Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

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ACRONYMS

Acronym	Explanation
AI	Artificial Intelligence
CEDEFOP	European Centre for the Development of Vocational Training
COVID-19	Coronavirus disease 2019 (COVID-19 pandemic)
CrowdLearn	Survey launched by the European Centre for the Development of Vocational Training (Cedefop) examines how EU online platform workers (gig workers) develop skills in the digital economy.
EC	European Commission
ESCO	European Skills, Competences, Qualifications and Occupations
EU	European Union
GISCO	Geographical Information System of the Commission
HHI	Herfindahl–Hirschman Index
ICT	Information and Communication Technology
ILO	International Labour Organization / International Labour Office
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
ISCO-ESCO	Mapping of ISCO occupational codes to ESCO skill profiles
ISCO	International Standard Classification of Occupations
LGBT+	Lesbian, gay, bisexual, transgender, and other sexual/gender minorities (plus)
MOOC	Massive Open Online Course
NBER	National Bureau of Economic Research
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
WP	Work Package

EXECUTIVE SUMMARY

This deliverable of T5.3 examines skill diversification and new types of work in the platform economy, focusing on how platform workers combine skills into portfolios, how motivations differ across types of platform activity, and how these differences relate to learning behaviour, task experiences, and labour market outcomes before and after the pandemic. It draws on complementary evidence from detailed platform-worker data and population-representative survey data, and applies a harmonised skills and occupation framework by linking occupational profiles to the 2022 ESCO taxonomy to identify and compare skill bundles in a consistent European language. The results point to substantial heterogeneity within platform work and a clear pattern of internal segmentation: higher-autonomy, project-based platform work is more strongly associated with diversified and transferable skill portfolios, professional and autonomy-oriented motivations, and more intensive deliberate learning, while routine and task-fragmented platform work is associated with narrower portfolios, lower autonomy, and weaker structured pathways for skill upgrading. At the same time, the evidence highlights an important tension between adaptability and economic security: platform workers often report relatively high adaptability and engagement with upskilling, yet workers who depend most heavily on platform income tend to exhibit greater financial strain and weaker financial buffers, suggesting that vulnerability can coexist with active skill investment. These findings inform policy discussions on classification, skill recognition, and targeted upskilling incentives and provide a direct handover to the next task on effective skills portfolios and labour market mobility, which extends the portfolio approach beyond platform work to identify the skill bundles and occupational distances that facilitate transitions toward green and digital jobs across European regions.

1. Introduction: Platform work, skill diversification, and new forms of labour

Over the past decade, platform-mediated work has expanded across Europe and its neighbourhood, becoming a more visible component of contemporary labour markets and a meaningful part of many workers' income strategies. Digital labour platforms now mediate a wide range of economic activities, from local services, transport, and delivery to online microwork and remote freelance services in creative, professional, and knowledge-intensive domains. This expansion has been enabled by advances in digital technologies, changing business models, and evolving worker and firm preferences: workers may value flexibility and autonomy, while firms increasingly demand adaptable, on-demand labour and short-cycle task completion. As a result, platform work has moved beyond a marginal phenomenon and increasingly intersects with mainstream employment, education, and self-employment trajectories.

At the same time, platform work is not a single category of labour. It spans distinct task regimes and work arrangements that differ markedly in skill requirements, discretion, income stability, and career prospects. Project-based freelancing often requires the combination of specialised expertise with communication, coordination, self-management, and reputation-building skills. By contrast, more task-fragmented forms of online work and other routine platform activities can be organised around standardised, repeatable tasks with limited discretion and weaker progression ladders. This heterogeneity implies that platform workers cannot be analysed as a homogeneous group and that a single "platform worker" category risks obscuring important differences in opportunities and risks across segments of the platform economy.

These realities pose significant challenges for occupational and skills measurement. Traditional classifications were developed for relatively stable jobs with clearly defined roles, whereas platform work is frequently characterised by hybrid roles, multi-tasking, short-term engagements, and the combination of multiple income sources. In this context, a portfolio perspective becomes essential. Workers often rely on diversified skill portfolios that cut across occupational boundaries and combine domain-specific competencies with basic and transferable skills such as digital literacy, communication, self-organisation, problem solving, and adaptability. A job-title approach can therefore underestimate both the breadth of skills involved and the complexity of how skills are combined and rewarded in platform-mediated work.

The COVID-19 pandemic further reshaped the landscape of platform work. For some individuals, platform work became a crucial buffer during periods of job loss, reduced hours, or uncertainty; for others it remained a supplementary or occasional activity. Demand shifted unevenly across platform types, intensifying the use of digital technologies and making vulnerabilities more visible, including income volatility and uneven access to protections. These changes also influenced motivations for participation and the perceived returns to skill investment, with platform work functioning for some as a flexible choice and for others as a response to constraint.

In parallel, the growing economic and social relevance of platform work has been accompanied by intensified policy debate and legislative activity at European level. Efforts to clarify employment status, improve working conditions, and strengthen access to social protection reflect the recognition that platform work can combine elements of autonomy with forms of control embedded in task design, monitoring, evaluation systems, and algorithmic allocation. Such developments matter for skills formation because the incentives to invest in training, and the ability to convert learning into better tasks and mobility, depend on how platform work is organised and how risks and responsibilities are distributed between workers, platforms, and institutions.

Against this backdrop, the analysis in this report examines platform work as a key setting in which skill diversification, motivation, and institutional change intersect. It combines complementary evidence from two sources. First, detailed platform-worker data provide a granular view of differences between major segments of online platform labour, documenting contrasts in occupational backgrounds, task characteristics, motivations, learning strategies, and reported skill upgrading. Second, population survey evidence provides a broader picture of platform work participation across countries and regions, including variation in engagement intensity, reliance on platform income, and socio-demographic gradients. Together, these sources allow platform work to be examined both from the inside (how platform segments differ in task regimes and learning environments) and from the outside (how platform participation is distributed across labour markets and how it relates to resilience and vulnerability).

A key methodological element is the harmonised description of skills portfolios using the 2022 ESCO taxonomy, which enables skills associated with new types of work to be expressed in a common European language and linked to occupational structures. This approach supports systematic comparison of skill bundles and helps reveal where classification systems struggle to capture hybrid and multi-task platform roles. It also provides an analytical basis for examining whether platform work operates as a broadly competitive market in which skills translate into opportunities in similar ways across segments, or whether it is internally segmented into distinct tracks characterised by different skills, motivations, learning returns, and exposures.

The overarching picture that emerges is one of substantial heterogeneity and meaningful segmentation within platform work. Higher-autonomy, project-based platform activity is more closely associated with diversified and transferable skill portfolios, autonomy-oriented motivations, and more intensive deliberate learning, while routine and task-fragmented activity is more closely associated with narrower skill portfolios, constrained discretion, and weaker structured pathways for upgrading. At the same time, the evidence points to a tension between adaptability and economic security: platform workers may display high adaptability and engagement with upskilling, yet those most reliant on platform income can face greater financial strain and weaker buffers. These patterns motivate a policy focus on classification, skill recognition, and targeted upskilling incentives, and they provide a foundation for subsequent analysis of effective skills portfolios and labour market mobility in times of change.

1.1 Purpose of the Deliverable

The purpose of this deliverable is to provide an evidence-based assessment of skill diversification and skills portfolios in platform-mediated work, and to examine how these portfolios relate to workers' motivations, learning behaviour, and labour market outcomes in the period surrounding the

COVID-19 pandemic. Building on earlier work on the measurement and classification of basic and transferable skills, the focus shifts here to new types of work associated with digital labour platforms and the gig economy, where hybrid roles, task-based engagements, and multiple income sources challenge conventional assumptions about jobs, occupations, and skill formation.

The deliverable pursues three closely related objectives. First, it identifies distinct skill profiles within platform work by adopting a skills portfolio perspective that captures how workers combine domain-specific competencies with transferable skills such as digital literacy, communication, and self-management. This perspective is used to document heterogeneity across platform work segments and to better understand how different task environments shape the deployment and development of skills. Second, it develops and applies mechanisms for identifying skill bundles and skill-task alignment in non-standard work settings, with particular attention to how occupational skill endowments relate to platform task content and to the conversion of transferable skills into upgrading outcomes. Third, it assesses how motivations and learning investments vary across segments of the platform economy, and how these differences contribute to segmentation in opportunities and vulnerability.

A further objective is to inform policy makers and practitioners about the likely implications of evolving European policy and regulatory developments for platform work. In particular, the analysis speaks to issues of worker classification, incentives for upskilling, and the risk that the platform economy may evolve into a segmented two-tier labour market. By combining detailed platform-worker evidence with population-representative survey evidence, the deliverable connects within-platform dynamics to broader patterns of participation, reliance on platform income, resilience, and financial vulnerability.

While the analysis addresses participation patterns and labour market outcomes associated with platform work, it does not examine labour market mobility or occupational distance across the wider economy. These topics are addressed in subsequent work, which extends the skills portfolio approach to transitions, occupational proximity, and mobility toward emerging job domains, including green and digital employment.

1.2 Relation with Other Deliverables and Tasks

Deliverable D5.3 draws on conceptual and empirical inputs from earlier TRAILS work packages addressing labour market transformation, task change, and skills demand, particularly WP1, WP2, and WP3. These inputs provide the broader context for understanding the emergence and growth of platform work and its implications for skills and employment.

Within WP5, Deliverable D5.3 occupies an intermediate position. It builds directly on Deliverable D5.2, which develops a new classification and measurement framework for basic and transferable skills, and applies this framework to the specific context of platform work and new forms of employment. At the same time, D5.3 provides key inputs into Deliverable D5.4, which extends the analysis to skills portfolios, occupational distance, and labour market mobility across European regions using combined primary and secondary data sources.

By focusing on platform workers and new types of work, D5.3 complements rather than overlaps with other WP5 outputs. It ensures analytical continuity across tasks while maintaining a clear division of scope between skill classification (D5.2), platform-specific skill portfolios and motivation (D5.3), and economy-wide mobility and transition analysis (D5.4).

1.3 Structure of the Document

Section 1 introduced platform work as an increasingly important but highly heterogeneous feature of European labour markets and situates the analysis in the context of post-pandemic labour market adjustments and evolving regulatory debate. The remainder of this document is organised as follows. Section 2 sets out the conceptual framework, motivating a skills portfolio perspective for analysing non-standard work and clarifying the role of motivation, autonomy, and precarity in shaping participation and learning in the gig economy.

Section 3 presents the first empirical foundation of the report by introducing the Joint CrowdLearn dataset and detailing the methodological pipeline used to anchor platform workers in their primary occupations. This section describes the occupational coding strategy to ISCO-08 at the 4-digit level and the linkage to the 2022 ESCO taxonomy, which enables the construction of harmonised occupational skill portfolios and derived measures such as diversification and transferability. Section 4 builds on this data source to assess whether the platform economy operates as a competitive market or is internally segmented, developing a stylised framework and implementing empirical tests that compare freelancers and microworkers in terms of skill portfolios, motivations, task regimes, learning investments, skill upgrading, and indicators of worker-like exposure.

Section 5 introduces the second empirical foundation of the report based on primary evidence from the TRAILS-I survey. It provides population-representative descriptive evidence on the prevalence and forms of platform work across countries and regions, distinguishing between different types of platform activities and different modes of participation (main income, supplementary income, and occasional activity), and documenting socio-demographic gradients. Section 6 then uses the TRAILS-I survey to examine whether platform work is more consistent with segmentation or mobility in workers' broader income and job portfolios. It analyses platform work typologies, task composition and perceived skill transferability, the role of platform work as a complement or substitute to standard employment, and patterns of resilience and vulnerability, including labour market adaptability and financial strain.

Section 7 synthesises the findings into policy implications, focusing on the classification of platform work, the design of incentives for upskilling, and the implications of segmentation for competitiveness and sustainable labour market outcomes. Section 8 concludes by summarising the main findings and contributions and providing a handover to the subsequent work on effective skills portfolios and labour market mobility.

2. Conceptual framework: Skills portfolios and motivation in the gig economy

2.1 Platform work as a distinct labour market segment

Platform work constitutes a distinct segment of contemporary labour markets, differing in important ways from standard forms of employment. Unlike traditional employment relationships, platform work is typically characterised by task-based or project-based engagements, mediated through digital platforms that match workers with clients or customers. Employment relationships are often ambiguous, with workers commonly classified as self-employed or independent contractors, and with limited access to employment protection, collective representation, or social security benefits. These features differentiate platform work from standard employment arrangements based on stable contracts, clearly defined job roles, and employer-provided protections (De Stefano, 2016; Berg et al., 2018).

A defining characteristic of platform work is the prevalence of multiple job holding and diversified income sources. Many platform workers combine platform-mediated activities with other forms of employment, education, or self-employment, resulting in fragmented work trajectories and complex labour market participation patterns. Income derived from platform work is often volatile and unpredictable, reflecting fluctuations in demand, algorithmic task allocation, and platform-specific pricing mechanisms. This income volatility can increase economic insecurity, but it may also incentivise workers to diversify their activities and skill sets as a strategy for managing risk (Kässi and Lehdonvirta, 2018; Wood et al., 2019).

These structural features have important implications for skill formation and use. Platform work often requires workers to deploy a combination of technical, basic, and transferable skills, including digital literacy, communication, self-management, problem-solving, and the ability to navigate platform interfaces and rating systems. At the same time, the absence of formal career ladders and employer-provided training can shift responsibility for skill development onto workers themselves, encouraging informal learning and self-directed upskilling. As a result, platform workers frequently rely on diversified skills portfolios rather than narrowly defined occupational skill sets, with skills acquired and applied across multiple tasks, platforms, and labour market contexts (OECD, 2019; Kost et al., 2020).

By conceptualising platform work as a distinct labour market segment marked by non-standard employment relationships, income volatility, and skill diversification, this section provides a foundation for analysing how skills portfolios and motivation are shaped in the gig economy. It also highlights why traditional approaches to skills measurement and occupational classification are often ill-suited to capturing the realities of platform-mediated work, motivating the portfolio-based perspective adopted in the remainder of this deliverable.

2.2 Skills portfolios in non-standard work

Non-standard forms of employment, and platform work in particular, challenge traditional approaches to skills that are based on single occupations or narrowly defined job roles. In standard employment, skills are often matched to relatively stable job descriptions, with workers expected to specialise in a limited set of competencies that evolve gradually over time. In contrast, platform-mediated work frequently requires workers to combine multiple skills across different tasks, clients, and work contexts, often within short time horizons. As a result, labour market participation in the gig economy is better understood through the lens of skills portfolios rather than single-skill matching.

A skills portfolio perspective emphasises the combination and complementarity of different types of skills, rather than the possession of isolated competencies. Platform workers often draw simultaneously on technical or task-specific skills, such as programming, design, driving, or content production, and on basic and transferable skills, including digital literacy, communication, adaptability, self-management, and problem-solving. These skills are deployed across diverse activities and platforms, enabling workers to navigate fragmented work arrangements, manage multiple clients, and respond to changing demand conditions (OECD, 2019; Green et al., 2021).

The complementarity between technical, basic, and transferable skills is particularly pronounced in non-standard work settings. Technical skills may enable access to specific tasks or platforms, but their effective use often depends on broader competencies that support learning, coordination, and decision-making. For example, digital and media literacy are critical for navigating platform interfaces and managing online reputations, while communication and organisational skills are essential for maintaining client relationships and coordinating multiple projects. This interdependence of skills suggests that focusing on single competencies risks underestimating both the complexity and the resilience of platform workers' skill endowments.

This deliverable builds on the classification of basic and transferable skills developed in Deliverable D5.2, applying it to the specific context of platform work without re-developing or duplicating the underlying framework. Rather than revisiting the conceptual foundations of skill domains, the analysis in Task 5.3 uses this classification as a reference point for identifying how different skills are combined into portfolios and how these portfolios vary across types of platform work. In doing so, the deliverable shifts the analytical focus from defining skills to examining how they are bundled, deployed, and rewarded in non-standard labour market settings.

By adopting a skills portfolio perspective, this section provides a conceptual basis for analysing heterogeneity within the gig economy and for understanding how skill diversification may contribute to both opportunity and vulnerability among platform workers. It also sets the stage for the empirical analysis of skill bundles, learning behaviour, and labour market outcomes presented in later sections of this deliverable.

2.3 Motivation, autonomy, and precarity

Motivation plays a central role in shaping participation in platform work and in influencing how workers invest in skills and engage with non-standard forms of employment. Existing research highlights a distinction between intrinsic and extrinsic motivations in the gig economy. Intrinsic motivations include preferences for autonomy, flexibility, task variety, and self-direction, while extrinsic motivations are often linked to income generation, employment constraints, or the absence of alternative job opportunities. The relative importance of these motivations varies across individuals and types of platform work, contributing to substantial heterogeneity within the gig economy (Kost et al., 2020; Wood et al., 2019).

Flexibility and autonomy are frequently cited as key attractions of platform work. Many workers value the ability to choose when, where, and how much they work, as well as the opportunity to combine platform activities with other forms of employment, education, or care responsibilities. Platform work can also serve as a mechanism for income smoothing, allowing workers to respond to short-term income shocks or fluctuations in labour demand by adjusting their participation across platforms or tasks. At the same time, the degree of autonomy experienced by platform workers is often constrained by algorithmic management, performance ratings, and platform-specific rules, which can limit effective control over work conditions and earnings (Berg et al., 2018; De Stefano, 2016).

Alongside flexibility, platform work is frequently associated with heightened precarity. Income volatility, uncertain access to tasks, limited social protection, and unclear employment status can expose workers to economic and social risks, particularly in lower-skilled or more routine segments of the gig economy. These conditions may affect not only workers' immediate well-being but also their longer-term incentives to invest in skills, as uncertainty and insecurity can discourage engagement in sustained upskilling or career planning (Benach et al., 2014; OECD, 2019).

Regulatory frameworks play a critical role in shaping the balance between autonomy and precarity in platform work. Recent and ongoing EU-level initiatives aimed at clarifying the employment status of platform workers, improving working conditions, and extending social protection have the potential to alter workers' motivations and behaviour. Changes in legal status, rights, and obligations may influence how platform workers perceive the risks and returns associated with skill investment, as well as how platforms themselves engage in training, skill recognition, and workforce development. Understanding these regulatory dynamics is therefore essential for assessing the future trajectory of platform work and its implications for skills development.

By situating motivation within the broader context of autonomy, precarity, and regulation, this section highlights the importance of institutional factors in shaping skills portfolios and labour market outcomes in the gig economy. It provides a conceptual bridge between the analysis of skills in non-standard work and the empirical examination of motivation, learning behaviour, and policy impacts presented in the subsequent sections of this deliverable.

3. Secondary data: The Joint CrowdLearn Dataset

This deliverable draws on a uniquely constructed joint dataset obtained by merging two CEDEFOP surveys on online platform work: the 2019 CrowdLearn Freelancer Survey and the 2020 CrowdLearn Platform Worker Survey. Both surveys were designed to capture detailed information on the skills, task content, motivations and labour market positioning of individuals engaged in digital platform work across Europe. While fielded in consecutive years and with partially distinct target groups, the two surveys share a common conceptual backbone centred on skills development, task characteristics, and the use of online platforms as a source of income and professional activity.

The 2019 CrowdLearn survey primarily targeted freelancers operating on digital labour platforms. It focused on individuals engaged in project-based, often higher-skill platform work (e.g. digital services, creative and professional tasks). The questionnaire collected detailed information on respondents' educational background, occupational history (ISCO-coded), skill profiles, learning strategies, task complexity, autonomy, and motivations for engaging in platform work. Particular emphasis was placed on how freelancers develop, update and deploy skills through platform-mediated work and how such work relates to their primary occupation.

The 2020 CrowdLearn survey broadened the scope to include a wider range of platform workers, including microworkers performing routine, standardised or highly fragmented tasks. While maintaining core modules comparable to the 2019 survey (demographics, education, work experience, skill development, task characteristics and motivations), the 2020 instrument extended coverage of routine task content, income dependence, and platform-specific working conditions. This expansion allows the dataset to capture both ends of the skill spectrum within the gig economy, from professional freelancers to more routine task-based workers.

The joint dataset harmonises the two surveys at the variable level, aligning common modules and constructing consistent indicators across waves. Key harmonised domains include: (i) socio-demographic characteristics and labour market status; (ii) educational attainment and total work experience; (iii) platform experience and intensity of engagement; (iv) platform task characteristics (e.g. routineness, autonomy, complexity, skill variety); (v) learning strategies and human capital investment behaviours; and (vi) self-reported skill upgrading outcomes. In addition, respondents' primary occupations were mapped to the 2022 ESCO taxonomy via ISCO codes, enabling the construction of detailed occupational skill portfolios and derived indices (e.g. skill shares, diversification, transferability, intensity measures).

The resulting merged dataset provides a comprehensive cross-sectional snapshot of European platform workers immediately prior to the COVID-19 pandemic. Crucially, it allows for systematic comparison between two analytically central segments: freelancers (more project-based, higher autonomy) and microworkers (more routine, task-fragmented). This structure makes it possible to examine segmentation versus competitiveness within the gig economy, identify skill bundles and task–occupation alignment mechanisms, and assess the relationship between occupational skill endowments, platform task allocation and skill upgrading.

By combining the depth of the 2019 freelancer-focused instrument with the broader coverage of the 2020 survey, the joint CrowdLearn dataset constitutes a uniquely rich secondary data source for analysing motivation, skills portfolios and labour market outcomes in platform work across the European Union. This section introduces the CrowdLearn platform dataset as a secondary evidence base that complements the primary TRAILS survey material. Its value is twofold. First, it offers a harmonised descriptive snapshot of online platform workers just before the pandemic, covering both work organisation and perceived skill development. Second, it enables a systematic comparison between two analytically central segments of platform labour, microwork and freelancing, allowing us to document how these segments vary across countries and how they differ in terms of socio-economic profiles, labour-market attachment, and task experience. The figures that follow therefore serve a dual purpose: they document cross-country heterogeneity in the prevalence of platform work types and provide a worker-level profile of individuals participating in each segment.

3.1 Descriptive profile of platform workers in the Joint CrowdLearn dataset

This sub-section introduces the descriptive evidence from the Joint CrowdLearn dataset and sets out what this secondary source contributes to the deliverable's objectives. CrowdLearn provides a structured snapshot of online platform workers immediately prior to the pandemic. Crucially, it distinguishes between two analytically central segments of platform labour: microwork and freelancing. This distinction allows us to move beyond treating "platform work" as a single category and instead document how participation and experiences differ across segments, countries, and socio-economic profiles. In doing so, the descriptive evidence establishes a baseline for the subsequent econometric analysis and clarifies the mechanisms through which segmentation may arise.

