. For example, younger workers benefiting from greater adaptability and retraining capabilities, while older workers draw on accumulated experience and professional networks. These opposing forces may balance out, leading to similar overall mobility responses to skill mismatch across age groups (Brynjolfsson et al., 2025).

5.3 Digital skill complexity

To examine whether the effect of digital skill mismatch varies with the complexity of digital competencies, we decompose digital skills into three categories reflecting increasing levels of digital intensity. Following ESCO classification, digital skills are grouped into user, practitioner, and developer levels. User-level skills correspond to basic digital literacy and routine use of digital tools, practitioner-level skills involve applied technical competencies in operating and adapting digital systems, while developer-level skills encompass advanced capabilities such as programming, system design, and maintenance. Using the ESCO skill database, we identify digital skills and assign them to these three levels based on the ESCO digital skills taxonomy. For each occupation, we then determine the dominant digital skill level based on the distribution of digital skills. Occupations with very limited digital skill content are classified separately as non-digital.

To incorporate this heterogeneity into the gravity specification, we introduce a set of indicator variables capturing transitions into occupations characterized by different digital skill levels. Specifically, we define four dummy variables, δ_{ij}^{NS}, δ_{ij}^{U}, δ_{ij}^{P} and δ_{ij}^{DE} , which take the value one if the destination occupation j is classified as non-digital level, user-level, practitioner-level, or developer-level in terms of digital skill requirements, respectively, and zero otherwise. These indicators allow us to identify whether mobility frictions differ depending on the level of digital expertise required in the destination occupation.

Table 7 shows the results. The findings show that transitions into occupations requiring developer-level digital skills from occupations that do not require such advanced competencies are associated with significantly larger mobility frictions. By contrast, transitions across user-level and practitioner-level occupations display smaller and statistically insignificant effects. This potentially imply that basic and intermediate digital competencies are relatively transferable across occupations, whereas movements into advanced digital roles involve substantially higher adjustment costs. These findings are consistent with the idea that advanced digital skills are more specialized and require greater investments in learning and adaptation, thereby limiting mobility into occupations that rely heavily on such competencies.

5.4 Temporal variation

To examine whether the effect of skill mismatch on occupational mobility has changed over time, we estimate our main specification in equations (8) and (11) for each year separately. This approach allows us to assess whether the relationship between skill mismatch and occupational transitions is stable over time or varies in response to broader labour market trends and technological advancements. Panel A in Figure 2, using equation (8), presents the estimated coefficients for the effect of total skill mismatch on the transition probability across years. We also distinguish between digital and non-digital skill mismatches to evaluate potential shifts in the importance of different skill dimensions, presented in panels B and C in Figure 2 (equation (11)). The coefficients are plotted with a 95% confidence interval.

The results indicate that the negative effect of total skill mismatch persists across the years (Panel A), though its magnitude fluctuates over time. The estimated coefficients show significant variation across the years, broadly aligning with the economic cycle. In Panel B, the estimated coefficients for digital skills mismatch consistently exhibit a strong negative effect on occupational transitions, with no significant variation over time. This suggests that digital skill requirements have remained a persistent barrier to mobility, reinforcing our earlier finding that workers lacking digital competencies face particular structural challenges in transitioning to new occupations. In contrast, Panel C shows that the impact of non-digital skill mismatch varies significantly across years, likely reflecting how the ease of occupation transition is affected by the state of the business cycle.

6. Conclusion

This study investigates the role of skill mismatch as a barrier to occupational mobility in Ireland, with a particular focus on digital skills in an increasingly technology-driven labour market. Building on a task-based framework of human capital transferability (Gathmann and Schonberg, 2010; Cortes and Gallipoli, 2018), we construct an asymmetric measure of skill dissimilarity between occupations using ESCO data, separately identifying digital and non-digital skill mismatches. We estimate a hybrid gravity-matching model on Irish LFS data from 2007 to 2023, and find that skill mismatches significantly reduce occupational transition probabilities, with digital skills mismatches exerting stronger negative effects than non-digital mismatches.

Our findings show that mobility costs are not only substantial and asymmetric, but transitions are also particularly costly when the destination occupation demands digital competencies absent from the source occupation. The stronger effects for digital mismatches are consistent with evidence that such skills are increasingly complementary to a broad range of tasks (Deming & Noray, 2020; Autor & Thompson, 2025), making their absence especially constraining. Our entry-exit cost analysis further reveals that occupations that are easy to enter tend to be difficult to leave, creating bottlenecks where skills are broadly applicable for entry but have limited transferability for upward or lateral mobility. These roles risk trapping workers in low-mobility segments of the labour market without targeted upgrading opportunities.