The descriptive analysis is organised around three interconnected dimensions that are directly relevant to the deliverable's targets. First, it documents cross-country heterogeneity in the prevalence of microwork and freelancing, showing that platform work is embedded in national labour-market settings rather than operating as a uniform European market. Cross-country variation is informative because it is consistent with differences in labour-market institutions, digital ecosystems, and the availability of remote service opportunities, all of which may shape the size and composition of platform labour. Second, the descriptive evidence profiles platform workers' broader labour-market attachment and occupational identity, linking segment participation to employment status, self-identification as freelancer or entrepreneur, and reported constraints in standard labour-market participation. This provides an initial indication of whether platform work functions primarily as a supplementary activity alongside conventional employment and education pathways, or as an alternative route for individuals facing labour-market frictions. Third, the descriptive section introduces the mechanisms through which platform work is experienced, focusing on motivations for participation, perceived skill development, and task characteristics.

These dimensions are central to understanding whether platforms operate as environments of skill accumulation and mobility or as segmented spaces characterised by routinisation, limited autonomy, and weaker opportunities for sustained upskilling. Importantly, the goal is not only to document differences between microwork and freelancing, but also to establish why segmentation should be expected to appear in measurable skill portfolios: segment distinctions are reflected both in the types of tasks performed and in the competence's respondents report developing through platform participation.

The presentation first provides a cross-country mapping of platform work and then develops a descriptive profile by situating segment participation within respondents' broader labour-market positioning and occupational self-understanding. It subsequently turns to the mechanisms of participation, such as motivations, learning, and task content, thereby providing the conceptual bridge to the later ESCO-based portfolio analysis, establishing that segment differences are reflected in both the nature of tasks performed and the skills respondents report developing through platform work. Taken together, this descriptive baseline provides a coherent foundation for the empirical chapters that follow, which formally test skill portfolio segmentation, learning mechanisms, and policy-relevant indicators of worker-like exposure.

Table 3-1 provides a descriptive overview of the Joint CrowdLearn platform economy, organised along the four conceptual blocks of the theoretical framework: sorting across segments (Panel A), task regimes (Panel B), learning and skill upgrading (Panel C), and worker-like exposure versus income dependence (Panel D). Even before turning to the regression analysis, the descriptive statistics reveal systematic and statistically significant differences between freelancers and microworkers.

Panel A shows clear evidence of sorting across the two segments. Microworkers are younger, more likely to be male, and more frequently located in weaker labour-market positions, as reflected in their higher likelihood of being unemployed, students, or unable to work in a standard job. Freelancers, in contrast, have substantially more total work experience and longer platform tenure. Differences in occupational skill portfolios reinforce this segmentation pattern. Freelancers' primary occupations are associated with higher diversification and significantly higher transferability of skills, whereas microworkers' occupational profiles are characterised by substantially higher physical or manual task intensity. Motivational patterns also diverge sharply. Freelancers are much more likely to cite autonomy, passion, and task choice as reasons for participating in platform work, while microworkers are far more likely to report motives related to time-filling, enjoyment, or simply engaging in a "fruitful activity." Taken together, these differences indicate that participation in the two segments reflects systematic sorting rather than random allocation of workers.

Panel B highlights strong differentiation in the task regimes that characterise each segment. Microwork is overwhelmingly associated with routine, repeatable tasks and significantly lower autonomy, whereas freelancing is far more likely to involve creative tasks, skill variety, and complex skills. The magnitude of these differences is substantial: for example, routine tasks are reported by

Table 3-1: Summary statistics – Joint Crowdlearn dataset

	Pooled (1)	Freelancers (2)	Microworkers (3)	Diff. (4)	Sig.
Panel A. Sorting: Demographics & Labour Market Position					
Male	61.3%	52.7%	69.8%	-17.1%	***
Immigration background	32.1%	32.6%	31.6%	1.0%	
Age	32.87	34.79	30.96	3.83	***
Master's degree	26.1%	29.0%	23.2%	5.8%	***
Bachelor's degree	30.8%	33.5%	28.2%	5.3%	**
Full-time employed	26.4%	19.2%	33.5%	-14.3%	***
Unemployed	6.9%	3.6%	10.1%	-6.5%	***
Student	18.4%	10.6%	26.%	-15.4%	***
Unable to work in standard labour market	10.5%	5.3%	15.6%	-10.3%	***
>10 years total work experience	35.9%	44.4%	27.5%	16.9%	***
Platform experience ≤6 months	42.5%	17.4%	67.4%	-50.0%	***
Platform experience 3–10 years	18.5%	34.4%	2.7%	31.7%	***
Occupational Skill Portfolios (ESCO-Based, Standardised)					
Cognitive skill intensity	3.7%	4.1%	3.2%	0.9%	***
Social skill intensity	6.6%	6.4%	6.8%	-0.4%	***
Physical/manual intensity	43.6%	37.6%	51.1%	-13.4%	***
Diversification index	0.596	0.603	0.591	0.014	***
Transferability index	-0.001	0.234	-0.297	0.531	***
Integrated adaptability index	0.000	0.076	-0.095	0.171	***
Motivations for Platform Work					
Autonomy motivation	37.4%	47.8%	27.1%	20.7%	***
Passion/interest	21.5%	34.9%	8.2%	26.7%	***
Task choice	32.7%	41.1%	24.4%	16.7%	***
Time-filling motive	25.8%	5.9%	45.5%	-39.6%	***
Enjoyment motive	31.0%	16.5%	45.3%	-28.8%	***
"Fruitful activity" motive	48.0%	35.9%	60.0%	-24.1%	***
Panel B. Task Regimes & Skill–Task Alignment					
Routine tasks	40.3%	16.2%	64.2%	-0.4802	***
Repeatable tasks	31.4%	12.7%	49.8%	-0.3706	***
Low autonomy	31.4%	12.7%	49.8%	-0.3706	***
Creative tasks	36.3%	48.8%	23.8%	0.2504	***
Skill variety	48.8%	64.2%	33.5%	0.3071	***
Complex skills	19.2%	29.4%	9.1%	0.2032	***
Panel C. Learning Investments & Skill Upgrading					
Follow developments	2.22	2.37	2.07	0.30	***
Read books/articles	2.01	2.26	1.76	0.51	***
Deep reflection	2.71	2.97	2.46	0.51	***
Free online courses	1.59	1.76	1.43	0.32	***
Collaborate for learning	1.53	1.63	1.44	0.20	***
New tasks encountered	2.64	2.40	2.88	-0.48	***
Belief learning is transferable	2.77	3.09	2.45	0.65	***
Use multiple sources	2.60	3.06	2.15	0.91	***
Apply prior lessons	2.85	3.22	2.49	0.73	***
Problem understanding	3.30	3.56	3.05	0.51	***
Notes/diagrams	1.98	2.29	1.67	0.62	***

Spillovers to other projects	2.85	3.22	2.49	0.73	***
Improved technical skills	48.7%	59.5%	38.1%	0.2135	***
Improved communication skills	30.5%	42.1%	19.1%	0.2296	***
Improved learning skills	29.5%	19.0%	39.8%	-0.2079	***
Improved analytical skills	25.6%	13.7%	37.4%	-0.2375	***
Improved computer literacy	19.8%	10.9%	28.5%	-0.1758	***
Improved language skills	34.4%	24.7%	44.1%	-0.1943	***
Panel D. Worker-Like Exposure & Income Dependence					
High income dependence (≥61%)	13.1%	20.4%	5.8%	14.6%	***
Low autonomy	13.5%	4.8%	22.2%	-0.1745	***
Routine task exposure	0.00	-0.46	0.46	-0.92	***
Worker-like exposure index (std.)	0.00	-0.26	0.26	-0.52	***

64% of microworkers compared with only 16% of freelancers. Conversely, freelancers are roughly three times more likely to report complex skill use. These descriptive contrasts confirm that the two segments operate under fundamentally different work organisations, consistent with the model's assumption that they represent distinct task regimes.

Panel C reveals similarly pronounced differences in learning behaviour and skill upgrading. Freelancers report substantially higher engagement in deliberate learning activities, including following developments, reading professional materials, engaging in deep reflection, and participating in courses or collaborative learning. They also report stronger self-regulated learning strategies and stronger beliefs that learning can be transferred across tasks. Microworkers, however, report encountering new tasks more frequently, suggesting greater task turnover but less structured skill accumulation. The upgrading outcomes further illustrate this divergence. Freelancers are significantly more likely to report improvements in technical and communication skills, whereas microworkers are more likely to report gains in learning skills, analytical abilities, computer literacy, and language skills. This pattern suggests that freelancing tends to support more specialised, occupation-specific skill development, while microwork is associated with more general or foundational skill improvements.

Panel D introduces an important distinction between organisational exposure and economic dependence. Microworkers report significantly higher routineness and lower autonomy, resulting in a substantially higher worker-like exposure index. At the same time, freelancers are more likely to depend heavily on platform income, with a much higher share reporting that at least 61% of their income derives from platform work. This divergence illustrates a key policy implication of the framework: organisational features resembling worker-like control can be concentrated in microwork even when economic dependence on the platform is relatively low. In other words, vulnerability may arise from work organisation rather than income reliance alone.

Overall, the descriptive evidence in Table 4-0 paints a consistent picture of a segmented platform economy. The two segments differ systematically in worker composition, task organisation, learning behaviour, and exposure to platform governance. These patterns suggest that freelancing and microwork should not be treated as interchangeable forms of platform labour but rather as distinct regimes with different opportunity structures and developmental trajectories. The regression analysis that follows examines these patterns more formally and evaluates whether they align with the theoretical predictions derived in Section 4.2.

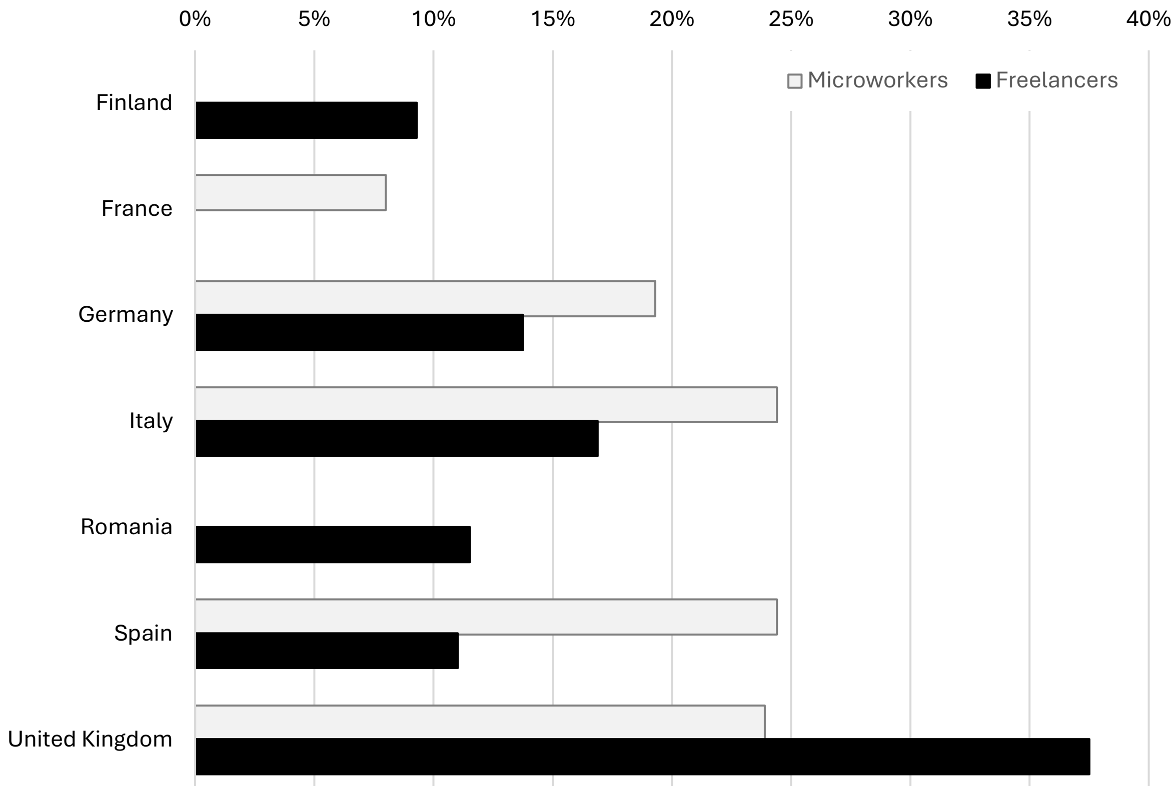
In what follows, the descriptive analysis is organised around three interconnected dimensions that are directly relevant to the deliverable's targets. First, it documents cross-country heterogeneity in the prevalence of microwork and freelancing, showing that platform work is embedded in national labour-market settings rather than operating as a uniform European market. Cross-country variation is informative because it is consistent with differences in labour-market institutions, digital ecosystems, and the availability of remote service opportunities, all of which may shape the size and composition of platform labour. Second, the descriptive evidence profiles platform workers' broader labour-market attachment and occupational identity, linking segment participation to employment status, self-identification as freelancer or entrepreneur, and reported constraints in standard labour-market participation. This provides an initial indication of whether platform work functions primarily as a supplementary activity alongside conventional employment and education pathways, or as an alternative route for individuals facing labour-market frictions. Third, the descriptive section introduces the mechanisms through which platform work is experienced, focusing on motivations for participation, perceived skill development, and task characteristics.

These dimensions are central to understanding whether platforms operate as environments of skill accumulation and mobility or as segmented spaces characterised by routinisation, limited autonomy, and weaker opportunities for sustained upskilling. Importantly, the goal is not only to document differences between microwork and freelancing, but also to establish why segmentation should be expected to appear in measurable skill portfolios: segment distinctions are reflected both in the types of tasks performed and in the competence's respondents report developing through platform participation.

The presentation first provides a cross-country mapping of platform work and then develops a descriptive profile by situating segment participation within respondents' broader labour-market positioning and occupational self-understanding. It subsequently turns to the mechanisms of participation, such as motivations, learning, and task content, thereby providing the conceptual bridge to the later ESCO-based portfolio analysis, establishing that segment differences are reflected in both the nature of tasks performed and the skills respondents report developing through platform work. Taken together, this descriptive baseline provides a coherent foundation for the empirical chapters that follow, which formally test skill portfolio segmentation, learning mechanisms, and policy-relevant indicators of worker-like exposure.

Figure 3.1 compares the distribution of microworkers and freelancers across the seven countries included in the CrowdLearn sample. The country composition differs notably by worker type. Microwork is relatively more prevalent in Spain and Italy, with both accounting for around 25% of microworkers, compared to 11% and 17% of freelancers, respectively. Germany also represents a larger share among microworkers, at around 19.3%, compared to 13.8% among freelancers. The United Kingdom displays a distinct pattern, with a markedly higher share of freelancers (35.7%), well above all other countries, while microwork also accounts for 23.9% of the country's sample. In contrast, the French sample consists exclusively of microworkers, whereas Romania and Finland are represented only by freelancer respondents.

Figure 3-1: Platform workers by country and by worker type (Microworker vs Freelancer)



Then Figure 3.2 presents the employment status composition of microworkers and freelancers, underscoring important differences in their labour-market attachment. Among microworkers, employment status is distributed across conventional categories: 33.5% report being full-time employed and 26.0% are students, followed by 16.4% in other statuses, 12.0% part-time employed, 10.1% unemployed, and 2.0% inactive. By contrast, the profile of freelancers is markedly more concentrated, with the "other" category accounting for 55.3%, while 19.2% report full-time employment; the remaining shares are comparatively small (10.6% students, 9.6% part-time, 3.6% unemployed, and 1.6% inactive).

A direct comparison across worker types shows that microworkers are more likely than freelancers to be in full-time employment (+14.3 percentage points), to report being students (+15.4 percentage points), and to be unemployed (+6.5 percentage points). Conversely, freelancers are substantially more likely to fall into "other" (non-standard) labour-market situations (+38.9 percentage points relative to microworkers). Overall, the figure indicates that, in this sample, microwork is more often undertaken alongside conventional labour-market positions (employment or study), whereas freelancing is more frequently associated with employment situations not captured by the standard status categories, as reflected in the dominance of the "other" group.

Figure 3-2: Labour market status of platform workers by worker type (Microworker vs Freelancer)

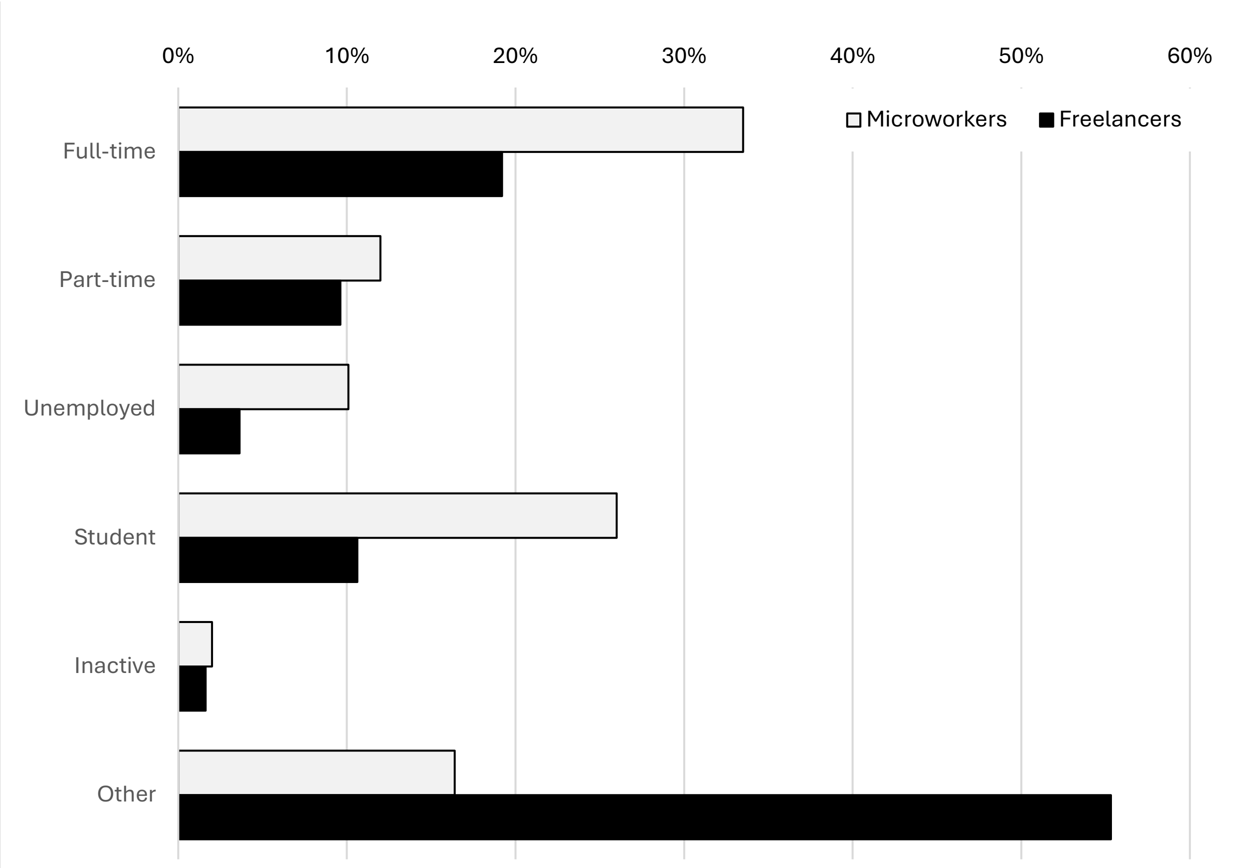
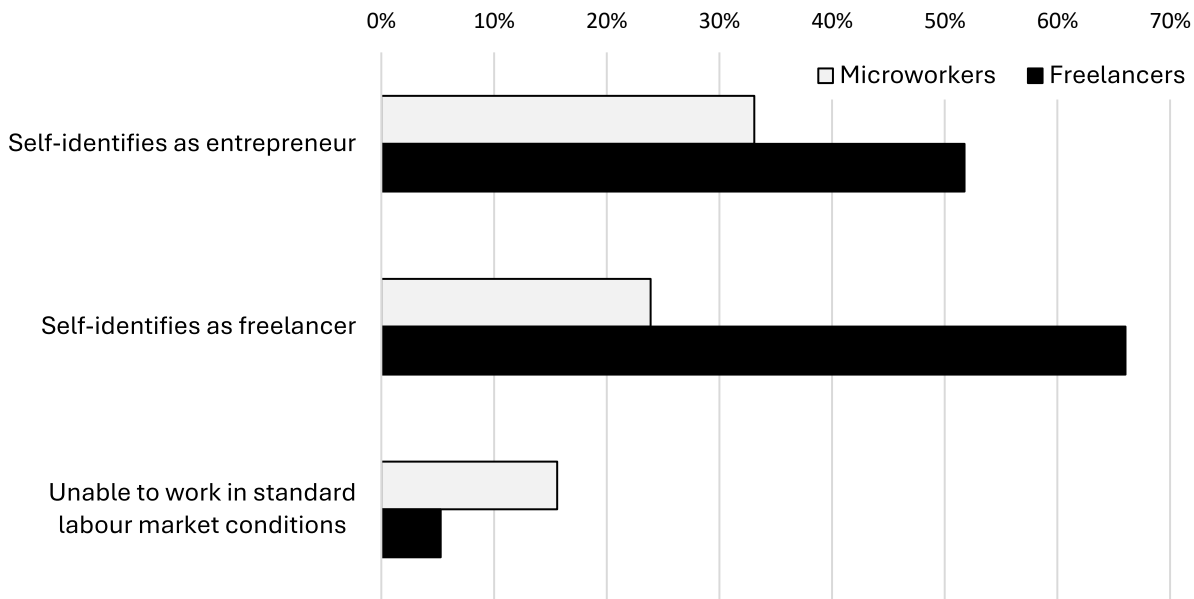


Figure 3.3 presents how respondents self-identify across types of platform work, indicating that freelancers are substantially more likely than microworkers to adopt a professional self-definition that aligns with independent work. About 51.8% of freelancers self-identify as entrepreneurs (vs 33.1% of microworkers) and 66.0% self-identify as freelancers (vs 23.9% of microworkers). In contrast microworkers more frequently report labour-market constraints, with 15.6% stating they are unable to work in standard labour market conditions, compared to 5.3% of freelancers. Taken together, the figure suggests that freelancing is more closely associated with an "entrepreneurial/freelancer" occupational identity, whereas microwork is more often reported by respondents who either do not primarily frame their activity in these terms and/or face stronger barriers to conventional employment (as indicated by the higher "unable to work" share).

Figure 3.4 reports the shares of microworkers and freelancers reporting different motivations for engaging in platform work, and it reveals two distinct motivational profiles. Among microworkers, the most frequently reported motivations are engaging in meaningful/productive activity (60.0%), filling idle time (45.5%), and enjoyment/fun (45.3%). Flexibility-related reasons are also common, e.g., flexible schedule control (33.2%) and remote work/no commute (30.7%), alongside

Figure 3-3: Self-identification and labour-market constraints among platform workers by worker type (Microworker vs Freelancer)

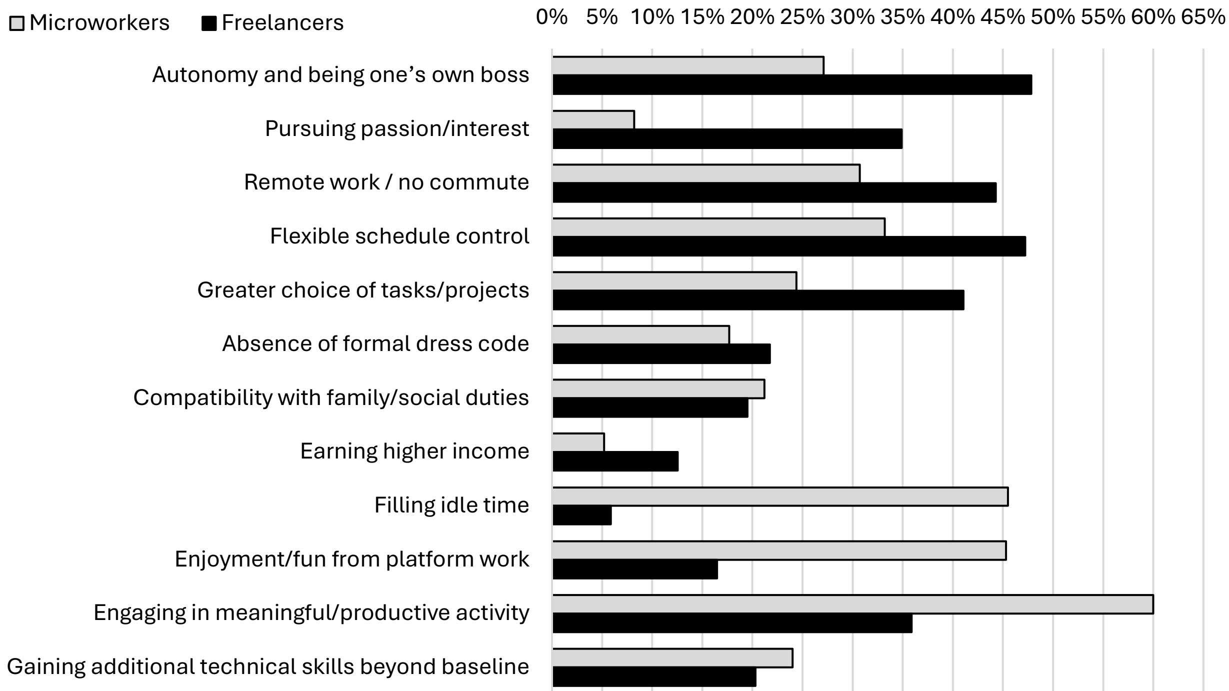


autonomy/being one's own boss (27.1%) and greater choice of tasks/projects (24.4%). By comparison, explicitly income-driven motives are less prominent, such as earning higher income (5.2%) and the pursuing passion/interest (8.2%). For freelancers, motivations are more strongly oriented toward autonomy and work design, e.g., autonomy/being one's own boss (47.8%), flexible schedule control (47.2%), remote work/no commute (44.3%), and greater choice of tasks/projects (41.1%) are the leading reasons. Relatively large shares also report engaging in meaningful/productive activity (35.9%) and pursuing passion/interest (34.9%), while motivations such as filling idle time (5.9%) and enjoyment/fun (16.5%) are less prevalent for freelancers.

Comparing the two groups, microworkers are much more likely to cite "filling idle time" (+39.64 percentage points) and "enjoyment/fun" (+28.8 percentage points) than freelancers and also report meaningful/productive activity more often (+24.1 percentage points). Freelancers, in turn, are more likely to emphasise pursuing passion/interest (+26.7 percentage points) and core autonomy/flexibility motivations such as being one's own boss (+20.7 percentage points), greater task/project choice (+16.7 percentage points), schedule control and remote work/no commute (+14 and +13.6 percentage points, respectively). Overall, the pattern suggests that microwork in this sample is more frequently framed around time-filling and enjoyment (alongside flexibility), whereas freelancing is more often framed as an autonomy- and choice-driven work arrangement, with stronger links to intrinsic interest/passion and work-organisation considerations.

Figure 3.5 reports the extent to which respondents perceive that they have developed different skill categories through platform work, separately for microworkers and freelancers, using a 1-4 frequency scale (1=never, 2=rarely, 3=frequently/weekly, 4=very frequently/daily). Overall, average scores mostly lie between "rarely" and "frequently", indicating that skill development is present but typically not described as a daily outcome of platform work.

Figure 3-4: Motivations for engaging in platform work by worker type (Microworker vs Freelancer)

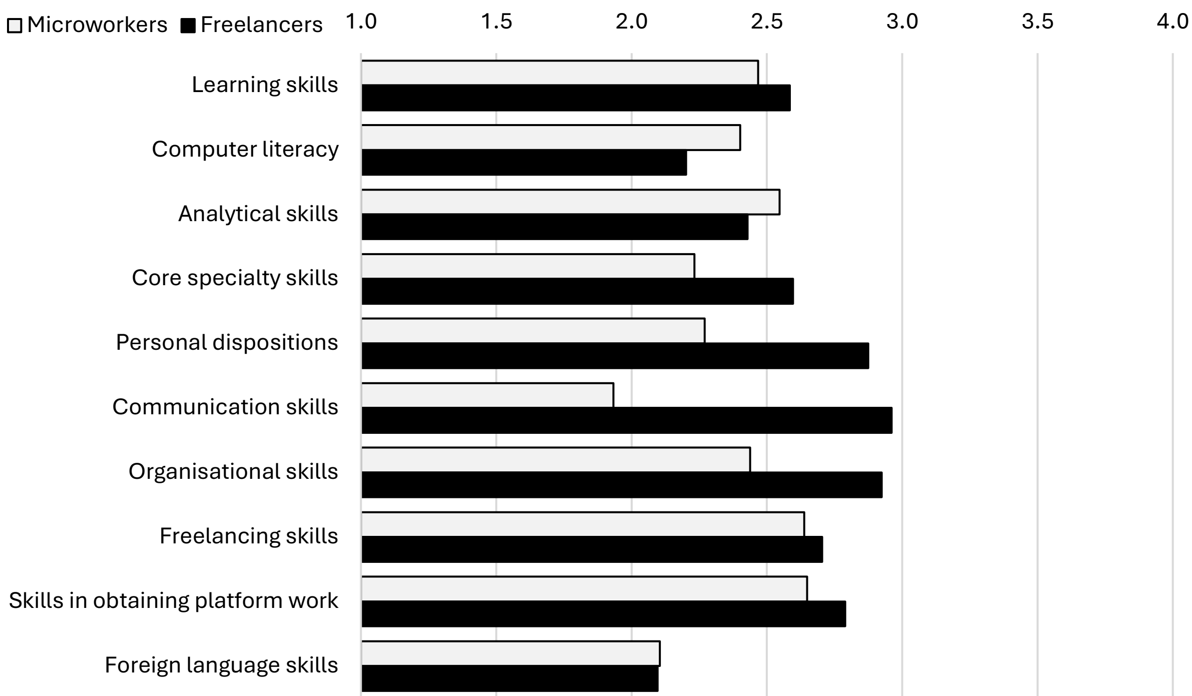


A clear pattern emerges for microworkers: the highest reported development is concentrated in platform- and work-acquisition related competences, notably skills in obtaining platform work (2.7) and freelancing skills (2.6), followed by analytical skills (2.5) and learning skills (2.4). In contrast, communication skills (1.9) stand out as the least developed category, alongside relatively modest scores for foreign language skills (2.1) and core specialty skills (2.2). This profile is consistent with microwork being organised around short, task-based activities where learning may primarily accrue through repeated engagement with platforms, task selection, and task execution, rather than through intensive client-facing interaction.

For freelancers, reported skill development is broader and reaches higher frequency levels in many categories. The highest averages are observed for communication skills (2.9), organisational skills (2.8) and personal dispositions (2.7), alongside relatively strong scores for skills in obtaining platform work (2.7) and freelancing skills (2.6). At the lower end, foreign language skills (2.1) and computer literacy (2.2) register the smallest increases, suggesting comparatively limited perceived development in these areas.

Compared to microworkers, freelancers report substantially more frequent development of communication (+1.0 points), personal dispositions (+0.6 points), organisational skills (+0.5 points), and higher core specialty skills (+0.4 points). Microworkers, by contrast, report slightly higher development in computer literacy (about +0.2 points in favour of microworkers) and analytical skills (+0.1 points). Taken together, Figure 3.5 points to two distinct sets of learning opportunities by platform work type. Freelancing is more strongly associated with the development of soft skills and

Figure 3-5: Skills reported to have been developed through platform work by worker type (Microworker vs Freelancer)

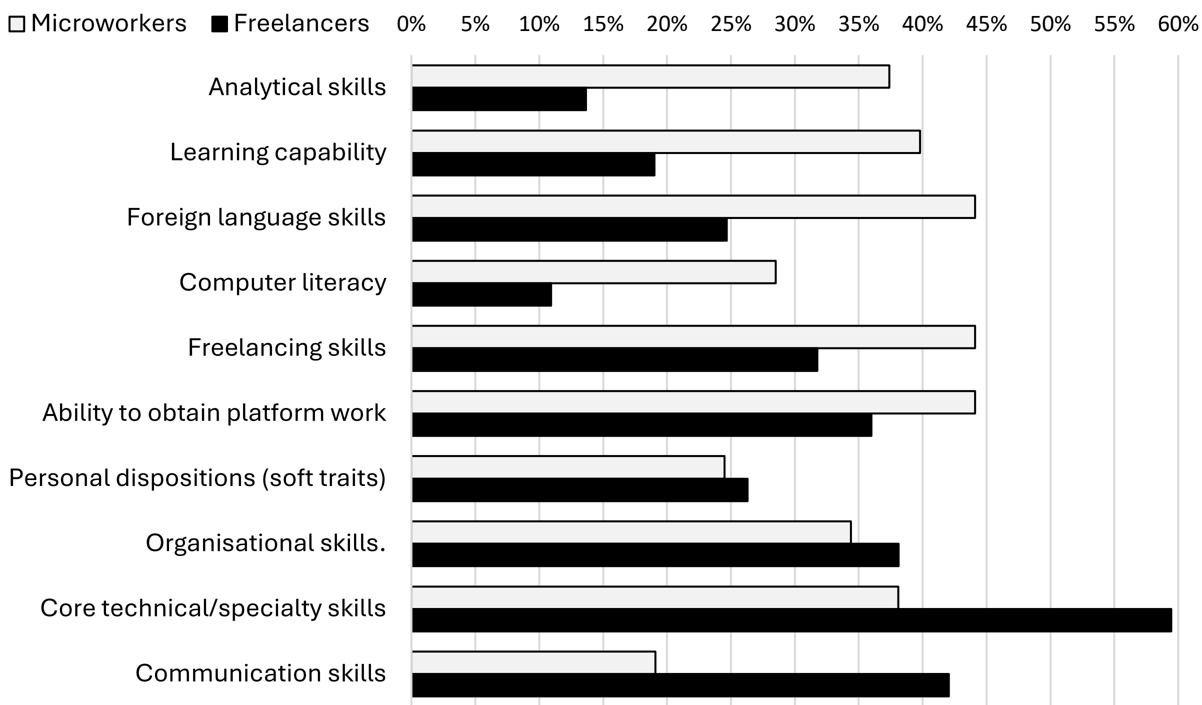


self-management competences, reflecting the greater emphasis on communication, coordination, and organising work. Microwork, in contrast, is more closely linked to platform-facing and task-related skill development, with comparatively weaker spillovers into communication-intensive domains.

Figure 3.6 reports the share of respondents (multiple responses allowed; coded 1 if selected and 0 otherwise) who state that particular skill categories have improved through platform work, disaggregated by microworkers and freelancers. Since respondents could select multiple descriptors, the reported percentages capture the share of each group associating their platform work with each skill category and therefore do not sum to 100%. Overall, the results point to two distinct skill-improvement profiles, alongside some commonalities.

Among microworkers, the most frequently reported improvements concern foreign language skills (44.1%), freelancing skills (44.1%), and the ability to obtain platform work (44.1%), followed by learning capability (39.8%) and analytical skills (37.4%). At the lower end, microworkers are least likely to report improvements in communication skills (19.1%) and personal dispositions/soft traits (24.5%), with computer literacy (28.5%) also relatively less often selected. This pattern suggests that microwork, as captured in this sample, is more strongly associated with perceived gains in general cognitive/learning-related competences and platform-facing know-how (finding and performing tasks), rather than skills typically developed through sustained client interaction.

Figure 3-6: Skills reportedly improved through platform work by worker type (Microworker vs Freelancer)

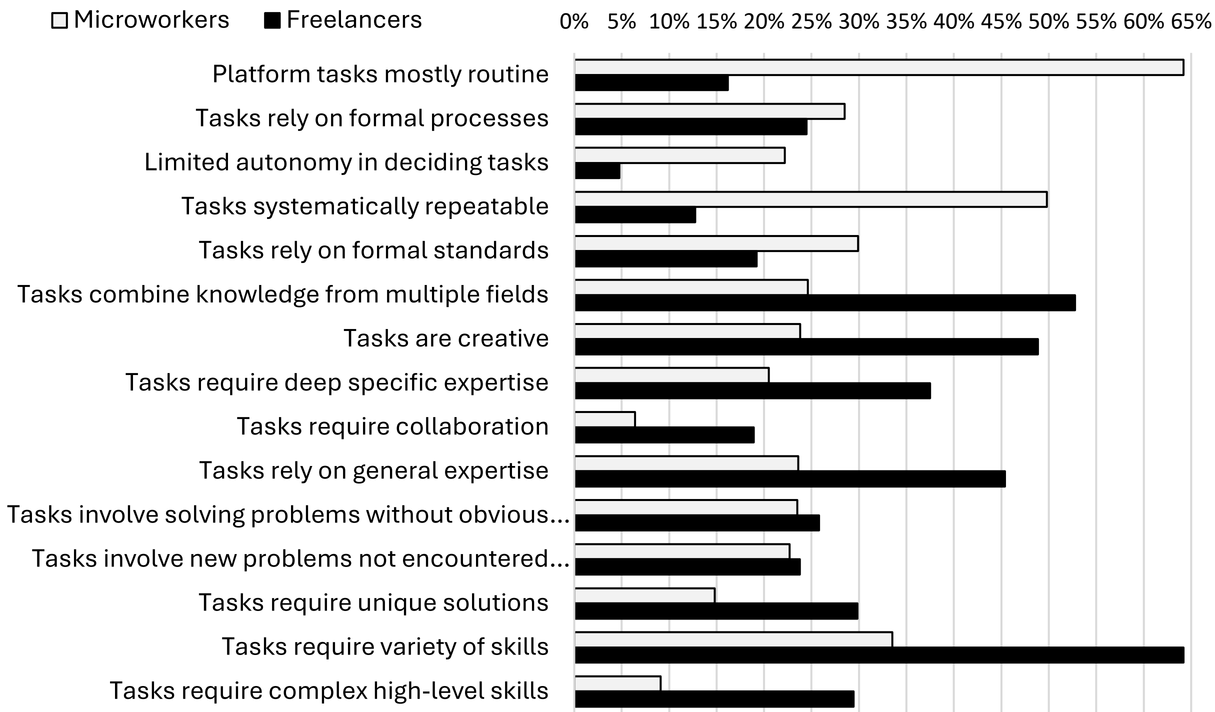


For freelancers, the highest share by a considerable margin is core technical/specialty skills (59.5%), followed by communication skills (42.1%) and organisational skills (38.1%), with sizeable shares also reporting improvement in the ability to obtain platform work (36.0%) and freelancing skills (31.6%). By contrast, freelancers least often select computer literacy (10.9%), analytical skills (13.6%), and learning capability (19.0%). Overall, this configuration is consistent with freelancing being more closely tied to specialised project work, where perceived gains concentrate in domain-specific expertise and the communication/coordination skills needed to manage tasks, clients, etc.

Comparing the two groups directly reinforces this distinction. Microworkers are substantially more likely than freelancers to report improvements in analytical skills (+23.7 percentage points), learning capability (+20.8 percentage points), foreign language skills (+19.4 percentage points), and computer literacy (+17.58 percentage points). Freelancers, in turn, are much more likely to report improvements in communication skills (+22.9 percentage points) and core technical/specialty skills (+21.4 percentage points), with smaller advantages for freelancers in organisational skills and personal dispositions (+3.8 and +1.8 percentage points, respectively). Taken together, Figure 3.6 suggests that platform work is linked to different perceived learning trajectories: microwork aligns more with general and platform-navigation capabilities, while freelancing aligns more with specialised professional skill deepening and communication-intensive competences.

Figure 3.7 summarises respondents' perceptions of the nature of platform tasks, disaggregated by microworkers and freelancers. Since respondents could select multiple descriptors (coded 1 if

Figure 3-7: Perceived nature of platform tasks by worker type (Microworker vs Freelancer)



selected and 0 otherwise), the reported percentages capture the share of each group associating their platform work with each task characteristic and therefore do not sum to 100%.

A clear divide emerges between the two worker types. Microworkers most often characterise their tasks as mostly routine (64.2%) and systematically repeatable (49.8%), and to a lesser extent as requiring a variety of skills (33.5%) or relying on formal standards (29.9%) and formal processes (28.5%). They are also more likely to report limited autonomy in deciding tasks (22.2%), while relatively few associate microwork with collaboration (6.4%), unique solutions (14.8%), or complex high-level skills (9.1%). This pattern is consistent with microwork being perceived primarily as standardised, task-based activity, where work content is often structured and repeatable.

By contrast, freelancers are far less likely to describe tasks as routine (16.2%) or repeatable (12.7%), and very rarely report limited autonomy (4.8%). Instead, they most frequently emphasise that platform tasks require a variety of skills (64.2%), combine knowledge from multiple fields (52.8%), and are creative (48.8%), alongside substantial shares selecting general expertise (45.4%), deep specific expertise (37.5%), unique solutions (29.8%), and complex high-level skills (29.4%).

Compared with microworkers, freelancers are therefore much more likely to frame their platform work as multi-skilled, knowledge-intensive, and solution-oriented, while microworkers are markedly more likely to frame theirs as routine and repeatable. The largest gaps concern tasks perceived as "mostly routine" (-48.0 percentage points for freelancers relative to microworkers) and "systematically repeatable" (-37.1 percentage points) underscoring the more standardised character of microwork relative to the more customised nature of freelance platform work.

3.2 Occupational coding to ISCO-08 4-digit unit groups and linkage to ESCO skill bundles

To analyse skill portfolios and segmentation among platform workers, we required a consistent occupational identifier at the ISCO-08 4-digit unit group level for each respondent's primary occupation, and a corresponding mapping from that occupation to the ESCO 2022 skill taxonomy. Occupational coding is non-trivial in platform-work settings because self-reported job titles are often non-standard, hybrid, or platform-specific (e.g., "freelancer", "consultant", "analyst"), and may not map cleanly to ISCO without additional contextual information. We therefore implemented a hierarchical coding strategy that combines (i) rule-based classification using normalised job titles and occupation dictionaries, with (ii) refinement using task-content and skill indicators available in the surveys. This approach balances granularity (4-digit unit groups) with classification reliability, and avoids mechanically forcing false precision where the information is insufficient.

This subsection documents the procedure used to derive respondent-level ISCO-08 4-digit unit group codes for primary occupations and to link these codes to ESCO 2022 skill bundles. The objective is to obtain a consistent occupational identifier and corresponding ESCO skill portfolio for each respondent, in a context where self-reported job titles in platform work are often ambiguous, hybrid, and not directly aligned with standard occupational taxonomies. The procedure is designed to balance granularity (ISCO 4-digit coding) with reliability (avoiding false precision), and to ensure that resulting ESCO portfolios can be interpreted as occupation-level skill requirements tied to respondents' primary occupations.

The pipeline produces two core outputs used throughout the empirical analysis:

- ISCO4 (primary occupation): respondent-level ISCO-08 4-digit unit group code for the respondent's primary occupation.
- ESCO portfolio variables: occupation-level ESCO skill bundles assigned to respondents via ISCO4, including skill counts, category shares, and composite indices (e.g., skill diversification, transferability, portfolio index).

These outputs enable systematic comparisons of occupational skill endowments across platform labour segments (microwork vs freelancing) and provide the basis for the task-occupation alignment analyses.

The coding and linkage procedure adapts standard occupational classification to the realities of platform labour by combining a strict hierarchical ISCO structure with contextual functional information from task and learning modules. It reduces misclassification risk by constraining refinement within plausible occupational families, avoids false precision through conservative assignment under ambiguity, and produces a reproducible ISCO4 variable that enables systematic ESCO mapping. The resulting ESCO portfolios provide a consistent basis to measure occupational skill composition, transferability, and segmentation within European platform work, and to connect platform task structures and learning outcomes to broader occupational skill endowments.

3.2.1 Scope, eligibility and analytical sample

Occupational coding was applied to all respondents who reported a primary occupation, defined as the job or occupation outside the platform context that the respondent identifies as their main labour-market position. Because the ESCO portfolio analysis requires a valid ISCO-08 4-digit unit group identifier, respondents were excluded from the ESCO-matched analysis if (i) occupational information was missing or unusable (e.g., empty, undefined, or non-interpretable titles), or (ii) an occupational code could not be assigned with sufficient confidence given the available information.

As a consequence, the ESCO-linked analytical sample is smaller than the full survey sample. The exact matched sample size depends on (a) availability of primary-occupation information and (b) successful linkage through the ISCO-ESCO crosswalk. In the current portfolio-based empirical results, the ESCO-matched sample is approximately N≈1,600 observations, while the number of distinct ISCO 4-digit unit groups depends on the filtering applied for each table (e.g., restricting to respondents with complete information across learning/task modules). Throughout the process, occupational coding is treated as a reproducible data transformation step, and the final ISCO4 variable is stored and carried forward for ESCO linkage and portfolio construction.

3.2.2 Establishing the 2-digit ISCO backbone

Because platform-related job titles are often broad or non-standard, the procedure begins by assigning each respondent to a 2-digit ISCO group, which acts as a structural "backbone" for later refinement. This step is essential for quality assurance: it reduces noise in downstream classification and prevents implausible 4-digit assignments across unrelated occupational families.

This process involves three steps:

1. Step 2.1 Title normalisation
2. Step 2.2 Dictionary matching to major occupational families
3. Step 2.3 Ambiguity resolution using functional signals

Self-reported job titles were normalised to maximise comparability across respondents and reduce purely cosmetic variation. Normalisation included: lowercasing and whitespace trimming; removal of punctuation and special characters; harmonisation of common abbreviations and variants; and consolidation of obvious synonyms where appropriate. The aim is not to "interpret" titles at this stage but to standardise them so that dictionary matching is consistent.

Normalised titles were matched against a curated occupation dictionary covering major ISCO families relevant for platform work (e.g., ICT, business and administration, creative professions, teaching, clerical support, drivers, elementary occupations). Where title matches were unambiguous, respondents were assigned directly to the corresponding 2-digit ISCO group. This yields a stable classification into broad families that can later be refined into unit groups.