Labour market conditions and worker characteristics shape these effects in important ways. High unemployment in the source occupation is associated with higher transition probabilities to other occupations, likely reflecting intensified search effort. However, once demand in the destination occupation is controlled for, the coefficient turns negative reflecting reduced mobility, consistent with deeper structural frictions. Also, under slack conditions, digital skill mismatches become more binding, suggesting unemployed workers face greater difficulties in transition due to a lack of digital skills. Furthermore, heterogeneity analysis by demographic characteristics shows statistically significant differences only by the education level of the workers. The results show that college educated workers are less mobile on average, although face fewer barriers due to digital skill mismatches when transitioning into a new role. However, age and gender differences are negligible.

From a policy perspective, these findings highlight the importance of addressing barriers created by digital skill mismatches, which consistently emerge as the most binding constraint on occupational mobility. Across both the static and dynamic specifications, digital skill gaps reduce transition probabilities substantially more than non-digital mismatches, indicating that policies aimed at strengthening digital competencies – particularly those associated with more specialised tasks – are likely to have the greatest impact in facilitating mobility. The analysis of digital skill complexity further suggests that mobility barriers are concentrated in transitions into developer-level digital occupations, where the required skills are highly specialised and involve larger learning costs. This implies that training policies should prioritise advanced digital capabilities rather than basic digital literacy alone.

The entry-exit cost analysis also identifies occupational bottlenecks, such as Cleaners, Helpers, and Food preparation assistants occupational group, where workers can enter relatively easily but face significant barriers when attempting to transition to other occupations due to limited skill transferability. Policies that improve pathways from these roles into occupations with stronger career progression – through targeted reskilling or modular digital training – may therefore be particularly effective. Our results further show that digital skill mismatches become more binding when unemployment is high, suggesting that workers displaced from declining occupations face additional constraints when attempting to transition into digitally intensive roles. This highlights the importance of facilitating occupational transitions, especially during periods of labour market slack, by improving access to training and skill acquisition opportunities. By aligning skill development policies with the evolving task demands of occupations, governments can promote more inclusive mobility and strengthen labour market resilience in the face of technological change. In addition, the methodological framework developed in this study can serve as a practical tool for policymakers to regularly monitor developments in occupational skill mismatches and mobility patterns.

Our study contributes to the broader literature on labour market polarisation, human capital transferability, and technological change by providing empirical evidence on how skill mismatches shape worker mobility patterns in an environment of shifting occupational demands. Future research could extend these results by linking occupation level skill mismatch to firm level hiring practices, exploring the role of informal and workplace-based learning in mitigating digital skill gaps, and tracking the long-run career trajectories of workers in occupational bottlenecks. As the pace of technological change accelerates, the ability of workers to acquire and update digital competencies will be a key determinant of both individual career resilience and aggregate labour market adaptability. Without targeted policies to address asymmetric and group-specific barriers, skill mismatches – particularly in digital domains – risk entrenching inequality and slowing efficient reallocation in the future of work.

Table 1: Summary statistics and examples of asymmetric skill mismatch

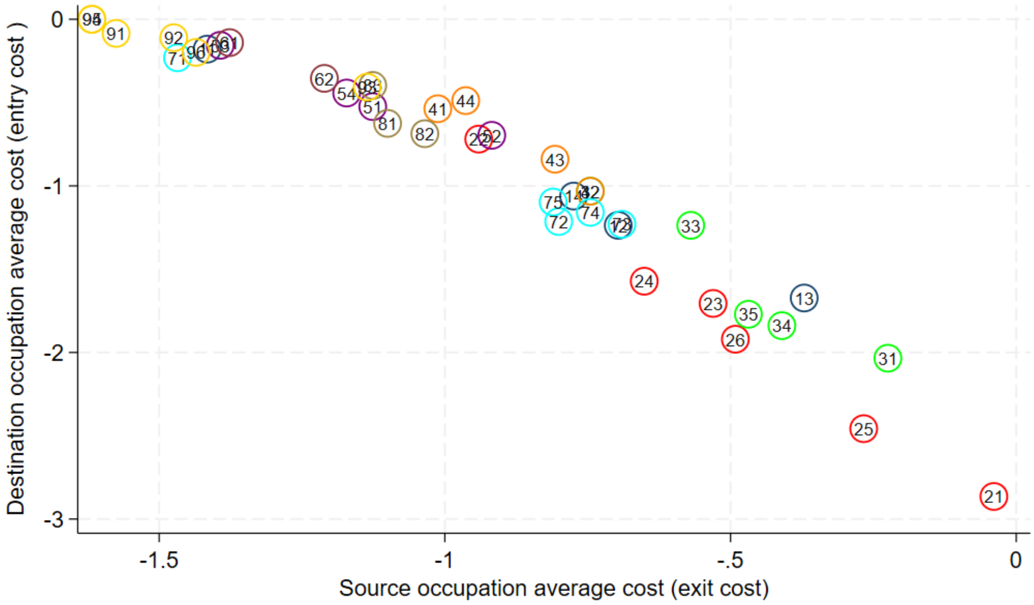
		$D_{\vec{ij}}$	$D_{\vec{ij}}^{D}$	$D_{\vec{ij}}^{N}$
Panel A				
Mean		73.58	7.45	66.12
Standard deviation		49.48	6.96	44.73
Panel B				
Source Occupation	*Destination Occupation*			
ICT Professionals	G&K Clerks	12	1	11
G&K Clerks	ICT Professionals	107	22	85
S&E Professionals	G&K Clerks	5	0	5
G&K Clerks	S&E Professionals	251	20	231
S&E Professionals	ICT Professionals	10	2	8
ICT Professionals	S&E Professionals	161	7	154

Notes: $D_{\vec{ij}}$=Total Skill mismatch; $D_{\vec{ij}}^{D}$= Digital skill mismatch; $D_{\vec{ij}}^{N}$= Non-Digital skill mismatch; ICT Professionals = Information and Communications Technology Professionals; GK Clerks = General and Keyboard Clerks; S&E Professionals = Science and Engineering Professionals.

Table 2: Estimated effect of skill mismatch on occupation mobility				
	(1)	(2)	(3)	(4)
$D_{\vec{\imath\jmath}}$	-0.034***		-0.038***	
	(0.003)		(0.004)	
$D_{\vec{\imath\jmath}}^{D}$		-0.124***		-0.135***
		(0.021)		(0.025)
$D_{\vec{\imath\jmath}}^{N}$		-0.026***		-0.030***
		(0.004)		(0.004)
$\ln(N_{jt}/N_{it})$	1.163***	0.963***	0.550***	0.559***
	(0.151)	(0.154)	(0.156)	(0.158)
$\ln v_{jt}$			0.457***	0.425***
			(0.120)	(0.119)
$\ln W_{jt}$			-1.042**	-0.997**
			(0.494)	(0.497)
Source-year FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Observations	25,249	25,249	7,258	7,258

Notes. The reported estimates are PPML coefficient estimates. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A – Digital skill mismatch mobility cost by occupation



Panel B – Non-digital skill mismatch mobility cost by occupation

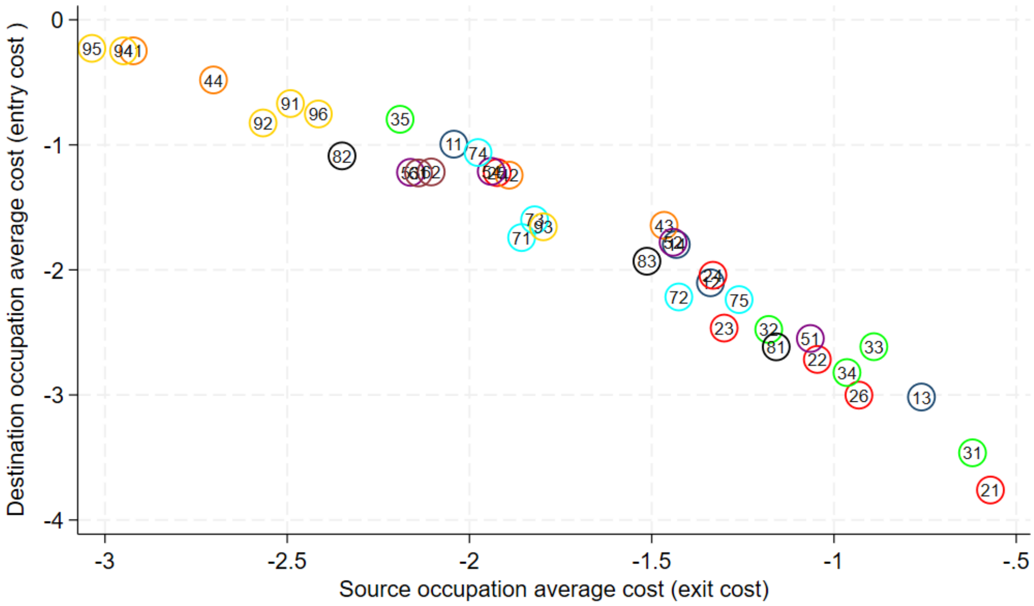


Figure 1: Average occupation mobility entry and exit costs – Digital and Non-digital skill mismatches

Notes. Refer to Table A.1 for occupation title for each occupation 2-Digit code. Additionally, occupations are grouped at the 1-digit ISCO level, with bubble colours representing their major occupational group.