Some titles are inherently ambiguous (e.g., "consultant," "analyst," "assistant," "freelancer"). For such cases, the 2-digit assignment was refined using respondent-level information that is informative about occupational family membership. Specifically, we used: education level (as a proxy for occupational level and skill requirements); composite task-structure measures derived from the Nature-of-Work module (NW1-NW15) capturing routineness, standardisation, autonomy, complexity/creativity, and collaboration; and task novelty measures where available (frequency of "new to me" tasks). These functional signals are used strictly to choose among plausible 2-digit families and reduce misclassification risk; they are not used to generate overly narrow occupational assignments unsupported by the title evidence.

3.2.3 Within-family refinement to ISCO-08 4-digit unit groups

Once each respondent is assigned to a 2-digit family, classification is refined to the ISCO-08 4-digit unit group level within that family.

Within each 2-digit group, we extracted the most frequent unique job titles in the dataset and expanded the dictionary to map these titles to specific 4-digit unit groups. This step increases occupational granularity while retaining interpretability. It is particularly important for distinguishing roles that are common in platform work but often reported using generic labels (e.g., different ICT roles, business/finance roles, creative roles).

To avoid "false precision," we applied a conservative rule: where title information (and any supporting evidence) did not clearly distinguish between multiple plausible unit groups, classification remained at the safest meaningful level within the family rather than forcing a narrow code. This rule is critical in platform contexts where job titles can be aspirational, incomplete, or multi-functional.

3.2.4 Skill- and task-informed refinement

Even after dictionary refinement, platform samples can disproportionately accumulate in generic categories (e.g., broad professional unit groups or residual elementary codes). To reduce overuse of such fallback categories, we introduced a refinement layer using skill and task signals, while keeping the ISCO hierarchy as a strict constraint.

We constructed standardised (z-score) indices from three sources in the survey:

- pre-existing skills (Previous_* variables),
- self-reported skill improvements (Improved_* variables), and
- platform skill development items (SD1-SD10).

These were grouped into interpretable dimensions such as technical/specialty skills, analytical skills, language skills, communication skills, organisational skills, and personal/social skills. These indices provide functional evidence that can help differentiate plausible 4-digit candidates within the same 2-digit family.

From NW1-NW15 we constructed composite indices capturing routine/standardisation, complexity/creativity/skill variety, autonomy constraints, collaboration intensity, and novelty (where available). These indicators are particularly informative in differentiating occupations where platform work can appear under generic labels but differs strongly in task structure.

At this stage, each respondent has a restricted set of plausible ISCO4 candidates defined by (i) the assigned 2-digit family and (ii) title-based dictionary matches. Candidates were evaluated using a transparent scoring logic: scores were increased for candidates whose typical task/skill profile aligns with the respondent's observed skill and task indicators; scores were computed only within the constrained candidate set to avoid cross-family drift; and where score differences were small (i.e., ambiguity remained), the conservative assignment rule was applied. Conceptually, this resembles probabilistic assignment, but operationally it is best described as hierarchical candidate scoring and selection constrained by the ISCO structure.

After coding, we conducted diagnostic checks to ensure the occupational distribution was not artificially concentrated in a few generic categories. This included reviewing the frequency of fallback unit groups and computing diversity/concentration measures (e.g., HHI and entropy-based indices). Where fallback categories remained dominant, we re-examined whether within-family refinements could be supported by the available evidence (title + task + skill) without violating the conservative assignment rule.

3.2.5 Linkage to ESCO and construction of occupational skill portfolios

The final ISCO4 codes were merged with an ISCO-ESCO mapping dataset. The mapping provides occupation-skill relationships from which occupation-level ESCO skill bundles are derived. Operationally, linkage proceeds by merging respondent-level records on ISCO4 to a crosswalk that contains, for each ISCO unit group, ESCO skill counts and their distribution across broad ESCO skill families.

For each ISCO occupation we extract: total ESCO skill count (skill breadth), category counts for ESCO skill families (green, digital, language, knowledge, competence, transversal, thinking, self-management, social, life, physical), and corresponding category shares. From these inputs we compute the portfolio measures used in the empirical analysis: skill breadth; skill diversification (1-HHI from category shares); intensity measures (digital, cognitive, social, physical/manual, green); a transferability proxy (standardised breadth + diversification + transversal component); an automation exposure proxy (physical/manual intensity minus cognitive intensity); and an integrated portfolio index combining breadth, digital/cognitive intensity, transferability, and (negatively) automation exposure, alongside a standardised version for comparability. Each respondent is then assigned the ESCO portfolio associated with their primary occupation ISCO4 code.

Table 3-2 reports the distribution of respondents' primary occupations in the Joint CrowdLearn dataset using ISCO-08 4-digit unit groups. This provides an important descriptive bridge between the platform segments (freelancing vs microwork) and the broader labour market. By anchoring workers in their main occupation, the table clarifies whether the two segments draw from similar occupational backgrounds or whether they reflect structurally different labour-market pools, which is central to the analysis of segmentation and competitiveness. The occupational distribution is reported for the pooled ESCO-linked analytical sample (N=1,608) and separately by segment (N=895 freelancers; N=713 microworkers).

A first striking feature is the strong concentration of observations in a small number of unit groups, alongside a long tail of professional occupations. The single largest category is “Elementary workers not elsewhere classified” (9629), which accounts for a substantial share of the matched sample. The presence of a large residual elementary category is not unusual in platform datasets, where job titles are often generic and respondents may report broad occupational identities. At the same time, the remainder of the distribution reveals meaningful heterogeneity, with sizeable representation in professional unit groups spanning ICT, business and administration, creative industries, and language-related professions. This mix indicates that platform labour intersects both lower-skill and higher-skill occupational strata rather than mapping neatly onto a single segment of the labour market.

Second, the table highlights clear differences in occupational composition across segments. Freelancers are more visibly represented in creative and language-intensive professions (e.g., graphic and multimedia designers, authors and related writers, translators and other linguists), as well as in ICT-related professional roles (e.g., systems analysts, software developers, web and multimedia developers). Microworkers, in contrast, show relatively greater concentration in clerical and task-fragmentation-compatible occupations such as data entry clerks, as well as in residual elementary work categories. This pattern aligns with the expectation that microwork is more closely linked to standardised, routine task environments, while freelancing is more strongly associated with professional and project-based work. It also reinforces the notion that segment differences are not only about what workers do on platforms, but also about their broader occupational positioning and skill endowments.

Third, Table 3-2 provides a practical justification for the ESCO portfolio mapping strategy used in later analysis. The fact that a substantial share of the sample is coded into identifiable 4-digit professional unit groups means that assigning ESCO skill bundles based on respondents’ primary occupations can capture meaningful variation in underlying occupational skill requirements. At the same time, the prominence of residual categories underscores an important measurement caveat: where occupational titles are generic and map to broad “not elsewhere classified” unit groups, the resulting ESCO portfolios necessarily reflect the skill structure of those broad groups. This reinforces the importance of combining occupation-based portfolios with additional task- and skill-based indicators and of interpreting ESCO-derived measures as occupation-level skill requirements rather than precise individual competencies.

Overall, Table 3-2 establishes that the ESCO-linked CrowdLearn sample covers a wide range of primary occupations but is unevenly distributed across unit groups, with a particularly large residual elementary category. The segment breakdown suggests that freelancing and microwork are embedded in systematically different occupational backgrounds: freelancing is more strongly linked to professional, creative, language-intensive, and ICT-related occupations, whereas microwork is more strongly linked to clerical and residual elementary profiles. This occupational stratification motivates the subsequent empirical focus on ESCO-based skill portfolios and provides an initial descriptive indication of segmentation within platform work.

Table 3-2: The 4-digit ISCO codes for primary occupation in the Joint Crowdlearn database

ISCO Code	ISCO-08 Unit Group Title	Pooled sampl	Freela ncers	Micro worker
	#Observations	*1,608*	*895*	*713*
1211	Finance Managers	2	1	1
1219	Business Services & Administration Managers Not Elsewhere Classified	162	91	71
2111	Physicists and Astronomers	10	4	6
2112	Meteorologists	45	31	14
2113	Chemists	1		1
2120	Mathematicians, Actuaries and Statisticians	3	2	1
2141	Industrial and Production Engineers	1		1
2142	Civil Engineers	1	1	
2144	Mechanical Engineers	6	1	5
2149	Engineering Professionals Not Elsewhere Classified	70	33	37
2161	Building Architects	25	17	8
2166	Graphic and Multimedia Designers	85	68	17
2211	Generalist Medical Practitioners	5	1	4
2221	Nursing Professionals	7	3	4
2263	Environmental & Occupational Health and Hygiene Professionals	1		1
2310	University and Higher Education Teachers	13	8	5
2359	Teaching Professionals Not Elsewhere Classified	46	16	30
2411	Accountants	3	1	2
2413	Financial Analysts	26	4	22
2421	Management and Organisation Analysts	88	52	36
2423	Personnel and Careers Professionals	25	22	3
2431	Advertising and Marketing Professionals	55	50	5
2433	Technical and Medical Sales Professionals (excluding ICT)	1	1	
2511	Systems Analysts	20	14	6
2512	Software Developers	68	37	31
2513	Web and Multimedia Developers	42	28	14
2519	Software and Applications Developers and Analysts Not Elsewhere Classified	1		1
2521	Database Designers and Administrators	1	1	
2529	Database and Network Professionals Not Elsewhere Classified	2	1	1
2641	Authors and Related Writers	49	42	7
2643	Translators, Interpreters and Other Linguists	98	80	18
2652	Musicians, Singers and Composers	72	45	27
2654	Film, Stage and Related Directors and Producers	25	20	5
3343	Administrative and Executive Secretaries	41	21	20
3411	Legal and Related Associate Professionals	1	1	
3512	Information and Communications Technology User Support Technicians	12	4	8
4132	Data Entry Clerks	85	14	71
7115	Carpenters and Joiners	1		1
7411	Building and Related Electricians	4	1	3
8322	Car, Taxi and Van Drivers	7		7
9629	Elementary Workers Not Elsewhere Classified	398	179	219

4. Competitiveness or Segmentation? Evidence from the Joint CrowdLearn Data

The previous chapter set out the conceptual framework and testable hypotheses guiding the empirical work in this deliverable. Building on the segmentation-competitiveness debate, it established the core mechanisms through which platform work may generate divergent worker trajectories: differences in occupational skill endowments, differences in platform task design and autonomy, and differences in learning opportunities and skill accumulation. It also clarified how these mechanisms map into policy-relevant concerns, particularly worker classification, vulnerability, and the design of incentives for upskilling, while motivating the use of ESCO (2022) as a common language for describing occupational skill portfolios.

Chapter 4 operationalises this framework using the Joint CrowdLearn dataset. The chapter provides empirical evidence on whether the gig economy functions as a largely competitive market in which skills are rewarded similarly across platform segments, or whether it is internally segmented into distinct "tracks" characterised by different worker profiles, task structures, learning behaviours, and degrees of worker-like exposure. The analysis proceeds by contrasting two major segments, namely freelancing and microwork, while anchoring workers in the broader labour market through their primary occupations and an ISCO-ESCO skill portfolio mapping. In doing so, the chapter translates the hypotheses from Chapter 3 into a coherent set of descriptive and regression-based tests that speak directly to the deliverable's targets: identifying skills profiles, proposing mechanisms for skill bundles and transferability, and informing policy debates on segmentation, competitiveness, and regulatory treatment of platform work.

The Joint CrowdLearn dataset is particularly well suited to this objective because it combines two CEDEFOP survey instruments that capture complementary parts of the platform labour spectrum in the period immediately prior to the COVID-19 pandemic. The merged database distinguishes clearly between respondents associated with freelancing (more project-based and discretionary platform work) and those associated with microwork (more fragmented, standardised task-based work). This distinction provides a natural empirical basis for assessing segmentation: if the gig economy is internally stratified, we expect to observe consistent differences across the two groups in occupational backgrounds, task design, learning strategies, and outcomes; if it is competitive and integrated, differences should be largely explained by observable skill endowments and should not systematically persist after accounting for worker characteristics and country context.

A distinctive feature of the CrowdLearn inquiry is that it allows platform workers to be anchored in the broader labour market through their primary occupation. Respondents reporting a primary occupation are assigned a harmonised occupational code at the ISCO-08 4-digit unit group level, which is then linked to the ESCO 2022 taxonomy. This produces occupation-level ESCO skill portfolios, capturing skill breadth, composition, and derived indices such as diversification and transferability, assigned to individuals based on their primary occupation. As a result, the chapter is able to connect the occupational skill structures workers bring from the wider labour market to the way they experience platform work, including the nature of tasks, learning behaviours, and self-reported skill upgrading.

The chapter proceeds in five steps. Section 4.1 introduces a basic model of segment choice, task allocation, learning investment and worker-like exposure, which yields the hypotheses tested in the empirical tables. Section 4.2 then sets out the measurement strategy and empirical implementation. Its subsections present the evidence, moving from occupational skill portfolios and motivations to task structure, learning behaviours, and skill upgrading, and then to mechanism tests linking occupational portfolios to platform task content and upgrading. The final subsection 4.3 synthesises the results in relation to the segmentation, competitiveness and hybrid narratives, and draws out policy-relevant implications for worker classification and upskilling incentives.

4.1 A simple model of segment choice, task allocation, learning, and worker-like exposure

Consider a population of workers i who can engage in online platform work in one of two segments: freelancing F and microwork M. The modelling logic combines (i) self-selection into segments based on comparative advantage and constraints in the spirit of Roy-type models (Roy, 1951; Heckman and Sedlacek, 1985; Heckman and Honoré, 1986), (ii) task-based differences between routine and non-routine work (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011), and (iii) an assignment mechanism mapping skills into tasks (Rosen, 1981), extended with segmentation and platform-governance considerations (Weil, 2014; Katz and Krueger, 2016; Berg et al., 2018; Wood et al., 2019).

Each worker has a skill portfolio S_i that summarises their occupational skill endowment derived from their primary occupation. In the empirical work, S_i is proxied by ESCO portfolio measures mapped from the worker's primary ISCO occupation: cognitive/thinking share, social share, physical/manual share, diversification, and composite indices such as transferability and an overall portfolio index. Workers also have an outside option in standard labour markets w_i and a constraint parameter $\kappa_i \geq 0$ capturing frictions (health constraints, limited access to standard work, local labour-market barriers). Finally, workers differ in autonomy preference A_i and in non-pecuniary motives J_i (interest, enjoyment, time-filling).

4.1.1 Segment regimes and segment choice

We conceptualise the Joint CrowdLearn platform economy as operating through two segments, freelancing (F) and microwork (M), which differ in task regimes, autonomy, and governance. Let $s \in \{F, M\}$. Each segment is characterised by a task regime T_s and an embedded level of discretion/autonomy α_s, with $\alpha_F > \alpha_M$. Workers differ in their occupational skill portfolios S_i, proxied empirically by ESCO skill profiles assigned via each respondent's primary ISCO occupation. Segment-specific productivity depends on skill–task complementarity:

$$q_{is} = a_s(S_i, T_s) \qquad (1)$$

To make the complementarity structure transparent, we use a parsimonious decomposition of S_i into components that matter differently across the two regimes:

$$q_{iF} = \theta_F(\lambda_C C_i + \lambda_{Soc} Soc_i + \lambda_D Div_i), q_{iM} = \theta_M(\mu_R R_i + \mu_B B_i) \qquad (2)$$

Here C_i denotes the cognitive/thinking content of the occupational portfolio, Soc_i its social/interaction content, and Div_i a diversification/transferability component; R_i and B_i capture routine-compatible/basic execution components. The maintained assumption is that $\partial q_{iF}/\partial C_i$, $\partial q_{iF}/\partial Soc_i$, and $\partial q_{iF}/\partial Div_i$ are positive and larger than their microwork counterparts, while routinised/basic components matter relatively more for microwork productivity.

Segment participation is modelled as a Roy-style self-selection problem. Worker i chooses the segment that maximises expected utility:

$$U_{is} = p_s q_{is} - c_s + \eta \alpha_s A_i + \xi_s J_i - \kappa_i + \varepsilon_{is} \qquad (3)$$

where p_s is the expected return to productivity in segment s, c_s captures entry/transaction costs, A_i measures the worker's preference for autonomy, J_i captures non-pecuniary motives (e.g., enjoyment or time-filling), κ_i captures constraints in standard labour markets, and ε_{is} is idiosyncratic. Define the utility difference $\Delta U_i \equiv U_{iF} - U_{iM}$, so that the worker chooses freelancing if $\Delta U_i \geq 0$. Substituting (1)-(2) into (3) yields:

$$\Delta U_i = [p_F q_{iF} - p_M q_{iM}] - (c_F - c_M) + \eta(\alpha_F - \alpha_M) A_i + (\xi_F - \xi_M) J_i + \varepsilon_i$$

This representation makes the following three Block A propositions immediate as comparative statics:

Proposition A₁ (Occupational sorting across segments): If freelancing rewards cognitive/social/diversified bundles more strongly, then higher values of C_i, Soc_i, and Div_i increase ΔU_i and therefore increase the likelihood of selecting freelancing. Formally, for any component $z \in \{C, Soc, Div\}$,

$$\frac{\partial \Delta U_i}{\partial z_i} = p_F \frac{\partial q_{iF}}{\partial z_i} - p_M \frac{\partial q_{iM}}{\partial z_i} > 0$$

under $\partial q_{iF}/\partial z_i > 0$ and $\partial q_{iM}/\partial z_i \approx 0$. Conversely, if R_i and B_i primarily raise microwork productivity, then $\partial \Delta U_i/\partial R_i < 0$ and $\partial \Delta U_i/\partial B_i < 0$. This implies that freelancers draw relatively more from occupations with higher cognitive/social and transferable/diversified bundles, while microwork is relatively more compatible with routine/basic execution profiles.

Proposition A₂ (Motivational sorting): Because autonomy enters utility with weight $\eta\alpha_s$ and $\alpha_F > \alpha_M$, workers with stronger autonomy preferences A_i are more likely to select freelancing:

$$\frac{\partial \Delta U_i}{\partial A_i} = \eta(\alpha_F - \alpha_M) > 0$$

Similarly, segment differences in the valuation of non-pecuniary motives imply:

$$\frac{\partial \Delta U_i}{\partial J_i} = (\xi_F - \xi_M)$$

so whichever segment places a higher weight on those motives attracts workers with higher J_i. This yields systematic differences in reported motivations across segments even after conditioning on observables.

Proposition A₃ (Task-regime differentiation): The task-regime distinction is built into the primitives of the model: microwork has lower autonomy (α_M) and a task regime T_M that embeds higher routineness/standardisation than T_F. This implies that, conditional on segment membership, reported task characteristics differ systematically: microwork features more routine, repeatable, platform-directed work with limited discretion, while freelancing features more complex, creative, multi-skill project work with higher discretion.

We translate these predictions into three testable hypotheses implemented as conditional comparisons of microworkers to freelancers, controlling for worker characteristics $X$and country fixed effects δ_c.

- **H₁** (Occupational skill portfolio segmentation; S_i): Microworkers come from primary occupations with weaker ESCO portfolios, i.e. lower cognitive/thinking and social content, lower diversification/transferability, and relatively higher physical/manual content. This hypothesis is tested in Table 4-1.
- **H₂** (Motivation segmentation; A_i, J_i): Freelancers are more autonomy-, interest-, and choice-oriented, while microworkers are more likely to report secondary or consumption-oriented motives such as time-filling, enjoyment, or "fruitful activity." This hypothesis is tested in Table 4-2.
- **H₃** (Task regime segmentation; T_s, α_s): Microwork is more routine, standardised, and low-autonomy, while freelancing is more complex, creative, and multi-skill. This hypothesis is tested in Table 4-3.

This Block A structure provides the first empirical entry point into the segmentation-versus-competitiveness question. If H1-H3 hold robustly after conditioning on $X$and δ_c, the evidence is consistent with distinct regimes and systematic sorting rather than a single integrated platform labour market.

4.1.2 Mechanisms: skill-task alignment and transferability conversion

Block A explains why microwork and freelancing can differ in composition and task regimes through selection into distinct environments. Block B then explains how occupational endowments translate into realised platform experiences and outcomes once workers are active in a segment. The model captures two mechanism propositions. The first is an assignment (alignment) mechanism: occupational skill portfolios shape the task content workers end up doing on the platform. The second is a conversion mechanism: occupational transferability raises the ability to convert platform participation into upgrading, but this conversion depends on the task regime and is therefore segment-specific.

Let x_{is}denote a summary index of realised task content experienced by worker $i$in segment s (e.g., complex/creative tasks, routinised tasks, collaborative tasks). We represent assignment with a reduced-form mapping:

$$x_{is} = \psi_s S_i + \omega_s + \nu_{is} \qquad (4)$$

Here, $S_i$is the occupational skill portfolio, $\psi_s$is a segment-specific loading vector translating occupational skills into platform task content, $\omega_s$is a segment-level shift capturing differences in the menu of tasks and governance, and ν_{is}captures idiosyncratic matching noise. The key mathematical implication is that task content responds to skill components with slopes given by ψ_s. For a particular component $z$of the portfolio (e.g., thinking share, physical share, social share), we have:

$$\frac{\partial x_{is}}{\partial z_i} = \psi_{s,z} \qquad (4')$$

Thus, Proposition B1 follows directly: if cognitive/thinking intensity raises access to complex tasks, then $\psi_{s,C} > 0$; if physical/manual intensity loads into routinised tasks, then $\psi_{s,P} > 0$; and if social intensity loads into collaborative tasks, then $\psi_{s,Soc} > 0$. Segment heterogeneity is captured by allowing these slopes to differ:

$$\psi_{F,z} \neq \psi_{M,z} \qquad (4'')$$

Empirically, this is exactly what the interaction specification tests: whether the slope linking a given occupational skill component to a given task index differs between microwork and freelancing.

Mechanism 2: Transferability-to-upgrading conversion (segment-specific learning production). Let ΔH_{is}denote the human-capital gain from platform work in segment s(measured empirically via reported skill improvement outcomes). We model upgrading with a segment-specific learning production function:

$$\Delta H_{is} = g_s(e_i, S_i, T_s) \qquad (5)$$

Learning effort $e_i$includes deliberate learning inputs (information search, courses, reflection, collaboration), while $T_s$captures the segment's task regime. Define $Trans_i$as a scalar index extracted from $S_i$that captures portability (e.g., breadth/diversification/transversal components). The marginal effect of transferability on upgrading is:

$$\frac{\partial \Delta H_{is}}{\partial Trans_i} = \frac{\partial g_s}{\partial Trans_i} \qquad (5')$$

Proposition B2 is the claim that this marginal effect is larger in freelancing than in microwork:

$$\frac{\partial g_F}{\partial Trans_i} > \frac{\partial g_M}{\partial Trans_i} \qquad (6)$$

The inequality in (6) is a comparative static implied by the task-regime difference: because $T_F$features more complex, autonomy-intensive tasks with richer feedback, transferable bundles can be deployed, recombined, and generalised into measurable upgrading more effectively than under routinised microtasks in T_M. In reduced form, this implies a segment interaction: if upgrading is regressed on $Trans_i$, microworker status, and their interaction, the interaction term captures the difference in slopes:

$$\Delta H_i = \beta_0 + \beta_1 Trans_i + \beta_2 1\{M\} + \beta_3 (Trans_i \times 1\{M\}) + \text{controls} + \varepsilon_i,$$

where $\beta_1$is the freelancing slope and $\beta_1 + \beta_3$is the microwork slope. Proposition B2 corresponds to:

$$\beta_3 < 0. \qquad (6')$$

That is, transferability predicts upgrading more strongly in freelancing than in microwork.