Table 3: Estimated effect of dynamic skill mismatch				
	(1)	(2)	(3)	(4)
$D_{\vec{ij}t}$	-0.042***		-0.045***	
	(0.005)		(0.005)	
$D^{D}_{\vec{ij}t}$		-0.130***		-0.141***
		(0.028)		(0.029)
$D^{N}_{\vec{ij}t}$		-0.030***		-0.031***
		(0.006)		(0.006)
$\ln(N_{jt}/N_{it})$	0.700***	0.534***	0.735***	0.809***
	(0.127)	(0.104)	(0.133)	(0.137)
$\ln v_{jt}$			0.513***	0.700***
			(0.111)	(0.128)
$\ln W_{jt}$			0.182	-0.186
			(0.327)	(0.417)
Source-year FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Observations	8288	8288	6882	6882

Notes. The reported estimates are PPML coefficient estimates. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimated effect of skill mismatch – unemployment rate

	(1)	(2)	(3)	(4)
$D_{\overrightarrow{ij}}$	-0.034***		-0.035***	
	(0.003)		(0.006)	
$D^{D}_{\overrightarrow{ij}}$		-0.202***		-0.239***
		(0.036)		(0.040)
$D^{N}_{\overrightarrow{ij}}$		-0.004		-0.011
		(0.007)		(0.008)
$\ln(N_{jt}/N_{it})$	1.171***	1.154***	1.158***	1.153***
	(0.152)	(0.151)	(0.206)	(0.141)
Un_rate_{it}	0.659***	0.434*	-0.467**	-0.504**
	(0.224)	(0.232)	(0.229)	(0.214)
$D_{\overrightarrow{ij}} * Un\_rate_{it}$	0.003*		0.001	
	(0.002)		(0.002)	
$D^{D}_{\overrightarrow{ij}} * Un\_rate_{it}$		-0.021**		-0.026**
		(0.010)		(0.011)
$D^{N}_{\overrightarrow{ij}} * Un\_rate_{it}$		0.006***		0.005**
		(0.002)		(0.002)
$\ln v_{jt}$			0.244**	0.552***
			(0.123)	(0.109)
$\ln W_{jt}$			-0.622	2.059***
			(0.484)	(0.585)
Source-year FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Observations	24724	24724	7068	7068

Notes. Un_rate_{it} is the unemployment rate in the source occupation i at time t. Standard errors in parentheses. The reported estimates are PPML coefficient estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Estimated effect of expertise-adjusted skill mismatch on occupation mobility				
	(1)	(2)	(3)	(4)
$D_{\vec{\imath}\vec{\jmath}}$	-0.070***		-0.079***	
	(0.006)		(0.007)	
$D^{D}_{\vec{\imath}\vec{\jmath}}$		-0.253***		-0.278***
		(0.041)		(0.050)
$D^{N}_{\vec{\imath}\vec{\jmath}}$		-0.053***		-0.061***
		(0.007)		(0.009)
$\ln(N_{jt}/N_{it})$	1.203***	0.981***	0.565***	0.825***
	(0.152)	(0.155)	(0.157)	(0.158)
$\ln v_{jt}$			0.441***	0.322***
			(0.119)	(0.112)
$\ln W_{jt}$			-1.037**	-0.805*
			(0.494)	(0.460)
Source-year FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Observations	25,249	25,249	7,258	7,258

Notes. The reported estimates are PPML coefficient estimates. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

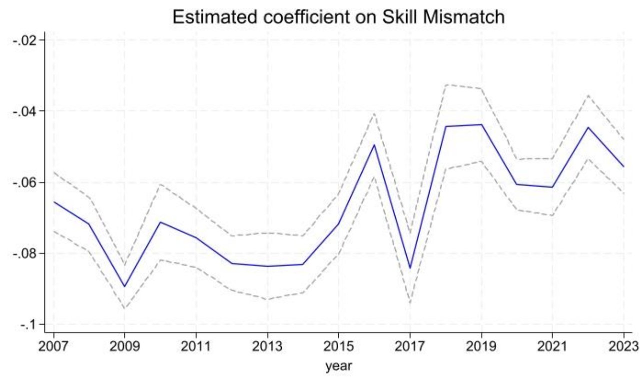
Table 6: Estimated effect of skill mismatch – Heterogeneity by group						
	(1)	(2)	(3)	(4)	(5)	(6)
	Gender		*College Educated*		*Age*	
$D_{\vec{ij}}$	-0.034***		-0.032***		-0.036***	
	(0.004)		(0.003)		(0.006)	
$D_{\vec{ij}}^{D}$		-0.124***		-0.176***		-0.113***
		(0.029)		(0.024)		(0.039)
$D_{\vec{ij}}^{N}$		-0.027***		-0.016***		-0.028***
		(0.006)		(0.004)		(0.008)
G	-3.457***	-0.043	-1.135*	-1.426**	0.382	0.016
	(1.247)	(0.595)	(0.685)	(0.669)	(1.134)	(1.330)
$G.D_{\vec{ij}}$	0.000		-0.006		0.005	
	(0.005)		(0.004)		(0.010)	
$G.D_{\vec{ij}}^{D}$		-0.000		0.134***		-0.019
		(0.028)		(0.031)		(0.062)
$G.D_{\vec{ij}}^{N}$		0.001		-0.023***		0.003
		(0.006)		(0.005)		(0.012)
Source-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,249	25,249	25,249	25,249	25,249	25,249

Notes. In columns 1 and 2, G refers to the proportion of males in the source occupation; in columns 3 and 4, G refers to the proportion of people with a college education in the source occupation; and in columns 5 and 6, G refers to the proportion of people greater than 35 years of age in the source occupation. The reported estimates are PPML coefficient estimates. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

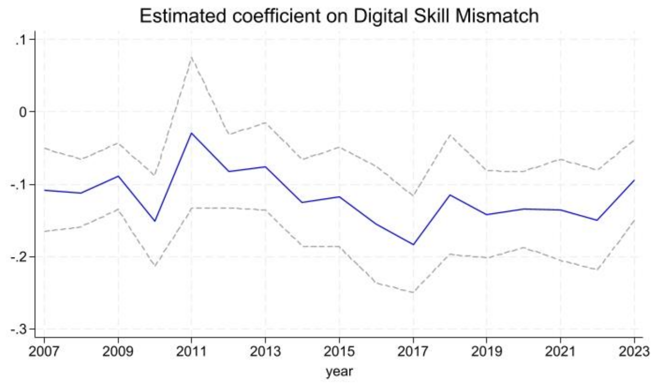
Table 7: Estimated effect of skill mismatch – by user, practitioner, and developer level		
	(1)	(2)
$D^{N}_{\vec{ij}}$	-0.033***	-0.037***
	(0.003)	(0.004)
δ^{NS}_{ij}	-0.136	-0.080
	(0.318)	(0.374)
δ^{U}_{ij}	-0.221	-0.171
	(0.166)	(0.182)
δ^{P}_{ij}	-0.003	-0.065
	(0.300)	(0.344)
δ^{DE}_{ij}	-0.810***	-0.902***
	(0.283)	(0.324)
$\ln(N_{jt}/N_{it})$	0.894***	-0.749***
	(0.171)	(0.110)
$\ln v_{jt}$		0.506***
		(0.102)
$\ln W_{jt}$		0.221
		(0.660)
Source-year FE	Yes	Yes
Destination-year FE	Yes	Yes
Observations	25,249	7,258

Notes: δ^{NS}_{ij}, δ^{U}_{ij}, δ^{P}_{ij}, and δ^{DE}_{ij} are dummy variables for occupation categorised as non-digital skill level, user-level, practitioner-level, developer-level digital skill requirement. The reported estimates are PPML coefficient estimates. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Total skill mismatch



Panel B: Digital skill mismatch



Panel C: Non-digital skill mismatch

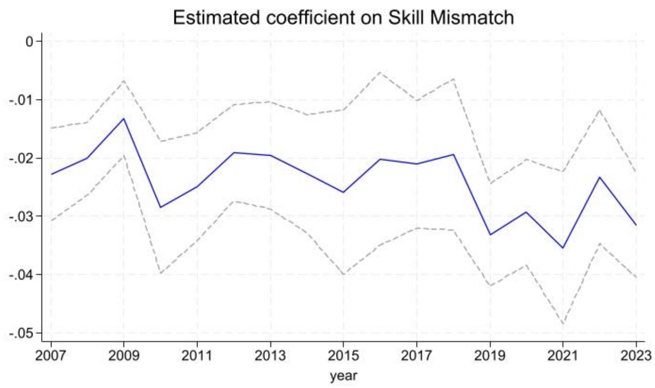


Figure 2: Temporal variation in effect of skill mismatch

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Appendix

Appendix A

Table A.1: ISCO-08 2-Digit occupation categories

2-Digit Occupation	2-Digit Code
Chief Executives, Senior Officials and Legislators	11
Administrative and Commercial Managers	12
Production and Specialized Services Managers	13
Hospitality, Retail and Other Services Managers	14
Science and Engineering Professionals	21
Health Professionals	22
Teaching Professionals	23
Business and Administration Professionals	24
Information and Communications Technology Professionals	25
Legal, Social and Cultural Professionals	26
Science and Engineering Associate Professionals	31
Health Associate Professionals	32
Business and Administration Associate Professionals	33
Legal, Social, Cultural and Related Associate Professionals	34
Information and Communications Technicians	35
General and Keyboard Clerks	41
Customer Services Clerks	42
Numerical and Material Recording Clerks	43
Other Clerical Support Workers	44
Personal Service Workers	51
Sales Workers	52
Personal Care Workers	53
Protective Services Workers	54
Market-oriented Skilled Agricultural Workers	61
Market-Oriented Skilled Forestry, Fishery and Hunting Workers	62
Building and Related Trades Workers (excluding Electricians)	71
Metal, Machinery and Related Trades Workers	72
Handicraft and Printing Workers	73
Electrical and Electronics Trades Workers	74
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	75
Stationary Plant and Machine Operators	81
Assemblers	82
Drivers and Mobile Plant Operators	83
Cleaners and Helpers	91
Agricultural, Forestry and Fishery Labourers	92
Labourers in Mining, Construction, Manufacturing and Transport	93
Food Preparation Assistants	94
Street and Related Sales and Service Workers	95
Refuse Workers and Other Elementary Workers	96