These two mechanisms generate the Block B propositions that are taken to the data in Section 4.3. The skill-task alignment proposition is tested by relating task-content indices to the relevant occupational skill components and allowing segment-specific slopes via interactions. The transferability conversion proposition is tested by relating upgrading outcomes to $Trans_i$ and estimating whether the $Trans_i$ slope is significantly smaller for microworkers than for freelancers. Together, these tests establish whether segment differences reflect only baseline regime shifts (ω_s) or also differences in how occupational endowments translate into realised task allocation and human-capital conversion (ψ_s and $\partial g_s / \partial Trans_i$).

The model predicts the following mechanism comparative statics:

- **Proposition B_1** (Skill-task alignment): Occupational skill composition predicts platform task content: higher cognitive/thinking components map into more complex tasks, higher physical/manual components map into more routine tasks, and higher social components map into more collaborative tasks. Because the task menu and governance differ by segment, the mapping may differ across microwork and freelancing.
- **Proposition B_2** (Transferability conversion differs by segment): Occupational transferability predicts technical upgrading more strongly in freelancing than in microwork, implying a weaker transferability-upgrading relationship for microworkers.

We translate these predictions into two testable hypotheses, evaluated conditional on worker controls X and country fixed effects δ_c, using interaction specifications that allow segment-specific slopes.

- **H_4** (Skill-task alignment; Equation 4): Occupational skill composition predicts platform task content, with potentially different mappings across segments. In particular, thinking shares should predict complex/creative task indices, physical/manual shares should predict routine task indices, and social shares should predict collaboration indices. This hypothesis is tested in Table 4-4 (Columns 1-3).
- **H_5** (Transferability-to-upgrading conversion; segment-dependent returns): Occupational transferability predicts technical upgrading more strongly for freelancers than for microworkers; empirically, the interaction between $Trans_i$ and microworker status is expected to be negative, implying a smaller marginal effect for microworkers. This hypothesis is tested in Table 4-4 (Columns 4-5).

Taken together, this block provides the mechanism evidence linking occupational skill bundles to platform task allocation and to the conversion of transferability into upgrading. This is an important step in the chapter's argument: it shows not only that microwork and freelancing differ, but also why they differ through segment-specific skill-task alignment and segment-specific returns to transferable occupational skill bundles.

4.1.3 Learning inputs and upgrading outcomes under segmented task regimes

Block B focuses on how occupational endowments map into realised task content and how transferability converts into upgrading differently across segments. Block C turns to the learning process itself: workers choose learning effort while active on platforms, and the task regime shapes the productivity of that effort. The central idea is that learning is not automatic. Workers invest time and attention in learning activities (e.g., seeking information, taking courses, reading, reflecting, collaborating), and these inputs translate into human-capital gains only insofar as the work environment provides scope for feedback, iteration, discretion, and multi-skill application. Because freelancing is characterised by more complex, autonomy-intensive work, the model treats the freelancing regime as a higher-return learning environment than microwork.

We represent human-capital gains in segment s by a segment-specific learning production function:

$$\Delta H_{is} = g_s(e_i, S_i, T_s) \qquad (7)$$

Here ΔH_{is} is the upgrading outcome (measured empirically through self-reported skill improvements), e_i is learning effort, S_i is the occupational skill portfolio, and T_s captures the task regime. Learning effort e_i is a choice variable and includes deliberate inputs such as following developments, reading, taking online courses, deep reflection, experimentation, and collaboration. To provide a minimal microfoundation, suppose worker i chooses $e_i \geq 0$ to maximise net returns to learning within their segment:

$$\max_{e \geq 0} V_{is}(e) = \pi_s \cdot g_s(e, S_i, T_s) - C(e)$$

where π_s is the value of upgrading in segment s (through higher productivity, better task access, or higher expected earnings) and $C(e)$ is the convex cost of effort. The first-order condition is:

$$\pi_s \frac{\partial g_s}{\partial e} = C'(e) \qquad (8)$$

Because freelancing tasks typically provide more scope for applying knowledge, receiving feedback, and accumulating project-based experience, we assume that learning effort is more productive under the freelancing regime:

$$\frac{\partial g_F}{\partial e} > \frac{\partial g_M}{\partial e} \qquad (9)$$

With standard convexity, (8)-(9) imply that the optimal learning effort is higher in freelancing:

$$e_F^* > e_M^* \qquad (10)$$

This yields the first Block C proposition: freelancers engage more in deliberate learning activities and self-regulated learning strategies than microworkers, even after conditioning on observables.

Block C also generates a proposition about the *type* of upgrading. Because the two regimes differ in task structure, the learning technology $g_s(\cdot)$ loads differently on skill outcomes. Complex, autonomy-intensive freelance projects are expected to generate upgrading in specialised technical and communication/market-facing competences (client interaction, project coordination, specialised tools). In contrast, standardised microwork may generate improvements that are more general or foundational (practice-based learning skills, generic analytical routines, computer literacy, language exposure), even if it provides fewer pathways for specialised professional upgrading. Formally, this is captured by allowing ΔH_{is} to be multi-dimensional and by allowing the mapping from learning effort and task regime to each dimension to differ across s.

Hence the two propositions are the following:

- **Proposition C_1** (Learning input differentiation): Because the return to learning effort is higher in freelancing, freelancers should invest more in learning while working on platforms. This should be visible both in higher rates of deliberate learning activities and in stronger self-regulated learning strategies and learning transfer beliefs.
- **Proposition C_2** (Segmented upgrading profiles): Because the learning environments and task regimes differ, the type of upgrading associated with platform participation should differ across segments. Freelancing should be more strongly associated with specialised technical and communication/market-facing upgrading, while microwork is more likely to generate improvements in more general or foundational skills (such as computer literacy, language, and some analytical/learning gains) rather than specialised professional upgrading.

We translate these two predictions into three testable hypotheses, evaluated as conditional differences between microworkers and freelancers controlling for worker characteristics $X$and country fixed effects δ_c.

- **H_6** (Learning activity gap; learning effort e_i): Freelancers engage more frequently in deliberate learning activities while doing platform work, while microworkers engage less. This hypothesis is tested in Table 4-5.
- **H_7** (Self-regulated learning strategy gap; learning capability and transfer beliefs): Freelancers exhibit stronger self-regulated learning strategies and stronger beliefs that platform learning transfers to future jobs than microworkers. This hypothesis is tested in Table 4-6.
- **H_8** (Segmented upgrading profiles; realised ΔH_{is}): Freelancers report stronger specialised technical and communication upgrading, while microworkers report more general/basic improvements (e.g., computer literacy, language, some analytical/learning gains). This hypothesis is tested in Table 4-7.

Together, Tables 4-5, 4-6 and 4-7 establish whether the two platform segments differ in learning investments and in the pattern of perceived skill upgrading, conditional on observable characteristics and national context. Combined with the mechanism evidence in Table 4-4, these results provide a coherent account of segmentation: differences between microwork and freelancing are not only compositional, but also reflect distinct task environments that shape learning behaviour and the kinds of skills workers accumulate through platform participation.

4.1.4 Worker-like exposure and regulatory relevance: control versus dependence

Block D links the model to classification and protection debates by formalising a policy-relevant concept of worker-like exposure that is distinct from income dependence. The aim is to separate two channels of vulnerability in platform work: (i) economic reliance on platform income, and (ii) organisational control embedded in task design and governance. The key proposition is that these channels need not move together, so dependence-based metrics can miss worker-like conditions that arise through routinisation and constrained discretion.

For worker $i$in segment s, define worker-like exposure as an organisational-control index:

$$W_{is} \equiv h(R_{is}, A_{is}, \mathcal{G}_s) \qquad (11)$$

where R_{is}measures routineness/standardisation of tasks performed, A_{is}measures autonomy/discretion (higher values mean more discretion), and $\mathcal{G}_s$captures the governance environment (monitoring, evaluation, acceptance rules, ranking, sanctions). We impose the monotonicity restrictions:

$$\frac{\partial h}{\partial R} > 0, \frac{\partial h}{\partial A} < 0, \frac{\partial h}{\partial \mathcal{G}} > 0 \qquad (12)$$

These sign restrictions encode the "control" idea: exposure rises when work is more routinised and standardised, falls when workers have more discretion, and rises when governance is tighter.

Proposition D₁ (Exposure is higher in microwork): Segment task regimes imply systematic differences in R_{is}, A_{is}, and governance. In the model primitives, microwork has higher routineness and lower discretion than freelancing, so:

$$E[R_{iM}] > E[R_{iF}], E[A_{iM}] < E[A_{iF}], \mathcal{G}_M \geq \mathcal{G}_F \qquad (13)$$

Applying (12) to (11), these inequalities imply the exposure ordering:

$$E[W_{iM}] > E[W_{iF}] \qquad (14)$$

This is the core "worker-like exposure" proposition: the microwork regime generates higher organisational exposure even if workers participate casually or intermittently, because exposure is driven by task design and governance, not by income reliance.

A practical advantage of this definition is that it separates organisational exposure from income dependence. Then, as a separate outcome, let income dependence be the share of total income derived from platform work:

$$D_i \in [0,1] \qquad (15)$$

In a reduced form, dependence can be expressed as:

$$D_i = \frac{y_i^{plat}}{y_i^{plat} + y_i^{other}} \qquad (16)$$

where y_i^{plat} is platform income and y_i^{other} is income from other sources. Importantly, D_i is governed by budgets and outside options (hours, wages, alternative employment), whereas W_{is} is governed by task design, discretion, and governance. The model does not impose any identity mapping $D_i = f(W_{is})$.

Income dependence can amplify vulnerability, but it is not a sufficient descriptor of employee-like organisation: workers can experience high routineness and low autonomy even when platform work is supplementary, and conversely can be highly dependent while retaining substantial discretion in how and which tasks they perform. This distinction matters for regulatory discussions around classification and protections, which often hinge on organisational dependence and control rather than earnings reliance alone.

Proposition D₂ (Control and dependence can diverge): Because $W_{is}$and $D_i$are determined by different objects, W_{is} by $(R_{is}, A_{is}, \mathcal{G}_s)$ and D_i by income composition, there is no theoretical necessity that they co-move. Formally, without an additional restriction that links governance to income shares, it is feasible that:

$$E[W_{iM}] > E[W_{iF}] \text{while} E[D_{iM}] \leq E[D_{iF}] \qquad (17)$$

This inequality captures the policy-relevant divergence: microwork can be highly worker-like in organisational terms (high exposure) even when it is not the main income source (low dependence). Conversely, freelancing can be income dependent while maintaining higher discretion and lower organisational exposure.

The final block of the model links the empirical analysis to the regulatory and policy debates motivating D5.3. The key premise is that vulnerability in platform work is not captured only by whether platform work is a main income source, but also by the degree to which work is organised through routinised tasks, constrained discretion, and strong platform governance. To reflect this, we introduce a policy-relevant concept of worker-like exposure that captures the extent to which platform work resembles an employment relationship in organisational terms.

We translate the 2 propositions of block D into two hypotheses evaluated conditional on worker controls X and country fixed effects δ_c.

- **H_9** (Worker-like exposure by segment): Microworkers exhibit higher worker-like exposure, higher routineness and lower autonomy than freelancers. This hypothesis is tested in Table 4-8 (Columns 2-4), using autonomy constraints, routine task indicators, and a composite exposure index.
- **H_{10}** (Control versus dependence; distinct vulnerability dimensions): Worker-like exposure and income dependence do not perfectly overlap; microworkers may show higher exposure even if they are not the most income dependent. This hypothesis is tested in Table 4-8 by comparing the segment association with high income dependence (Column 1) to the association with routineness/autonomy/exposure (Columns 2-4). Columns 5-6 provide supplementary evidence by relating exposure to key outcomes (upgrading and enjoyment), highlighting how organisational vulnerability can translate into worker outcomes.

Taken together, this final block closes the model-to-policy loop. It uses the Joint CrowdLearn evidence to distinguish between economic reliance and organisational control, and it motivates why policy discussions about classification and protection may need to consider indicators of autonomy and routinisation alongside income dependence when assessing segmentation and vulnerability in platform work.

4.2 Empirical tests of segmentation, mechanisms, learning and exposure

This subsection translates the mechanisms introduced in Section 4.1 into a set of testable hypotheses with clear counterfactual statements and a transparent mapping to the empirical implementation. The model implies that freelancing and microwork constitute two distinct task regimes with different skill-task complementarities, learning returns, and degrees of organisational control. Each hypothesis therefore has a natural "counterfactual world" corresponding to a competitive, integrated gig economy in which segment differences are fully explained by observable worker characteristics and occupational skill portfolios, and segment membership has limited residual predictive power once these are controlled for.

Empirically, hypotheses are tested using regression models of the form:

$$Y_{ic} = \alpha + \beta\, Microworker_{ic} + X_{ic}'\gamma + \delta_c + \varepsilon_{ic} \quad (9)$$

and, for mechanism hypotheses, interaction models of the form:

$$Y_{ic} = \alpha + \beta_1 Z_{ic} + \beta_2 Microworker_{ic} + \beta_3 (Z_{ic} \times Microworker_{ic}) + X_{ic}'\gamma + \delta_c + \varepsilon_{ic} \quad (10)$$

where Y_{ic} is the outcome of interest for respondent i in country c, $Microworker_{ic}$ indicates membership of the microwork segment (freelancing is the reference group), X_{ic} is a set of controls (demographics, education, labour-market status, experience), and δ_c are country fixed effects. Standard errors are clustered by country. In the next sub-sections, we present eight tables that implement these tests in coherent thematic blocks.

Hypotheses H_1-H_6 test whether segmentation appears in occupational endowments, motivations, task regimes, learning behaviour, and upgrading profiles. Hypotheses H_7-H_8 provide the mechanism tests that validate skill-task complementarity and the segment-dependent conversion of transferability into upgrading. Hypotheses H_9-H_{10} translate these findings into policy-relevant dimensions by distinguishing organisational worker-like exposure from pure income dependence and evaluating their relationship across segments.

4.2.1 Block A: Sorting and task regimes (H_1-H_3)

Table 4-1 tests H_1 by asking whether microworkers and freelancers differ in the ESCO skill portfolios associated with their primary occupations (ISCO-08 4-digit), conditional on demographics, education, labour-market status, work and platform experience, and country fixed effects. The dependent variables are occupation-level ESCO portfolio measures assigned to individuals via their primary occupation. Columns (1)-(3) report composition shares (in percentage points): the cognitive component is the "thinking" share, the relational component is the "social" share, and the manual component is the "physical" share. Column (4) measures skill diversification as $1 - \text{HHI}$, where HHI is the Herfindahl Index computed from squared ESCO category shares. Column (5) is a transferability composite index (sum of standardised breadth, diversification, and transversal components), and Column (6) is an overall adaptive skill portfolio index (standardised).

The microworker coefficients are statistically significant and consistent across all six outcomes. Relative to freelancers, microworkers' primary occupations exhibit significantly lower cognitive/thinking share (-0.815 percentage points) and lower social share (-0.599 percentage points), alongside a higher physical/manual share (+0.096 percentage points). The table also reports the corresponding relative effect measures next to these percentage-point estimates: for Columns (1)-(3), the "%Microworker Effect" is computed as coefficient divided by the relevant linear prediction (coefficient/linear prediction), which summarises the microworker-freelancer gap as a proportional difference around the baseline predicted level. This makes the composition gaps easy to interpret in both absolute (pp) and relative (%) terms.

Beyond composition, microworkers are associated with systematically weaker portfolio structure. Diversification (1-HHI) is significantly lower for microworkers (-0.016), indicating a more concentrated skill mix across ESCO categories. The transferability composite is also substantially lower (-0.625), and the overall adaptive portfolio index is lower by -0.168 standard deviations. For these index outcomes (Columns 4-6), the reported effect-size measure is computed as coefficient divided by the sample standard deviation (coefficient/standard deviation), so the magnitudes can be read as standard-deviation gaps rather than proportional changes.

Interpreted against H1, Table 4-1 provides strong evidence of occupational skill segmentation between platform segments: microworkers appear anchored in primary occupations with less cognitive and social skill content, more manual content, and lower diversification and transferability. This pattern signals a market structure closer to a segmented gig economy than a fully competitive integrated one, because differences are visible already in the occupational skill endowments workers bring from outside the platform and persist after conditioning on observed characteristics and country context. From a policy perspective, this supports treating microwork and freelancing as distinct targets for skills and labour-market interventions: microworkers' weaker transferability and diversification profiles suggest higher risk of limited mobility and weaker returns to general upskilling unless pathways are created that improve portability (e.g., recognition of competences, structured progression routes, and targeted training linked to more complex task categories), while regulatory discussions about classification should consider that occupational endowments and task regimes jointly shape vulnerability rather than assuming a uniform "platform worker" category.

Table 4-2 tests H_2 by examining whether microworkers and freelancers report systematically different motivations for participating in platform work, conditional on the same broad set of controls and country fixed effects. Each dependent variable is a binary indicator for whether the respondent selected a given motivation. Columns (1)-(3) capture "professional/autonomy" motives, namely autonomy ("own boss"), interest ("passion"), and task choice ("more choice"). Columns (4)-(6) capture "consumption/secondary" motives, such as leisure or idle time ("kill time"), enjoyment ("fun"), and meaningful activity ("fruitful activity"). Coefficients can be read as percentage-point differences in the probability of endorsing each motive.

Table 4-1: Do microworkers and freelancers differ in the ESCO skill portfolios of their primary occupations?

	Cognitive Component (%Thinking Share)	Relational Component (%Social Share)	Manual Component (%Physical Share)	Skill Diversification (1-HHI)	Skill transferability (composite index)	Adaptive skill portfolio (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)
Microworker	-0.815***	-0.599**	0.096**	-0.016***	-0.625***	-0.168***
	[0.115]	[0.194]	[0.038]	[0.003]	[0.127]	[0.039]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Female	-0.306	0.524*	-0.005	-0.009**	-0.302*	-0.183***
	[0.168]	[0.232]	[0.018]	[0.003]	[0.137]	[0.044]
LGBT+	-0.881**	-0.707	-0.305***	0.009	-0.33	0.200*
	[0.243]	[0.944]	[0.065]	[0.019]	[0.529]	[0.094]
Immigration background	-0.226	-0.468*	0.021	-0.004	-0.137	0.022
	[0.123]	[0.216]	[0.036]	[0.002]	[0.079]	[0.057]
Unable to work in standard job	0.338	-0.294	-0.058	0.002	0.049	0.119
	[0.259]	[0.472]	[0.065]	[0.008]	[0.166]	[0.124]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.157	-0.301	-0.016	0.001	0.135	0.095
	[0.128]	[0.407]	[0.023]	[0.004]	[0.140]	[0.064]
Age 39-48	-0.220**	-0.311	0.004	-0.003	-0.109	-0.034
	[0.072]	[0.660]	[0.052]	[0.006]	[0.191]	[0.073]
Age 49-58	0.325	-0.143	-0.045	0.001	0.276	0.171**
	[0.211]	[0.208]	[0.045]	[0.007]	[0.294]	[0.058]
Age 59-68	0.269	0.547	0.007	-0.002	-0.423**	-0.227**
	[0.506]	[0.422]	[0.065]	[0.008]	[0.117]	[0.074]
Doctorate degree	0.686**	-0.598	0.432**	0.012	1.206**	0.295**
	[0.238]	[0.361]	[0.136]	[0.010]	[0.388]	[0.117]
Master's degree	0.662***	0.580**	0.188***	0.014***	0.526***	0.022
	[0.172]	[0.179]	[0.048]	[0.004]	[0.058]	[0.033]
University	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	-0.912***	-0.171	0.175***	-0.017**	-0.516***	-0.274***
	[0.159]	[0.102]	[0.039]	[0.005]	[0.088]	[0.044]
Professional qualification	-0.590***	0.590	0.229***	-0.013	-0.185	-0.248
	[0.079]	[0.401]	[0.028]	[0.007]	[0.368]	[0.164]
Vocational/technical qualific.	-1.143***	-0.978**	0.253**	-0.020*	-0.802**	-0.359*
	[0.286]	[0.303]	[0.099]	[0.009]	[0.313]	[0.156]
High school diploma	-1.450***	-0.347	0.290***	-0.024***	-0.774***	-0.472***
	[0.100]	[0.184]	[0.018]	[0.004]	[0.108]	[0.042]
Some high school (no diploma)	-1.397**	-0.202	0.333***	-0.028***	-0.997***	-0.561***
	[0.459]	[0.328]	[0.083]	[0.007]	[0.209]	[0.138]
No formal schooling	-2.285	0.362	0.615**	-0.047	-1.701**	-1.080***
	[1.259]	[0.925]	[0.234]	[0.025]	[0.479]	[0.187]
Full-time employed	0.025	0.624***	0.051	0.018***	0.548**	0.116
	[0.130]	[0.103]	[0.032]	[0.002]	[0.206]	[0.094]

Part-time employed	0.002	0.065	0.091**	0.001	0.186	0.090*
	[0.175]	[0.231]	[0.026]	[0.004]	[0.129]	[0.040]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.040	-0.260	0.176**	0.001	-0.412	-0.201*
	[0.449]	[0.436]	[0.050]	[0.006]	[0.268]	[0.089]
Inactive	-0.637	-0.564	0.062	-0.011*	0.227	0.128
	[0.429]	[0.464]	[0.084]	[0.005]	[0.238]	[0.079]
Student	-0.604**	-0.674*	0.217*	-0.011	-0.165	-0.044
	[0.219]	[0.315]	[0.094]	[0.010]	[0.303]	[0.168]
>10 years work experience	0.421**	0.760**	-0.044	0.014**	0.182	0.015
	[0.145]	[0.247]	[0.035]	[0.005]	[0.158]	[0.090]
3-10 years work experience	0.297	0.48	-0.051	0.005	0.059	0.017
	[0.283]	[0.315]	[0.036]	[0.008]	[0.194]	[0.067]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	0.136	-0.065	-0.004	-0.004	-0.236	-0.125
	[0.233]	[1.275]	[0.065]	[0.007]	[0.305]	[0.227]
Platform exp. 3-10 years	-0.116	-0.574**	0.011	-0.001	0.180	0.101
	[0.137]	[0.226]	[0.052]	[0.005]	[0.190]	[0.071]
Platform exp. 2-3 years	-0.441	-0.198	0.058	-0.013**	-0.272	-0.120*
	[0.297]	[0.416]	[0.038]	[0.004]	[0.216]	[0.052]
Platform exp. 1-2 years	-0.049	-0.092	-0.030	-0.001	-0.085	-0.04
	[0.202]	[0.346]	[0.055]	[0.007]	[0.122]	[0.059]
Platform exp. 7-12 months	-0.021	0.225	0.014	0.008	0.028	-0.072
	[0.137]	[0.253]	[0.022]	[0.005]	[0.254]	[0.060]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.240**	0.313	0.056*	0.001	0.328	0.053
	[0.068]	[0.212]	[0.023]	[0.003]	[0.175]	[0.036]
Germany	-0.155**	-0.224	0.159***	0.003	-0.05	-0.089**
	[0.060]	[0.153]	[0.006]	[0.003]	[0.122]	[0.027]
Italy	-0.311***	-0.781***	0.061***	-0.005*	-0.457***	-0.101***
	[0.054]	[0.132]	[0.016]	[0.002]	[0.093]	[0.018]
Romania	-0.598***	-1.062***	0.095***	-0.015***	-0.575***	-0.086*
	[0.068]	[0.162]	[0.023]	[0.001]	[0.047]	[0.037]
Spain	-0.031	-0.205*	0.032	0.004*	-0.199	-0.125***
	[0.055]	[0.102]	[0.016]	[0.002]	[0.122]	[0.031]
United Kingdom	0.318***	-0.059	0.064***	0.012***	-0.114	-0.081***
	[0.056]	[0.118]	[0.015]	[0.002]	[0.079]	[0.013]
Constant	4.403***	6.794***	0.163***	0.598***	0.389*	0.260***
	[0.099]	[0.211]	[0.036]	[0.004]	[0.167]	[0.065]
%Microworker Effect	*-22.0%*	*-9.0%*	*21.9%*	*-24.2%*	*-26.9%*	*-16.8%*
Linear Prediction	*3.7049*	*6.629*	*0.4359*	*0.5975*	*-0.0013*	*0.000*
No. of Observations	*1,608*	*1608*	*1,608*	*1,608*	*1,608*	*1,608*

The microworker coefficients show a sharp and coherent split in motivation profiles. Relative to freelancers, microworkers are significantly less likely to cite autonomy (-0.163), interest/passion (-0.286), and task choice (-0.082). In parallel, microworkers are substantially more likely to cite leisure/idle time (+0.376), enjoyment (+0.270), and meaningful activity (+0.183). Taken together, the sign pattern is exactly what H2 predicts: microwork participation is more strongly associated with "secondary/consumption" motives, while freelancing is more strongly associated with autonomy- and interest-driven motives that align with a more work- and career-oriented use of platforms.