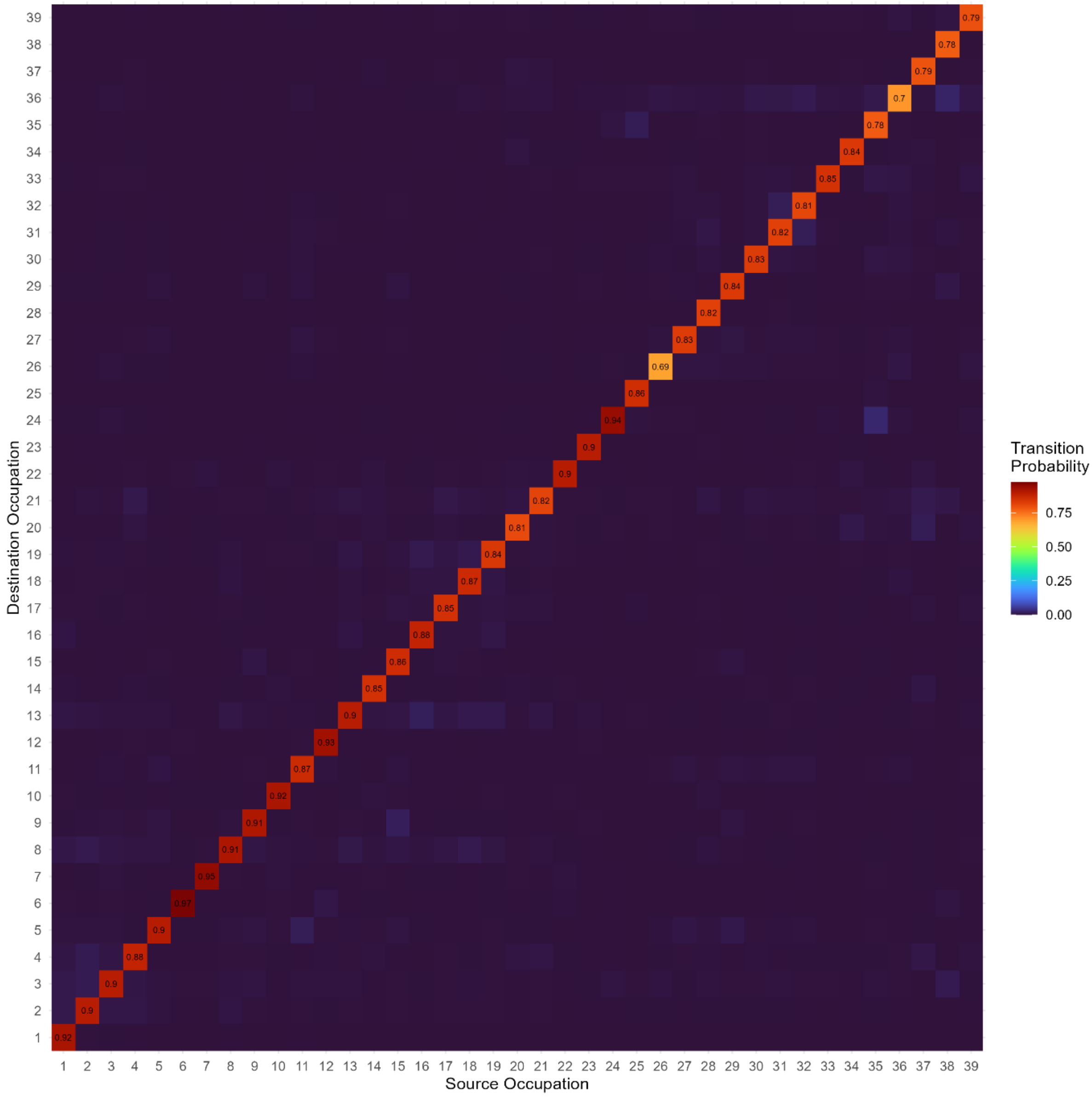

Figure A.1: Aggregate transition probability between occupation (2007-2023)

Notes: The occupation numbers refers to the following 2-Digit code: 1=11; 2=12; 3=13; 4=14; 5=21; 6=22; 7=23; 8=24; 9=25; 10=26; 11=31; 12=32; 13=33; 14=34; 15=35; 16=41; 17=42; 18=43; 19=44; 20=51; 21=52; 22=53; 23=54; 24=61; 25=62; 26=71; 27=72; 28=73; 29=74; 30=75; 31=81; 32=82; 33=83; 34=91; 35=92; 36=93; 37=94; 38=95; 39=96. Refer to Table A.1 for occupation title for each occupation 2-Digit code.

Appendix B

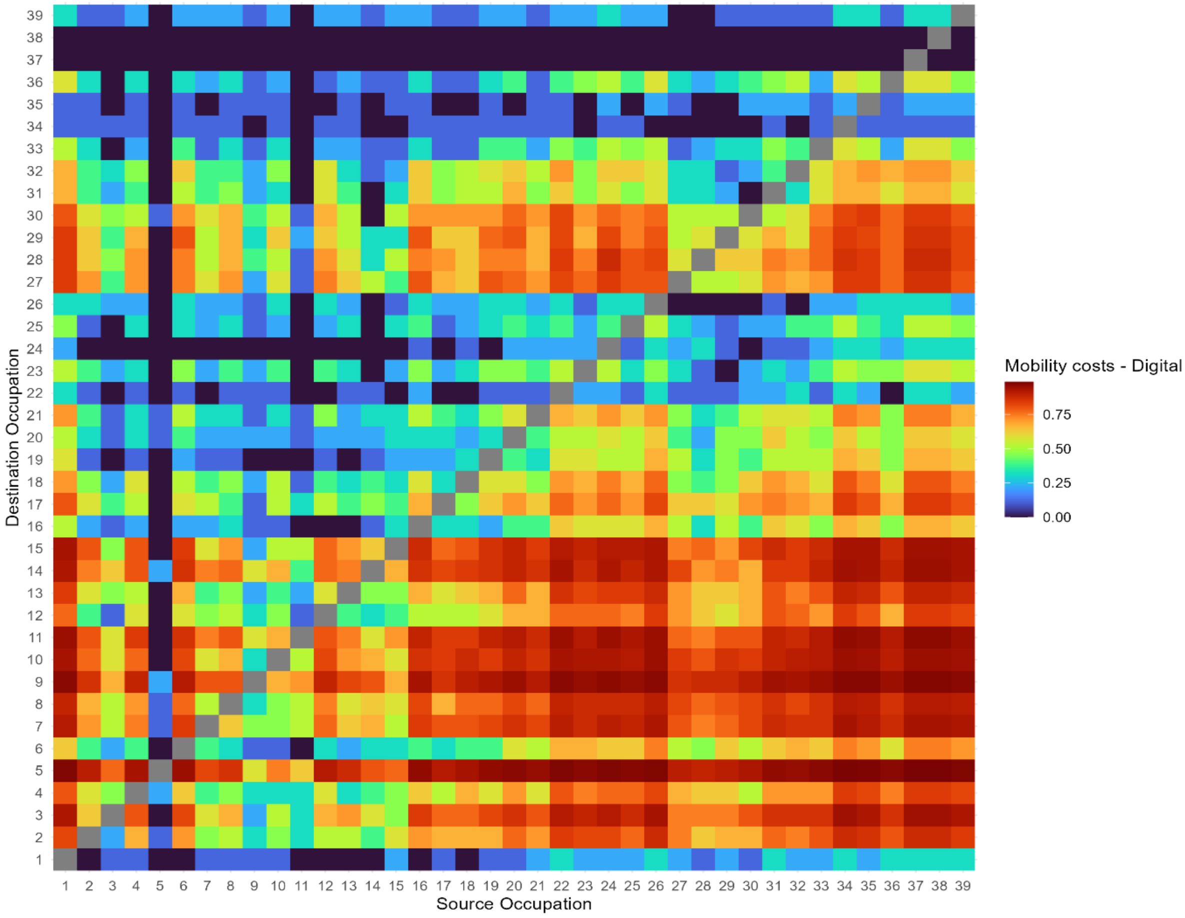

Figure B.1 Estimated Occupation mobility costs due to Digital skills mismatch across each occupation pair

Notes: The occupation numbers refers to the following 2-Digit code: 1=11; 2=12; 3=13; 4=14; 5=21; 6=22; 7=23; 8=24; 9=25; 10=26; 11=31; 12=32; 13=33; 14=34; 15=35; 16=41; 17=42; 18=43; 19=44; 20=51; 21=52; 22=53; 23=54; 24=61; 25=62; 26=71; 27=72; 28=73; 29=74; 30=75; 31=81; 32=82; 33=83; 34=91; 35=92; 36=93; 37=94; 38=95; 39=96. Refer to Table A.1 for occupation title for each occupation 2-Digit code.