The "%Microworker Effect" row should be interpreted with care but is informative about relative magnitude. Here it is computed as coefficient divided by the linear prediction (coefficient/linear prediction), giving the microworker-associated proportional difference around the predicted baseline probability. This is why several relative effects can appear very large in absolute value (e.g., -133.4% for "passion"): the baseline predicted probability in that column is comparatively small (about 0.215), so a -0.286 coefficient implies a change that is larger than the baseline level. In these cases, the percentage-point coefficient is the more stable metric for interpretation, while the relative effect highlights that microworkers' probability of reporting the motive is dramatically lower (or higher) relative to the baseline.

In relation to H2 and the broader market narrative, Table 4-2 strongly supports a segmented interpretation rather than a fully integrated competitive platform market. A competitive/integrated view would predict that, once worker characteristics and country context are controlled for, motivational profiles should not differ so starkly by segment; instead, workers would appear to choose tasks primarily on price and skill fit. The observed pattern suggests that microwork and freelancing represent different "use cases" of platform work: freelancing is closer to autonomy and intrinsic/professional engagement, whereas microwork is more consistent with supplementary participation, time-filling, and low-commitment engagement. From a policy perspective, this matters because segment-specific motivations imply segment-specific leverage points: measures aimed at professional upskilling and career progression are likely to resonate more with freelancers, while microworkers may require different interventions (e.g., outreach, modular training compatible with intermittent participation, and pathways that convert casual engagement into more portable skills) if policy goals include mobility and reduced segmentation.

Table 4-3 provides the core empirical test of H3 by comparing how microworkers and freelancers characterise the nature of their platform tasks, conditional on the same control set and country fixed effects. Each dependent variable is a binary indicator for whether the respondent agrees with a specific task characteristic, grouped here to reflect the model's "task regime" distinction between routinised/low-discretion work and complex/creative, multi-skill work. Columns (1)-(3) capture the routinisation and control side of the regime (routine tasks, repeatable tasks, and low autonomy), while columns (4)-(6) capture the complexity side (creative tasks, variety of skills, and complex/high-level skills). Coefficients are interpretable as percentage-point differences in the probability of endorsing each statement.

Table 4-2: Are microworkers and freelancers motivated by systematically different reasons for participating in platform work?

	Autonomy (Own boss) (1)	Interest (Passion) (2)	Task choice (More choice) (3)	Leisure/idle time (Kill time) (4)	Enjoyment (Fun) (5)	Meaningful activity (Fruitful) (6)
Microworker	-0.163***	-0.286***	-0.082***	0.376***	0.270***	0.183***
	[0.042]	[0.030]	[0.022]	[0.031]	[0.013]	[0.033]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Female	0.039**	0.023	0.022	-0.063***	0.014	-0.033*
	[0.015]	[0.019]	[0.038]	[0.014]	[0.012]	[0.015]
LGBT+	-0.121	-0.099	-0.222	-0.040	-0.180	-0.200
	[0.133]	[0.112]	[0.166]	[0.095]	[0.162]	[0.141]
Immigration background	0.015	0.008	0.012	-0.056	-0.053**	-0.073***
	[0.019]	[0.011]	[0.025]	[0.038]	[0.014]	[0.020]
Unable to work in standard job	0.106**	-0.013	0.062**	-0.016	0.004	-0.061**
	[0.032]	[0.022]	[0.020]	[0.023]	[0.058]	[0.024]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.022	0.019	-0.004	-0.018	0.036	0.016
	[0.032]	[0.015]	[0.031]	[0.017]	[0.037]	[0.020]
Age 39-48	0.06	0.022	0.027	-0.047	0.038	-0.019
	[0.046]	[0.034]	[0.052]	[0.027]	[0.045]	[0.034]
Age 49-58	-0.012	-0.033	-0.035	-0.088**	-0.018	-0.033
	[0.073]	[0.026]	[0.052]	[0.028]	[0.046]	[0.035]
Age 59-68	-0.137	-0.128**	-0.044	-0.147***	-0.023	0.039
	[0.091]	[0.045]	[0.102]	[0.028]	[0.036]	[0.064]
Doctorate degree	0.039	-0.103	0.031	0.045	-0.04	-0.015
	[0.051]	[0.072]	[0.083]	[0.051]	[0.066]	[0.089]
Master's degree	-0.082**	-0.067	-0.084**	-0.02	-0.019	-0.026
	[0.029]	[0.035]	[0.026]	[0.028]	[0.023]	[0.037]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	-0.008	0.021	-0.030	0.034*	0.023	0.033
	[0.015]	[0.025]	[0.026]	[0.016]	[0.019]	[0.041]
Professional qualification	0.102	-0.037	-0.001	-0.033	0.003	-0.192***
	[0.053]	[0.046]	[0.019]	[0.045]	[0.041]	[0.032]
Vocational/technical qualification	-0.055	0.032	-0.097*	-0.011	-0.008	-0.046*
	[0.046]	[0.048]	[0.043]	[0.031]	[0.035]	[0.023]
High school diploma	-0.039	0.004	0.007	0.033	0.057	0.017
	[0.033]	[0.037]	[0.018]	[0.027]	[0.049]	[0.060]
Some high school (no diploma)	0.021	0.011	-0.066	-0.090**	-0.04	-0.093
	[0.093]	[0.025]	[0.040]	[0.029]	[0.042]	[0.051]
No formal schooling	-0.170**	-0.040	0.043	-0.051	-0.069	-0.201*
	[0.055]	[0.131]	[0.084]	[0.178]	[0.152]	[0.103]
Full-time employed	-0.191***	-0.051*	-0.145***	0.092**	0.086**	0.132**
	[0.031]	[0.024]	[0.022]	[0.031]	[0.026]	[0.043]
Part-time employed	-0.155**	-0.014	-0.078	-0.013	0.086**	0.175**

	[0.046]	[0.043]	[0.043]	[0.015]	[0.028]	[0.058]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.150***	0.002	-0.125*	0.062	0.035	0.004
	[0.036]	[0.021]	[0.056]	[0.035]	[0.029]	[0.064]
Inactive	-0.120**	0.096	-0.127	0.034	0.067	0.151*
	[0.035]	[0.087]	[0.089]	[0.071]	[0.043]	[0.074]
Student	-0.164**	-0.083**	-0.049	0.071**	0.045**	0.156**
	[0.048]	[0.028]	[0.027]	[0.026]	[0.016]	[0.046]
>10 years total work experience	-0.02	-0.055***	0.012	-0.036	-0.02	0.02
	[0.019]	[0.013]	[0.025]	[0.039]	[0.039]	[0.024]
3-10 years total work experience	-0.009	-0.049**	0.024	-0.035	0.035	0.037
	[0.016]	[0.016]	[0.025]	[0.026]	[0.029]	[0.023]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	0.013	-0.121*	0.232	0.086*	-0.175***	-0.048
	[0.102]	[0.055]	[0.126]	[0.035]	[0.041]	[0.111]
Platform exp. 3-10 years	-0.061	-0.032	0.021	0.048*	-0.051**	-0.102**
	[0.036]	[0.021]	[0.026]	[0.025]	[0.021]	[0.040]
Platform exp. 2-3 years	-0.002	-0.049***	0.037	0.032	-0.003	-0.052
	[0.042]	[0.008]	[0.025]	[0.031]	[0.021]	[0.034]
Platform exp. 1-2 years	-0.033	-0.003	-0.032	0.042	-0.021	-0.033
	[0.039]	[0.032]	[0.027]	[0.022]	[0.044]	[0.029]
Platform exp. 7-12 months	-0.029	-0.001	-0.025	0.028	0.021	-0.041
	[0.017]	[0.030]	[0.021]	[0.025]	[0.023]	[0.022]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.147***	0.025	-0.167***	-0.070*	-0.260***	-0.182***
	[0.039]	[0.032]	[0.020]	[0.030]	[0.021]	[0.033]
Germany	-0.02	-0.041	-0.069***	-0.035	-0.138***	-0.142***
	[0.027]	[0.022]	[0.012]	[0.019]	[0.011]	[0.015]
Italy	-0.147***	0.004	-0.151***	-0.029	-0.166***	-0.093***
	[0.027]	[0.021]	[0.013]	[0.020]	[0.014]	[0.015]
Romania	-0.071***	-0.018*	-0.041***	-0.044**	-0.159***	-0.033**
	[0.011]	[0.009]	[0.010]	[0.016]	[0.019]	[0.011]
Spain	-0.079**	-0.062*	-0.122***	-0.041	-0.151***	-0.116***
	[0.029]	[0.027]	[0.018]	[0.023]	[0.011]	[0.024]
United Kingdom	-0.103***	-0.075***	-0.052**	0.032	-0.143***	-0.120***
	[0.020]	[0.016]	[0.015]	[0.022]	[0.010]	[0.016]
Constant	0.682***	0.473***	0.527***	0.111*	0.279***	0.486***
	[0.048]	[0.040]	[0.042]	[0.047]	[0.028]	[0.054]
%Microworker Effect	*-43.7%*	*-133.4%*	*-25.2%*	*145.9%*	*87.3%*	*38.1%*
Linear Prediction	*0.3741*	*0.2147*	*0.3268*	*0.2579*	*0.3097*	*0.4801*
No. of Observations	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*
* p<0.10, ** p<0.05, *** p<0.01						

Table 4-3: Is microwork organised around more routine and lower-autonomy tasks than freelancing?

	Routine tasks (standar-dised) (1)	Repeatable tasks (systematic) (2)	Low autonomy (limited discretiion) (3)	Creative tasks (4)	Skill variety (multi-skill tasks) (5)	Complex/ high-level skills (6)
Microworker	0.488***	0.357***	0.173***	-0.225***	-0.255***	-0.169***
	[0.033]	[0.018]	[0.017]	[0.031]	[0.039]	[0.011]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Female	0.002	0.003	0.001	-0.028	0.02	-0.069***
	[0.008]	[0.015]	[0.012]	[0.019]	[0.047]	[0.009]
LGBT+	-0.001	0.245*	0.043	0.068	-0.125	-0.103
	[0.130]	[0.123]	[0.043]	[0.139]	[0.146]	[0.073]
Immigration background	-0.031*	0.014	-0.007	0.014	0.016	0.028
	[0.014]	[0.036]	[0.019]	[0.021]	[0.023]	[0.017]
Unable to work in standard job	0.041	0.083**	0.051*	0.01	0.084*	0.035
	[0.025]	[0.028]	[0.021]	[0.022]	[0.036]	[0.024]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.008	-0.044	-0.001	-0.034	-0.044	0.008
	[0.036]	[0.023]	[0.028]	[0.051]	[0.037]	[0.031]
Age 39-48	-0.071**	-0.050***	-0.013	-0.062	-0.063	-0.013
	[0.020]	[0.009]	[0.023]	[0.076]	[0.035]	[0.033]
Age 49-58	-0.110**	-0.128**	0.01	-0.029	-0.018	0.068
	[0.040]	[0.043]	[0.038]	[0.045]	[0.060]	[0.081]
Age 59-68	-0.162**	-0.151*	-0.014	-0.107	0.04	0.058
	[0.061]	[0.066]	[0.053]	[0.140]	[0.039]	[0.074]
Doctorate degree	-0.075	-0.094*	0.031	-0.068	0.109	0.154*
	[0.068]	[0.043]	[0.068]	[0.064]	[0.081]	[0.065]
Master's degree	-0.058**	-0.052*	-0.032**	-0.046*	-0.042	0.054**
	[0.017]	[0.022]	[0.012]	[0.021]	[0.039]	[0.016]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	-0.015	0.029	0.026	-0.021	-0.051**	-0.021
	[0.017]	[0.016]	[0.022]	[0.018]	[0.015]	[0.025]
Professional qualification	-0.047*	-0.125	-0.032	-0.055	-0.02	0.065
	[0.020]	[0.103]	[0.019]	[0.064]	[0.030]	[0.064]
Vocational/technical qualification	0.006	-0.04	0.002	-0.079	-0.119***	-0.017
	[0.048]	[0.056]	[0.049]	[0.064]	[0.032]	[0.020]
High school diploma	-0.057***	-0.033	-0.018	-0.001	-0.025	-0.040*
	[0.014]	[0.028]	[0.032]	[0.019]	[0.043]	[0.017]
Some high school (no diploma)	-0.078	-0.058	-0.024	-0.08	-0.111**	-0.055
	[0.067]	[0.091]	[0.031]	[0.071]	[0.031]	[0.029]
No formal schooling	-0.096	-0.433***	-0.021	-0.320***	-0.032	0.134
	[0.121]	[0.070]	[0.056]	[0.041]	[0.159]	[0.085]
Full-time employed	-0.015	-0.028	0.03	-0.057	-0.005	-0.054**
	[0.029]	[0.015]	[0.028]	[0.032]	[0.034]	[0.020]

Part-time employed	0.014	0.017	0.044*	-0.012	0.034	-0.069*
	[0.040]	[0.037]	[0.020]	[0.034]	[0.034]	[0.034]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	0.015	-0.006	-0.053	-0.001	-0.104**	-0.101**
	[0.044]	[0.052]	[0.027]	[0.030]	[0.035]	[0.037]
Inactive	0.015	0.025	-0.008	0.018	-0.156**	-0.061
	[0.074]	[0.040]	[0.049]	[0.098]	[0.061]	[0.089]
Student	0.019	0.001	0.015	-0.028	-0.034	-0.062**
	[0.024]	[0.034]	[0.021]	[0.031]	[0.036]	[0.023]
>10 years work experience	0.029	0.038	0.031*	0.02	0.099**	-0.013
	[0.018]	[0.030]	[0.016]	[0.033]	[0.028]	[0.021]
3-10 years work experience	0.015	0.017	0.001	0.022	0.045**	0.001
	[0.021]	[0.036]	[0.022]	[0.032]	[0.012]	[0.012]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	-0.114	0.052	-0.029	-0.203**	0.076	0.063
	[0.079]	[0.114]	[0.037]	[0.070]	[0.070]	[0.071]
Platform exp. 3-10 years	0.044	-0.018	-0.013	-0.02	0.019	0.050
	[0.054]	[0.017]	[0.014]	[0.015]	[0.025]	[0.046]
Platform exp. 2-3 years	-0.008	-0.026	-0.017	0.016	0.014	0.005
	[0.036]	[0.026]	[0.024]	[0.026]	[0.028]	[0.023]
Platform exp. 1-2 years	0.014	0.017	0.009	-0.011	0.004	0.021
	[0.020]	[0.020]	[0.013]	[0.038]	[0.026]	[0.028]
Platform exp. 7-12 months	0.011	-0.01	0.022	0.008	0.023	-0.02
	[0.032]	[0.017]	[0.020]	[0.040]	[0.032]	[0.015]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.059	-0.006	-0.088***	-0.084	-0.139**	0.066***
	[0.034]	[0.027]	[0.021]	[0.046]	[0.043]	[0.011]
Germany	0.024	0.012	-0.065***	-0.093**	-0.083***	0.073***
	[0.016]	[0.019]	[0.012]	[0.028]	[0.022]	[0.009]
Italy	0.009	0.057*	-0.004	-0.116***	-0.063**	0.066***
	[0.020]	[0.024]	[0.009]	[0.027]	[0.019]	[0.008]
Romania	-0.054***	0.064***	-0.050***	-0.022	-0.046*	0.062***
	[0.009]	[0.017]	[0.011]	[0.015]	[0.022]	[0.006]
Spain	-0.014	0.03	-0.072***	-0.109**	-0.036	0.069***
	[0.024]	[0.021]	[0.014]	[0.034]	[0.028]	[0.005]
United Kingdom	0.052**	0.041**	-0.029**	-0.043	-0.043*	0.080***
	[0.016]	[0.016]	[0.009]	[0.024]	[0.021]	[0.006]
Constant	0.179***	0.137**	0.073	0.624***	0.666***	0.242***
	[0.037]	[0.053]	[0.038]	[0.036]	[0.051]	[0.034]
Effect (Δ/Pred)	*121.1%*	*113.6%*	*127.7%*	*-62.0%*	*-52.2%*	*-87.9%*
Linear Prediction	*0.4032*	*0.3137*	*0.1352*	*0.3625*	*0.4877*	*0.1921*
No. of Observations	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*
* p<0.10, ** p<0.05, *** p<0.01						

The microworker coefficients are large, precisely estimated, and all have the expected sign pattern. Microworkers are substantially more likely than freelancers to report that their tasks are routine (+0.488), repeatable (+0.357), and low-autonomy (+0.173). At the same time, they are significantly less likely to report that their tasks are creative (-0.225), require a variety of skills (-0.255), or require complex/high-level skills (-0.169). This is exactly the "two task regimes" prediction: microwork is associated with standardised, platform-directed task execution, whereas freelancing is associated with richer task content requiring discretion and broader skill deployment.

The "Effect (Δ/Pred)" row complements the percentage-point estimates by expressing the microworker gap relative to the baseline predicted level in each column (coefficient/linear prediction). The relative effects are particularly striking on the routinisation side: given baseline predicted probabilities of roughly 0.31-0.40 for routine and repeatable tasks and 0.14 for low autonomy, the microworker-associated increases correspond to very large proportional differences (over 100% relative to baseline in Columns 1-3). On the complexity side, the negative effects are also economically meaningful: the microworker-associated reductions in creativity, skill variety, and complex skills correspond to sizeable relative declines from baseline predicted levels (roughly −52% to −88% depending on the column). As with the motivation table, very large relative effects are most likely when baseline predictions are comparatively low; the percentage-point coefficients remain the most stable summary of magnitude.

Interpreted against H_3, Table 4-3 offers strong evidence that microwork and freelancing are not simply two labels applied to similar work but correspond to materially different task organisations. This supports a segmented view of the platform economy: microworkers systematically report a task environment that is more routinised and more tightly governed, while freelancers report a task environment that is more complex and multi-skill. From a policy perspective, this difference matters because it speaks directly to worker-like exposure and to the likely returns to upskilling. Where work is routinised and discretion is limited, skill accumulation and mobility may be constrained unless platforms or policy instruments create progression routes (e.g., certification pathways, access to more complex task types, structured training tied to task upgrading). Conversely, the richer task content reported by freelancers suggests a stronger environment for skill application and development, implying that incentives aimed at advanced upskilling and recognition of competences may be more readily taken up and converted into productivity within that segment.

4.2.2 Block B: Skill-task alignment and transferability conversion (H_4-H_5)

Table 4-4 provides the core mechanism evidence for Block B by directly testing H_4 (skill–task alignment) and H_5 (transferability-to-upgrading conversion). The table is organised around two linked questions. First, do occupational ESCO skill bundles (derived from the primary occupation) map into the type of platform tasks workers report, and does this mapping differ between microwork and freelancing (Columns 1-3). Second, does occupational skill transferability translate into reported upgrading differently across segments (Columns 4-5). Finally, column (6) then offers a summary check using an overall skill-task alignment index.

Columns (1)-(3) indicate strong baseline differences in task environments across segments, consistent with the regime distinction documented in Table 4-3, but more importantly they clarify which components of occupational skill composition actually map into platform task content. In Column (1), the thinking share is a strong and precisely estimated predictor of complex task content for freelancers (+0.089***), and the interaction with microworker status is small and statistically insignificant (−0.009). This implies that occupational cognitive intensity is meaningfully associated with more complex tasks, and that this within-segment mapping is not dramatically different between microworkers and freelancers. At the same time, the large negative microworker level effect (-0.563***) shows that microworkers operate in a substantially less complex task environment overall, even when occupational thinking intensity is held constant. In Column (2), microworkers report far more routine tasks (+1.213***). The physical share slope is small for freelancers (+0.030, not significant), while the interaction is large and negative (-0.506***), indicating that within microwork the relationship between occupational physical intensity and routine task reporting is substantially weaker (and may turn negative) relative to freelancing. This suggests that routineness in microwork is driven more by the segment's task design and governance than by the physical/manual content of the worker's primary occupation. In Column (3), microworkers report lower collaboration (-0.310**), but neither the social share slope (+0.008) nor its interaction (-0.009) is statistically significant, implying limited evidence that occupational social composition is a strong predictor of collaborative task features in the platform environment once controls and fixed effects are included.

Columns (4)-(5) provide the most direct evidence for H5. In Column (4), the occupational transferability index is positively associated with technical upgrading for freelancers (+0.018*), but the negative interaction with microworker status (-0.024*) indicates that this conversion is significantly weaker for microworkers. The marginal effects reported at the bottom make this intuitive: for freelancers, transferability predicts a modest increase in the probability of reporting improved technical skills (ME ≈ 0.018), whereas for microworkers the implied marginal effect is close to zero or slightly negative (ME ≈ -0.005). This is exactly the "conversion" mechanism: transferable occupational bundles can be turned into technical upgrading in freelancing, but the microwork environment appears to constrain that process. Column (5) shows a weaker relationship for analytical upgrading: the transferability slope is small and statistically insignificant (+0.011) and the interaction is also insignificant (+0.004), suggesting that segment-dependent conversion is clearest for technical upgrading rather than analytical upgrading in this specification.

Column (6) is best read as a robustness-style summary rather than the main mechanism test. The alignment index and its interaction are not precisely estimated, while the microworker level effect remains strongly negative. This indicates that the aggregate alignment measure, as constructed here, does not capture additional variation in upgrading beyond the component-based mapping in Columns (1)-(5). Practically, this points to a simple implication for presentation: the most informative evidence comes from the targeted, theory-aligned components (thinking to complex tasks; transferability to technical upgrading), rather than from the overall alignment index.

Table 4-4: Do occupational skill portfolios and transferability predict platform task content and upgrading differently across microworkers and freelancers?

	Complex tasks: Thinking share channel	Routine tasks: Physical share channel	Collaborative tasks: Social share channel	Technical upgrading: Transfer-ability	Anytical upgrading: Transfer-ability	Technical upgrading: Skill-task alignment
	(1)	(2)	(3)	(4)	(5)	(6)
Microworker	-0.563***	1.213***	-0.310**	-0.211***	0.243***	-0.247***
	[0.129]	[0.116]	[0.103]	[0.029]	[0.026]	[0.043]
Thinking share	0.089***	–	–	–	–	–
	[0.007]					
Microworker×Thinking share	-0.009	–	–	–	–	–
	[0.018]					
Physical share	–	0.030	–	–	–	–
		[0.024]				
Microworker×Physical share	–	-0.506***	–	–	–	–
		[0.055]				
Social share	–	–	0.008	–	–	–
			[0.018]			
Microworker×Social share	–	–	-0.009	–	–	–
			[0.014]			
Occup. skill transferability	–	–	–	0.018*	0.011	–
				[0.009]	[0.007]	
Microworker×Skill transferability	–	–	–	-0.024*	0.004	–
				[0.011]	[0.008]	
Skill-task alignment index	–	–	–	–	–	-0.056
						[0.029]
Microworker × Alignment index	–	–	–	–	–	-0.032
						[0.056]
Female	-0.045	0.004	-0.04	-0.113**	-0.078***	-0.115***
	[0.047]	[0.014]	[0.064]	[0.031]	[0.009]	[0.029]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
LGBT+	-0.576***	0.071	-0.382***	-0.159	-0.289***	-0.153
	[0.118]	[0.148]	[0.063]	[0.082]	[0.040]	[0.080]
Immigration background	0.016	0.062	0.107	0.016	0.029	0.015
	[0.056]	[0.063]	[0.086]	[0.020]	[0.025]	[0.021]
Unable to work in standard job	0.329***	0.209**	0.04	0.013	0.031	0.013
	[0.050]	[0.060]	[0.075]	[0.040]	[0.031]	[0.041]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.130**	-0.044	0.045	0.012	-0.005	0.01
	[0.044]	[0.043]	[0.079]	[0.018]	[0.021]	[0.019]
Age 39-48	-0.162	-0.125*	0.003	-0.029	-0.014	-0.032
	[0.087]	[0.052]	[0.061]	[0.025]	[0.039]	[0.024]
Age 49-58	0.039	-0.231**	0.041	0.008	0.046	0.004
	[0.119]	[0.089]	[0.190]	[0.071]	[0.055]	[0.076]
Age 59-68	0.045	-0.211	-0.035	-0.131*	-0.024	-0.139*

	[0.160]	[0.184]	[0.139]	[0.061]	[0.070]	[0.064]
Doctorate degree	0.355*	-0.216	-0.03	-0.008	0.135**	-0.003
	[0.154]	[0.154]	[0.262]	[0.079]	[0.051]	[0.090]
Master's degree	0.018	-0.163***	0.049	-0.02	0.001	-0.016
	[0.046]	[0.040]	[0.038]	[0.037]	[0.041]	[0.035]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	0.056	0.086*	0.056	0.070***	-0.005	0.060**
	[0.030]	[0.037]	[0.056]	[0.018]	[0.022]	[0.017]
Professional qualification	0.128	-0.22	-0.109	-0.014	0.065	-0.027
	[0.166]	[0.126]	[0.134]	[0.070]	[0.034]	[0.068]
High school diploma	0.028	-0.199***	-0.034	0.122*	0.021	0.119*
	[0.091]	[0.043]	[0.043]	[0.053]	[0.040]	[0.055]
Some high school (no diploma)	-0.245**	-0.249**	-0.031	-0.016	0.049	-0.023
	[0.072]	[0.084]	[0.134]	[0.061]	[0.041]	[0.057]
Vocational/technical qualific.	-0.098	-0.026	0.04	0.016	-0.095***	0.006
	[0.085]	[0.094]	[0.082]	[0.042]	[0.022]	[0.042]
No formal schooling	-0.514***	-0.554**	0.185	0.092	0.028	0.082
	[0.080]	[0.205]	[0.527]	[0.160]	[0.183]	[0.185]
Full-time employed	-0.163*	-0.062	-0.066	-0.033	-0.019	-0.033
	[0.076]	[0.043]	[0.070]	[0.030]	[0.023]	[0.031]
Part-time employed	-0.035	0.049	-0.041	-0.022	0.014	-0.025
	[0.065]	[0.078]	[0.061]	[0.053]	[0.058]	[0.053]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.069	0.016	-0.082	0.016	0.062	0.017
	[0.104]	[0.147]	[0.082]	[0.034]	[0.040]	[0.037]
Inactive	-0.141	-0.049	-0.220**	0.024	0.086	0.05
	[0.139]	[0.144]	[0.081]	[0.082]	[0.079]	[0.078]
Student	-0.032	0.057	0.027	-0.044	-0.046	-0.038
	[0.052]	[0.113]	[0.112]	[0.056]	[0.028]	[0.054]
>10 years work experience	0.254***	0.143***	-0.015	0.011	0.033	0.004
	[0.043]	[0.038]	[0.081]	[0.026]	[0.031]	[0.026]
3-10 years work experience	0.121	0.016	-0.052	-0.029	0.058***	-0.036
	[0.065]	[0.111]	[0.087]	[0.022]	[0.010]	[0.021]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	0.046	-0.027	-0.440*	-0.159	0.004	-0.146
	[0.127]	[0.102]	[0.185]	[0.151]	[0.111]	[0.161]
Platform exp. 3-10 years	0.069	0.045	0.007	-0.058*	-0.089***	-0.048
	[0.134]	[0.037]	[0.087]	[0.030]	[0.017]	[0.033]
Platform exp. 2-3 years	0.144*	-0.038	0.004	-0.012	0.001	-0.015
	[0.071]	[0.082]	[0.139]	[0.017]	[0.027]	[0.017]
Platform exp. 1-2 years	0.024	0.024	-0.095	0.001	0.009	0.001
	[0.110]	[0.032]	[0.096]	[0.040]	[0.015]	[0.040]
Platform exp. 7-12 months	0.017	0.110**	-0.023	-0.007	-0.026	-0.008
	[0.036]	[0.038]	[0.108]	[0.047]	[0.022]	[0.048]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*

Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.100	-0.206*	0.150**	-0.179***	0.129***	-0.192***
	[0.078]	[0.100]	[0.046]	[0.027]	[0.024]	[0.023]
Germany	0.041	-0.009	0.245***	-0.117***	0.037**	-0.124***
	[0.031]	[0.052]	[0.029]	[0.009]	[0.014]	[0.006]
Italy	-0.163***	0.06	0.069	-0.102***	0.035**	-0.104***
	[0.033]	[0.057]	[0.042]	[0.009]	[0.013]	[0.011]
Romania	0.001	0.002	0.123*	-0.031**	0.100***	-0.043**
	[0.061]	[0.034]	[0.062]	[0.011]	[0.010]	[0.014]
Spain	-0.072	-0.109	0.018	-0.147***	0.067***	-0.147***
	[0.049]	[0.068]	[0.026]	[0.013]	[0.017]	[0.013]
United Kingdom	0.001	0.124*	0.109**	-0.031*	0.072***	-0.040**
	[0.036]	[0.051]	[0.032]	[0.013]	[0.013]	[0.014]
Constant	-0.001	-0.504***	0.066	0.738***	0.104***	0.697***
	[0.087]	[0.074]	[0.078]	[0.051]	[0.016]	[0.059]
ME (Freelancers)				*0.018*	*0.011*	*0.0001*
ME (Microworkers)				*-0.005*	*0.015*	*-0.247*
No. of Observations	*1,608*	*1,608*	*1,608*	*1,608*	*1608*	*1,608*
* p<0.10, ** p<0.05, *** p<0.01						

Overall, Table 4-4 supports a mechanism-consistent segmentation narrative. For H_4, the evidence is strongest for the cognitive channel: occupational thinking intensity predicts complex task content, but microworkers still face a lower-complexity environment on average. For H_5, the evidence is clearer: occupational transferability converts into technical upgrading for freelancers but is significantly attenuated for microworkers, consistent with lower learning returns under routinised, constrained task regimes. In policy terms, this helps explain why microwork can remain a "low-mobility" segment even when workers bring transferable occupational skills: the binding constraint is not only who enters the segment, but the limited scope for converting transferable portfolios into higher-level upgrading within the microwork task environment.

4.2.3 Block C: Learning inputs and upgrading outcomes (H_6-H_8)

Table 4-5 tests H6 by examining whether microworkers and freelancers differ in learning activities undertaken while working on the platform, conditional on the standard set of controls and country fixed effects. The dependent variables correspond to frequency-based learning activity items: "New tasks" captures how often respondents perform tasks that are new to them; "Follow developments" measures how often they follow new developments in their field; "Read books/articles" captures reading to acquire relevant knowledge; "Deep reflection" measures how often they think deeply about their work; "Free online courses" captures participation in free online courses; and "Collaborate with others" measures the frequency of collaborating with others to complete platform projects. Coefficients are interpretable as conditional differences between microworkers and freelancers in the scale of each learning activity measure.

The results show a clear regime contrast that is highly consistent across five of the six outcomes. Microworkers report significantly lower learning activity intensity for “Follow developments” (-0.275***), “Read books/articles” (-0.528***), “Deep reflection” (-0.615***), “Free online courses” (-0.403***), and “Collaborate with others” (-0.192***). This pattern supports H6: relative to freelancers, microworkers appear less engaged in deliberate and cumulative learning behaviours that are typically associated with professional skill formation (tracking field knowledge, reading, reflective learning, structured online learning, and collaboration). At the same time, microworkers report a higher frequency of “New tasks” (+0.468***). This is important substantively: microwork can expose workers to frequent task novelty or variety in the sense of encountering tasks that are new to them, but this does not translate into higher engagement in deeper learning investments. The combination, high novelty but low deliberate learning, fits well with an interpretation of microwork as fragmented work that may be varied in content yet offers limited scope or incentive for cumulative skill development.

The “%Microworker effect” row expresses the microworker coefficient relative to the baseline linear prediction in each column (coefficient/linear prediction). This helps gauge relative magnitude: the microworker increase in “New tasks” is modest in proportional terms (about +17.7% relative to the predicted baseline), whereas the reductions in deliberate learning items are economically meaningful, ranging from roughly -12% (collaboration) to around -25% (deep reflection, free courses, reading) relative to baseline predicted levels. These relative effects reinforce that the largest segment gaps arise for activities that most clearly reflect deliberate learning investments rather than incidental exposure.

Overall, Table 4-5 provides strong evidence in favour of H6 and aligns with the segmented-regime interpretation developed earlier. Freelancing appears embedded in a learning environment characterised by deliberate knowledge acquisition and reflective practices, while microwork is associated with weaker engagement in these learning behaviours despite higher reported exposure to “new tasks.” In market terms, this pattern is difficult to reconcile with a fully integrated competitive platform market in which comparable workers would face similar learning opportunities across segments; instead, it supports a segmented or hybrid structure in which the microwork regime constrains the depth of learning and the accumulation of transferable human capital.

Table 4-6 tests H7 by examining whether microworkers and freelancers differ in self-regulated learning strategies and beliefs about transferability of learning, conditional on the standard control set and country fixed effects. The dependent variables are frequency/intensity measures capturing core self-regulated learning behaviours and metacognitive beliefs: (1) transferable learning belief (belief that what is learned on the platform is useful for future jobs), (2) multiple sources (collecting information from many sources when learning), (3) apply prior lessons (using lessons from previous work on platform projects), (4) problem understanding (when challenged, focusing on understanding

Table 4-5: Do microworkers and freelancers differ in how intensively they engage in learning activities while working on platforms?

	New tasks (1)	Follow developments (2)	Read books / articles (3)	Deep reflection (4)	Free online courses (5)	Collaborate with others (6)
Microworker	0.468***	-0.275***	-0.528***	-0.615***	-0.403***	-0.192***
	[0.095]	[0.031]	[0.046]	[0.082]	[0.048]	[0.031]
Female	0.014	-0.087*	-0.035	0.070**	-0.150***	-0.143***
	[0.022]	[0.043]	[0.030]	[0.025]	[0.022]	[0.009]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
LGBT+	-0.09	-0.472*	-0.578**	-0.346	-0.205	-0.323**
	[0.063]	[0.230]	[0.188]	[0.222]	[0.123]	[0.089]
Immigration background	0.048	0.059	0.115	0.157**	0.180***	0.004
	[0.057]	[0.093]	[0.061]	[0.060]	[0.044]	[0.049]
Unable to work in standard job	0.013	-0.054	0.09	0.057	-0.005	0.028
	[0.041]	[0.083]	[0.088]	[0.034]	[0.083]	[0.031]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.096*	0.079	0.065	0.03	0.100	0.076
	[0.046]	[0.045]	[0.049]	[0.049]	[0.078]	[0.063]
Age 39-48	-0.294***	0.072*	0.057	0.024	0.035	-0.051
	[0.048]	[0.035]	[0.044]	[0.075]	[0.084]	[0.037]
Age 49-58	-0.108*	0.108	0.082	0.056	0.113	0.009
	[0.048]	[0.082]	[0.075]	[0.061]	[0.068]	[0.107]
Age 59-68	-0.384***	-0.042	0.154	-0.155	-0.047	-0.222
	[0.080]	[0.138]	[0.140]	[0.097]	[0.109]	[0.173]
Doctorate degree	0.096	-0.028	-0.154	-0.318*	-0.122	-0.111
	[0.209]	[0.153]	[0.186]	[0.158]	[0.184]	[0.086]
Master's degree	-0.056	0.08	0.02	-0.046	0.066	0.078
	[0.081]	[0.076]	[0.084]	[0.060]	[0.051]	[0.047]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	0.035	-0.002	0.070**	0.097**	-0.026	0.023
	[0.030]	[0.041]	[0.027]	[0.039]	[0.034]	[0.025]
Professional qualification	-0.138*	0.067	0.023	0.068	0.038	0.094
	[0.057]	[0.113]	[0.178]	[0.090]	[0.148]	[0.156]
Vocational/technical qualific.	-0.014	-0.042	-0.003	-0.066	0.154	0.097
	[0.031]	[0.064]	[0.123]	[0.093]	[0.089]	[0.091]
High school diploma	0.087	0.001	0.046	0.003	0.062	-0.043
	[0.066]	[0.061]	[0.031]	[0.079]	[0.043]	[0.049]
Some high school (no diploma)	-0.086	0.030	0.095	0.145	0.204***	0.066
	[0.073]	[0.059]	[0.101]	[0.092]	[0.055]	[0.147]
No formal schooling	-0.545	-0.451	-0.008	-0.208	0.139	0.636*
	[0.442]	[0.304]	[0.366]	[0.447]	[0.169]	[0.265]
Full-time employed	-0.065	-0.057	-0.012	-0.072	-0.064	-0.024
	[0.060]	[0.076]	[0.068]	[0.053]	[0.067]	[0.028]
Part-time employed	0.061	0.018	0.059	-0.036	0.05	0.056

	[0.051]	[0.050]	[0.095]	[0.050]	[0.100]	[0.059]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.269	-0.209*	-0.284***	-0.23	-0.155**	-0.124*
	[0.145]	[0.090]	[0.072]	[0.138]	[0.062]	[0.053]
Inactive	0.115	0.069	-0.035	0.046	0.162*	-0.165
	[0.141]	[0.075]	[0.100]	[0.149]	[0.077]	[0.198]
Student	-0.116	-0.167**	-0.198**	-0.160*	-0.165*	-0.067
	[0.099]	[0.058]	[0.064]	[0.070]	[0.081]	[0.040]
>10 years total work experience	-0.001	-0.248**	-0.130*	-0.099**	-0.223***	-0.108**
	[0.063]	[0.067]	[0.060]	[0.040]	[0.057]	[0.032]
3-10 years work experience	0.052	-0.104	-0.086	0.015	-0.084*	-0.011
	[0.051]	[0.057]	[0.060]	[0.031]	[0.039]	[0.026]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	-0.131	-0.223	-0.05	-0.364***	-0.192	0.008
	[0.181]	[0.276]	[0.157]	[0.081]	[0.377]	[0.116]
Platform exp. 3-10 years	-0.207**	-0.06	-0.110**	-0.364***	-0.162	0.107**
	[0.056]	[0.078]	[0.030]	[0.063]	[0.113]	[0.040]
Platform exp. 2-3 years	-0.069	0.089	-0.033	-0.286***	-0.054	0.219**
	[0.044]	[0.080]	[0.039]	[0.057]	[0.065]	[0.060]
Platform exp. 1-2 years	-0.092*	-0.011	-0.048	-0.118	-0.127**	0.086*
	[0.039]	[0.072]	[0.061]	[0.071]	[0.052]	[0.044]
Platform exp. 7-12 months	-0.117*	0.013	-0.047	-0.13	0.003	-0.024
	[0.056]	[0.057]	[0.060]	[0.069]	[0.119]	[0.057]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.127	-0.06	0.099*	-0.016	0.128*	0.191***
	[0.102]	[0.045]	[0.044]	[0.070]	[0.053]	[0.025]
Germany	-0.043	-0.082**	-0.095**	-0.029	-0.05	0.105***
	[0.066]	[0.030]	[0.026]	[0.036]	[0.029]	[0.019]
Italy	0.025	0.028	0.091**	0.235***	-0.044	0.124***
	[0.057]	[0.028]	[0.034]	[0.038]	[0.032]	[0.025]
Romania	0.362***	0.320***	0.319***	0.433***	0.308***	0.034**
	[0.025]	[0.037]	[0.028]	[0.015]	[0.007]	[0.014]
Spain	-0.002	0.015	0.120*	0.136**	0.054	0.128***
	[0.068]	[0.054]	[0.051]	[0.056]	[0.042]	[0.018]
United Kingdom	0.031	-0.036	0.001	0.082	-0.113**	0.058**
	[0.046]	[0.041]	[0.036]	[0.051]	[0.031]	[0.016]
Constant	2.579***	2.490***	2.292***	3.040***	1.938***	1.555***
	[0.068]	[0.038]	[0.082]	[0.062]	[0.108]	[0.051]
%Microworker effect	*17.7%*	*-12.42%*	*-26.3%*	*-22.7%*	*-25.3%*	*-12.5%*
Linear Prediction	*2.6405*	*2.2182*	*2.009*	*2.7124*	*1.5943*	*1.5339*
No. of Observations	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*
* p<0.10, ** p<0.05, *** p<0.01						

the problem), (5) notes/diagrams (using written notes/diagrams to organise thinking), and (6) spillovers to other projects (reflecting on how platform learning affects other projects). Coefficients can be interpreted as conditional mean differences in these learning-strategy measures between microworkers and freelancers.

Across all six outcomes, microworkers score substantially lower than freelancers, with large magnitudes and very strong statistical significance. The microworker coefficients range from -0.439*** to -0.927***, indicating systematically weaker self-regulated learning practices and weaker learning-transfer beliefs among microworkers. The strongest gap appears in “multiple sources” (-0.927***), but the pattern is highly consistent: microworkers are less likely to report that their learning is transferable (-0.685***), less likely to apply prior lessons (-0.694***), less likely to engage in deliberate problem understanding (-0.439***), less likely to use notes/diagrams (-0.653***), and less likely to report spillovers of learning to other projects (−0.643***). This coherence matters for interpretation because these items capture a common underlying mechanism: the extent to which workers structure, monitor, and generalise learning while performing platform work.

The effect-size summary at the bottom (“%Microworker Effect”) expresses the microworker coefficient relative to the baseline linear prediction in each column (coefficient/linear prediction). The proportional differences are large across the board (roughly −13% to −36%), reflecting economically meaningful gaps in self-regulated learning intensity, not merely small statistical deviations. Importantly, because the outcomes are measured on a frequency/intensity scale, these negative coefficients indicate that microworkers are systematically less engaged in behaviours typically associated with cumulative human-capital formation and generalisation of learning beyond immediate tasks.

Interpreted against H7 and the broader market narrative, Table 4-6 strongly supports a segmented view of platform work: even after conditioning on observable characteristics and country context, microwork is associated with markedly weaker self-regulated learning strategies and weaker beliefs that platform learning transfers to future work. This complements Table 4-5, where microworkers reported higher exposure to “new tasks” but lower engagement in deliberate learning activities. Taken together, the two tables suggest a consistent mechanism: microwork may involve novelty or variation, yet the task and governance environment does not foster the same depth of self-regulated, transferable learning that characterises freelancing. From a policy perspective, this strengthens the case for segment-specific upskilling approaches: interventions aimed at improving portability and progression for microworkers likely need to be more structured and supported (e.g., guided learning pathways, credentialing, scaffolded reflection/feedback mechanisms) rather than relying on self-directed learning incentives that appear to be more naturally aligned with the freelancing segment.

Table 4-7 provides the core test of H8 by examining whether microworkers and freelancers report different types of skill upgrading from platform work, conditional on the standard control set and country fixed effects. Each dependent variable is a binary indicator equal to 1 if the respondent reports having improved the specific skill “last month through work on the platform”. The six outcomes are: improved technical/specialty skills (1), improved communication skills (2), improved

Table 4-6: Do microworkers and freelancers differ in self-regulated learning strategies and beliefs about learning transferability?