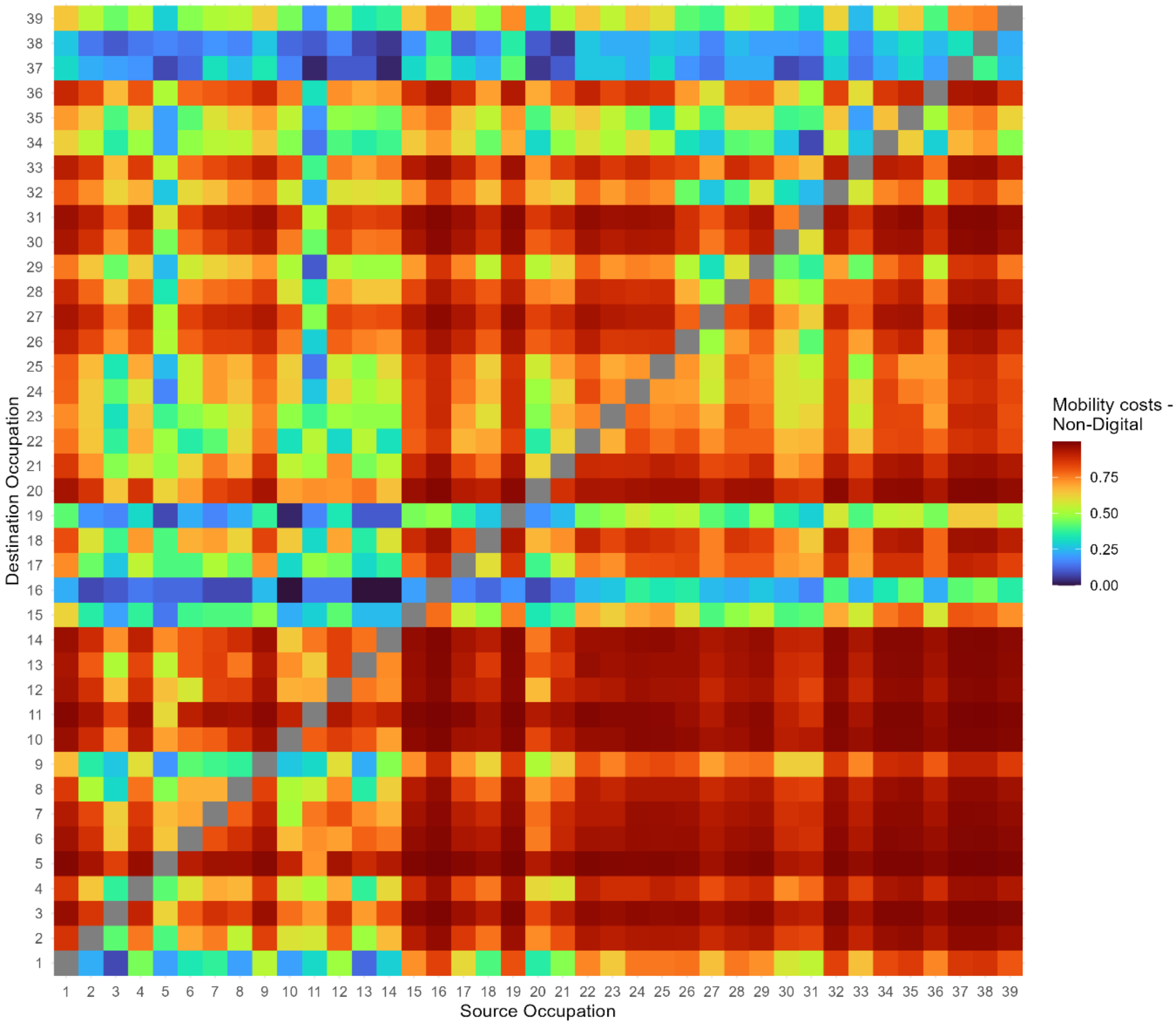

Figure B.2 Estimated Occupation mobility costs due to Non-Digital skills mismatch across each occupation pair

Notes: The occupation numbers refers to the following 2-Digit code: 1=11; 2=12; 3=13; 4=14; 5=21; 6=22; 7=23; 8=24; 9=25; 10=26; 11=31; 12=32; 13=33; 14=34; 15=35; 16=41; 17=42; 18=43; 19=44; 20=51; 21=52; 22=53; 23=54; 24=61; 25=62; 26=71; 27=72; 28=73; 29=74; 30=75; 31=81; 32=82; 33=83; 34=91; 35=92; 36=93; 37=94; 38=95; 39=96. Refer to Table A.1 for occupation title for each occupation 2-Digit code.

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