	Transferable learning belief	Multiple sources	Apply prior lessons	Problem understanding	Notes/ diagrams	Spillovers to other projects
	(1)	(2)	(3)	(4)	(5)	(6)
Microworker	-0.685***	-0.927***	-0.694***	-0.439***	-0.653***	-0.643***
	[0.072]	[0.054]	[0.066]	[0.069]	[0.040]	[0.038]
Female	0.177***	0.038	0.126***	0.085**	0.041	0.088***
	[0.038]	[0.029]	[0.020]	[0.028]	[0.052]	[0.022]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
LGBT+	-0.124*	-0.369**	-0.039	-0.418	0.042	-0.259
	[0.059]	[0.125]	[0.395]	[0.237]	[0.324]	[0.185]
Immigration background	0.113*	0.137***	0.204***	0.024	0.104**	0.102
	[0.047]	[0.033]	[0.044]	[0.020]	[0.029]	[0.057]
Unable to work in standard job	0.035	-0.025	0.131*	0.022	-0.006	0.035
	[0.089]	[0.033]	[0.056]	[0.059]	[0.092]	[0.049]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	0.050	-0.030	-0.081**	-0.106	-0.015	0.021
	[0.076]	[0.047]	[0.030]	[0.058]	[0.100]	[0.065]
Age 39-48	0.029	-0.003	-0.232**	-0.118**	-0.096	-0.079
	[0.104]	[0.062]	[0.063]	[0.040]	[0.091]	[0.086]
Age 49-58	0.013	0.011	-0.183***	0.089	-0.059	-0.011
	[0.065]	[0.062]	[0.049]	[0.120]	[0.110]	[0.097]
Age 59-68	-0.046	0.012	-0.204***	-0.059	-0.112	-0.269***
	[0.123]	[0.137]	[0.043]	[0.093]	[0.110]	[0.069]
Doctorate degree	-0.155	-0.011	0.001	-0.098	0.229**	-0.027
	[0.103]	[0.158]	[0.182]	[0.161]	[0.089]	[0.169]
Master's degree	-0.084	0.061	-0.12	-0.119*	0.075*	-0.037
	[0.068]	[0.072]	[0.071]	[0.055]	[0.034]	[0.065]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	0.079	0.118***	0.084	-0.023	-0.035	0.034
	[0.053]	[0.029]	[0.070]	[0.051]	[0.050]	[0.072]
Professional qualification	-0.052	0.095	-0.059	0.074	0.340***	0.005
	[0.139]	[0.183]	[0.104]	[0.066]	[0.082]	[0.203]
Vocational/technical qualific.	-0.015	0.037	0.012	-0.198	0.040	-0.064
	[0.092]	[0.068]	[0.065]	[0.114]	[0.079]	[0.039]
High school diploma	-0.03	0.048	-0.084	-0.023	-0.047	-0.054
	[0.059]	[0.086]	[0.094]	[0.054]	[0.087]	[0.068]
Some high school (no diploma)	0.135	0.181*	-0.043	-0.169	0.253	0.053
	[0.080]	[0.077]	[0.078]	[0.088]	[0.160]	[0.079]
No formal schooling	-0.375	0.083	-0.861***	-1.232***	0.270	-0.277
	[0.309]	[0.278]	[0.164]	[0.071]	[0.320]	[0.297]
Full-time employed	-0.080	-0.057	-0.091*	-0.082	-0.148	-0.019
	[0.066]	[0.036]	[0.046]	[0.051]	[0.084]	[0.069]

Part-time employed	0.110**	0.016	-0.067	0.042	-0.075	0.086
	[0.040]	[0.085]	[0.079]	[0.041]	[0.091]	[0.108]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.234**	-0.008	-0.112	-0.117*	-0.323**	-0.095
	[0.074]	[0.082]	[0.114]	[0.053]	[0.124]	[0.096]
Student	-0.173**	-0.250**	-0.190**	-0.151***	-0.327***	-0.116
	[0.060]	[0.077]	[0.066]	[0.032]	[0.082]	[0.107]
Inactive	-0.340**	-0.102	-0.160**	-0.029	-0.165	0.161**
	[0.107]	[0.121]	[0.056]	[0.079]	[0.108]	[0.062]
>10 years work experience	-0.210**	-0.045	0.053*	0.127	-0.103	-0.081
	[0.075]	[0.053]	[0.022]	[0.081]	[0.087]	[0.052]
3-10 years work experience	-0.072	-0.006	-0.048**	0.046	-0.087	-0.031*
	[0.052]	[0.037]	[0.019]	[0.055]	[0.073]	[0.016]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	-0.116	-0.082	0.095	0.022	-0.38	-0.376**
	[0.370]	[0.082]	[0.236]	[0.159]	[0.201]	[0.145]
Platform exp. 3-10 years	-0.135*	-0.157*	-0.055	-0.047	-0.135*	-0.217***
	[0.056]	[0.079]	[0.040]	[0.049]	[0.058]	[0.041]
Platform exp. 2-3 years	-0.140*	-0.150*	-0.015	-0.052	-0.199**	-0.074
	[0.067]	[0.076]	[0.051]	[0.086]	[0.077]	[0.081]
Platform exp. 1-2 years	-0.065	-0.068	0.003	0.029	-0.038	-0.154*
	[0.075]	[0.067]	[0.063]	[0.036]	[0.049]	[0.077]
Platform exp. 7-12 months	-0.085	-0.163*	-0.041	-0.084	-0.151**	-0.137*
	[0.067]	[0.078]	[0.046]	[0.080]	[0.055]	[0.062]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.049	-0.165***	-0.051	-0.118**	0.382***	-0.248***
	[0.044]	[0.043]	[0.072]	[0.038]	[0.053]	[0.030]
Germany	-0.077**	-0.107**	-0.082	-0.013	0.191***	-0.118***
	[0.026]	[0.033]	[0.042]	[0.019]	[0.036]	[0.016]
Italy	0.100***	0.001	0.041	-0.086***	0.190***	0.067**
	[0.025]	[0.021]	[0.042]	[0.019]	[0.022]	[0.023]
Romania	0.223***	0.237***	0.163***	0.071***	0.284***	-0.043*
	[0.035]	[0.030]	[0.014]	[0.018]	[0.017]	[0.019]
Spain	0.066	-0.068**	-0.015	0.061**	0.333***	-0.014
	[0.035]	[0.027]	[0.041]	[0.019]	[0.043]	[0.032]
United Kingdom	-0.146***	-0.236***	-0.049*	-0.021	0.275***	-0.173***
	[0.036]	[0.030]	[0.020]	[0.014]	[0.028]	[0.035]
Constant	3.231***	3.222***	3.297***	3.626***	2.271***	2.930***
	[0.101]	[0.126]	[0.065]	[0.074]	[0.108]	[0.074]
%Microworker Effect	*-24.8%*	*-35.6%*	*-24.3%*	*-13.3%*	*-33.0%*	*-26.5%*
Linear Prediction	*2.7677*	*2.6013*	*2.8542*	*3.2991*	*1.9814*	*2.4274*
No. of Observations	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*
Notes: * p<0.10, ** p<0.05, *** p<0.01						

learning skills (3), improved analytical skills (4), improved computer literacy (5), and improved language skills (6). Coefficients are interpretable as percentage-point differences in the probability of reporting each improvement between microworkers and freelancers.

The estimates show a clear pattern of differential upgrading profiles across the two segments rather than uniform "more" or "less" upgrading. Microworkers are significantly less likely to report improvement in technical skills (-0.203***) and communication skills (-0.245***), outcomes that align closely with professional task environments that require specialised expertise, client interaction, and project management. At the same time, microworkers are significantly more likely to report improvements in learning skills (+0.173***), analytical skills (+0.239***), computer literacy (+0.161***), and language skills (+0.141***). This combination is consistent with the idea that microwork generates more general-purpose or foundational forms of human-capital accumulation (practice, exposure, basic digital and analytical routines), while freelancing is more conducive to upgrading in specialised technical and communication dimensions.

The bottom "Effect (Δ/Pred)" row expresses each microworker coefficient relative to the baseline linear prediction in that column (coefficient/linear prediction). This highlights how large the segment gaps are relative to baseline probabilities. For example, the technical upgrading gap (-0.203) is sizeable relative to a predicted baseline of about 0.487 (≈ -41.7%), and the communication gap (-0.245) is very large relative to its baseline (≈ -80.4%). Conversely, the positive gaps for learning and analytical upgrading are large relative to their baselines (≈ +58.7% and +93.3%, respectively), and the gains for computer literacy and language are also substantial in proportional terms. As in earlier tables, the proportional measure can become very large when baseline predicted probabilities are small; the percentage-point coefficients remain the most stable summary.

Interpreted against H8 and the broader market narrative, Table 4-7 supports a hybrid form of segmentation. The results do not suggest that microworkers "do not learn"; rather, they suggest that microworkers' upgrading is concentrated in more general skills, while freelancers' upgrading is concentrated in specialised technical and communication dimensions. In a fully integrated competitive market, one would expect skill upgrading to track occupational portfolios and task content similarly across segments; instead, the pattern here reinforces the regime distinction: microwork appears to provide fewer pathways for specialised, market-facing skill formation, while freelancing provides richer conditions for developing specialised and communicative competences. From a policy perspective, this implies that upskilling interventions should be segment-specific: for microworkers, policies may need to focus on converting general learning gains into portable credentials and progression routes toward higher-complexity work; for freelancers, the priority may be recognition, advanced upskilling, and support for sustaining specialised expertise and communication/market skills.

Table 4-7: Do microworkers and freelancers experience different types of skill upgrading from platform work?

	Upgrading technical skills	Upgrading communication skills	Upgrading learning skills	Upgrading analytical skills	Upgrading computer literacy	Upgrading language skills
	(1)	(2)	(3)	(4)	(5)	(6)
Microworker	-0.203***	-0.245***	0.173***	0.239***	0.161***	0.141***
	[0.031]	[0.015]	[0.033]	[0.014]	[0.020]	[0.027]
Female	-0.112***	0.034	-0.009	-0.073***	-0.011	0.058*
	[0.021]	[0.024]	[0.018]	[0.005]	[0.006]	[0.026]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
LGBT+	-0.102	-0.099	0.173	-0.093	0.209	0.069
	[0.103]	[0.188]	[0.160]	[0.167]	[0.192]	[0.133]
Immigration background	0.013	0.011	0.060**	0.035	0.043	-0.072
	[0.016]	[0.039]	[0.023]	[0.025]	[0.029]	[0.054]
Unable to work in standard job	-0.006	0.018	0.078*	0.003	0.02	0.005
	[0.028]	[0.030]	[0.034]	[0.031]	[0.014]	[0.025]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	0.015	0.023	0.035	0.006	0.016	0.036
	[0.013]	[0.032]	[0.034]	[0.015]	[0.028]	[0.026]
Age 39-48	-0.028	-0.015	0.080**	0.001	0.026	0.034
	[0.018]	[0.021]	[0.028]	[0.035]	[0.043]	[0.023]
Age 49-58	0.012	-0.047*	0.007	0.06	0.033	0.001
	[0.066]	[0.019]	[0.045]	[0.048]	[0.027]	[0.055]
Age 59-68	-0.133*	-0.083*	0.057	0.01	0.155**	-0.097
	[0.056]	[0.042]	[0.071]	[0.060]	[0.061]	[0.060]
Doctorate degree	-0.006	0.082	0.008	0.147*	-0.106	0.003
	[0.074]	[0.070]	[0.067]	[0.061]	[0.069]	[0.045]
Master's degree	-0.021	0.001	0.022	0.011	-0.018	0.009
	[0.037]	[0.026]	[0.029]	[0.041]	[0.027]	[0.047]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Some university (no degree)	0.02	0.001	0.042	0.008	0.039	-0.017
	[0.027]	[0.019]	[0.022]	[0.014]	[0.028]	[0.043]
Professional qualification	-0.028	-0.032	0.01	0.069	0.024	0.069
	[0.074]	[0.035]	[0.039]	[0.039]	[0.046]	[0.079]
Vocational/technical qualification	-0.02	-0.093***	0.061*	-0.076**	-0.061	-0.005
	[0.047]	[0.018]	[0.029]	[0.027]	[0.039]	[0.039]
High school diploma	0.136**	0.023	0.062	0.005	0.039	0.019
	[0.042]	[0.028]	[0.052]	[0.025]	[0.025]	[0.024]
Some high school (no diploma)	-0.019	0.047	0.001	-0.057	0.019	0.017
	[0.053]	[0.032]	[0.062]	[0.030]	[0.032]	[0.063]
No formal schooling	0.154	0.150	0.065	-0.009	0.038	-0.060
	[0.179]	[0.283]	[0.307]	[0.158]	[0.073]	[0.103]
Full-time employed	-0.039	-0.078	-0.042	-0.006	0.003	-0.003
	[0.038]	[0.044]	[0.027]	[0.021]	[0.026]	[0.035]

Part-time employed	-0.020	0.059*	0.033	0.022	0.028	0.080**
	[0.049]	[0.027]	[0.028]	[0.038]	[0.036]	[0.029]
Unemployed	0.039	-0.009	-0.057	-0.054	-0.005	-0.081
	[0.029]	[0.032]	[0.045]	[0.039]	[0.024]	[0.045]
Student	-0.082***	-0.064***	-0.013	-0.028	0.011	0.066
	[0.015]	[0.016]	[0.033]	[0.026]	[0.048]	[0.052]
Inactive	0.037	-0.003	0.003	0.081	-0.037	0.072
	[0.075]	[0.028]	[0.056]	[0.070]	[0.039]	[0.092]
>10 years total work experience	0.001	-0.044	-0.012	0.028	-0.025	-0.005
	[0.026]	[0.026]	[0.037]	[0.025]	[0.038]	[0.015]
3-10 years total work experience	-0.039	0.012	0.016	0.072***	-0.029	-0.023
	[0.021]	[0.027]	[0.025]	[0.015]	[0.021]	[0.026]
0-3 years work experience	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Platform exp. >10 years	-0.098	-0.276***	0.056	0.043	0.138**	0.296*
	[0.139]	[0.056]	[0.118]	[0.105]	[0.041]	[0.145]
Platform exp. 3-10 years	-0.04	-0.06	-0.093	-0.069***	-0.045*	0.026
	[0.031]	[0.033]	[0.049]	[0.016]	[0.019]	[0.029]
Platform exp. 2-3 years	-0.001	-0.055*	-0.065	0.013	-0.016	-0.025
	[0.025]	[0.026]	[0.041]	[0.018]	[0.014]	[0.037]
Platform exp. 1-2 years	0.006	-0.044	-0.012	0.035	-0.028	0.013
	[0.023]	[0.025]	[0.046]	[0.022]	[0.027]	[0.031]
Platform exp. 7-12 months	-0.012	0.035	-0.025	-0.01	-0.025	-0.063**
	[0.044]	[0.039]	[0.041]	[0.021]	[0.025]	[0.025]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	-0.162***	-0.019	0.036*	0.049*	-0.028**	-0.01
	[0.022]	[0.013]	[0.015]	[0.021]	[0.008]	[0.008]
Germany	-0.124***	0.018**	0.039***	0.001	-0.045***	0.007
	[0.012]	[0.006]	[0.008]	[0.014]	[0.005]	[0.008]
Italy	-0.101***	-0.033**	0.034**	0.018	-0.054***	-0.002
	[0.017]	[0.010]	[0.014]	[0.011]	[0.009]	[0.026]
Romania	-0.045***	-0.054***	0.151***	0.084***	-0.003	-0.124***
	[0.010]	[0.014]	[0.014]	[0.008]	[0.009]	[0.019]
Spain	-0.155***	0.013	0.099***	0.054**	-0.037***	0.047***
	[0.016]	[0.011]	[0.011]	[0.016]	[0.007]	[0.013]
United Kingdom	-0.026	0.058***	-0.005	0.047***	-0.020**	-0.339***
	[0.015]	[0.009]	[0.013]	[0.011]	[0.006]	[0.018]
Constant	0.750***	0.458***	0.134**	0.093***	0.147*	0.348***
	[0.053]	[0.022]	[0.037]	[0.017]	[0.061]	[0.039]
Effect (Δ/Pred)	*-41.7%*	*-80.4%*	*58.7%*	*93.3%*	*81.4%*	*40.8%*
Linear Prediction	*0.4872*	*0.3052*	*0.2946*	*0.2559*	*0.1976*	*0.3444*
No. of Observations	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*	*1,989*
* p<0.10, ** p<0.05, *** p<0.01						

4.2.4 Block D: Worker-like exposure and regulatory relevance (H_9-H_{10})

Table 4-8 tests H9-H10 by asking whether microworkers face higher worker-like exposure than freelancers, and whether this organisational exposure differs from (and can diverge from) income dependence. The table is structured to separate these concepts empirically. Column (1) uses a binary indicator for high income dependence (platform income share ≥61%) as a dependence-based measure. Columns (2)-(3) capture two core organisational ingredients of worker-like exposure, low autonomy and routine tasks, and Column (4) combines these into a worker-like exposure index. Columns (5)-(6) then relate worker-like exposure to outcomes (technical upgrading and enjoyment), allowing for differential associations by segment through an interaction.

The results provide strong evidence that the microwork segment is more "worker-like" in organisational terms even when it is not more income dependent. In Column (1), the microworker coefficient is negative and significant (-0.132***), indicating that microworkers are *less likely* than freelancers to be highly income dependent, conditional on controls. In contrast, Columns (2)-(4) show large, positive, and precisely estimated microworker effects on organisational exposure: microworkers are more likely to report low autonomy (+0.179***), far more likely to report routine tasks (+0.952***), and score substantially higher on the composite exposure index (+0.567***). This is a textbook "control vs dependence" divergence: organisational exposure is higher in microwork, but high-income dependence is lower.

These patterns map tightly to the hypotheses. H9 (worker-like exposure is higher in microwork) is strongly supported by the positive and significant microworker coefficients in Columns (2)-(4). H10 (control ≠ dependence) is supported by the contrast between Column (1) and Columns (2)-(4): a dependence-based lens alone would suggest lower vulnerability for microworkers, but the organisational lens shows the opposite, microwork is the segment where routineness and constrained discretion are most pronounced. The inclusion of occupational portfolio controls reinforces this interpretation: the integrated occupational portfolio index is positively associated with routineness and exposure (Columns 3-4), while higher transferability is associated with *lower* routineness and lower exposure (Columns 3-4), consistent with the idea that more portable occupational bundles correlate with less worker-like task structures.

Columns (5)-(6) provide supplementary evidence on how exposure relates to outcomes. In Column (5), microworkers report significantly less technical upgrading (-0.224***), and higher adaptive occupational portfolios predict more technical upgrading (+0.088***), while transferability predicts less (+/- depending on sign here: it is negative and significant, -0.057**, in this specification). The worker-like exposure index itself is not precisely estimated in Column (5), and neither is its interaction with microworker status, suggesting that within this specification exposure does not add strong marginal explanatory power for technical upgrading beyond segment membership and occupational portfolio controls. In Column (6), enjoyment is lower for microworkers (-0.128***), while exposure again does not show a strong incremental association once controls are included. Substantively, this means the clearest message of Table 4-8 is not the exposure to outcome slope, but the segmentation of organisational exposure itself and its divergence from income dependence.

Table 4-8: Do microworkers face higher worker-like exposure than freelancers, and does this differ from income dependence?

	High income dependence (>=61%) (1)	Low autonomy (2)	Routine tasks (3)	Worker-like exposure (4)	Tech-upgrading worker-like exposure (5)	Enjoyment ~ Worker-like exposure (6)
Microworker	-0.132***	0.179***	0.952***	0.567***	-0.224***	-0.128***
	[0.027]	[0.020]	[0.107]	[0.091]	[0.027]	[0.011]
Integrated occup. skill portfolio index	0.008	0.017	0.204**	0.144**	0.088***	-0.009
	[0.010]	[0.022]	[0.059]	[0.057]	[0.015]	[0.021]
Skill transferability (standardised)	-0.005	-0.004	-0.148**	-0.092*	-0.057**	-0.002
	[0.008]	[0.016]	[0.048]	[0.043]	[0.023]	[0.024]
Worker-like exposure index	–	–	–	–	0.007	-0.006
					[0.016]	[0.011]
Microworker×Worker-like exposure index	–	–	–	–	0.026	-0.005
					[0.026]	[0.019]
Female	0.009	-0.007	0.03	0.019	-0.107**	0.069*
	[0.022]	[0.017]	[0.016]	[0.037]	[0.032]	[0.031]
Male	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
LGBT+	0.092	0.051	0.103	0.275*	-0.191**	-0.203
	[0.071]	[0.046]	[0.137]	[0.134]	[0.074]	[0.192]
Immigration background	0.017	0.002	0.048	0.055	0.011	0.009
	[0.019]	[0.021]	[0.060]	[0.051]	[0.021]	[0.025]
Unable to work in standard job	0.001	0.034	0.204**	0.159	0.002	0.003
	[0.027]	[0.045]	[0.071]	[0.113]	[0.040]	[0.048]
Age 18-28	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age 29-38	-0.002	0.001	-0.052	-0.03	0.005	0.019
	[0.017]	[0.022]	[0.037]	[0.047]	[0.017]	[0.056]
Age 39-48	-0.044	-0.016	-0.109**	-0.149	-0.03	0.029
	[0.031]	[0.019]	[0.044]	[0.084]	[0.026]	[0.034]
Age 49-58	-0.041*	-0.009	-0.227**	-0.195***	0.003	-0.019
	[0.021]	[0.029]	[0.083]	[0.048]	[0.072]	[0.072]
Age 59-68	-0.139***	-0.013	-0.184	-0.331	-0.116	0.001
	[0.035]	[0.045]	[0.174]	[0.176]	[0.061]	[0.056]
Doctorate degree	0.017	0.003	-0.247	-0.098	-0.001	0.098**
	[0.080]	[0.064]	[0.163]	[0.138]	[0.089]	[0.027]
Master's degree	-0.023	-0.038**	-0.164***	-0.178***	0.001	-0.044
	[0.022]	[0.012]	[0.031]	[0.040]	[0.039]	[0.041]
Undergraduate degree	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Professional qualification	0.006	-0.035	-0.198	-0.147	0.004	0.032
	[0.034]	[0.020]	[0.142]	[0.107]	[0.070]	[0.028]
Vocational/technical qualification	0.080***	0.024	-0.057	0.13	0.018	-0.03
	[0.017]	[0.047]	[0.095]	[0.101]	[0.043]	[0.052]
High school diploma	-0.005	-0.031	-0.213***	-0.166*	0.145**	0.007
	[0.018]	[0.044]	[0.045]	[0.079]	[0.054]	[0.030]
Some high school (no diploma)	-0.021	-0.047	-0.278**	-0.249**	0.014	0.063

	[0.046]	[0.026]	[0.094]	[0.097]	[0.059]	[0.033]
Some university (no degree)	0.009	0.03	0.094*	0.109	0.073***	0.009
	[0.026]	[0.030]	[0.045]	[0.076]	[0.015]	[0.030]
No formal schooling	-0.100	-0.161**	-0.551*	-0.688***	0.152	-0.196
	[0.056]	[0.058]	[0.227]	[0.059]	[0.170]	[0.295]
Full-time employed	-0.137***	0.027	-0.039	-0.191**	-0.027	0.003
	[0.021]	[0.022]	[0.039]	[0.066]	[0.030]	[0.013]
Part-time employed	-0.122***	0.047*	0.036	-0.099	-0.026	-0.01
	[0.027]	[0.020]	[0.087]	[0.094]	[0.054]	[0.039]
Other activity	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Unemployed	-0.075	-0.053*	-0.035	-0.215	0.026	-0.052
	[0.052]	[0.023]	[0.134]	[0.116]	[0.035]	[0.029]
Inactive	-0.026	-0.005	-0.094	-0.097	0.029	0.035
	[0.065]	[0.044]	[0.183]	[0.099]	[0.081]	[0.070]
Student	0.041	0.020	-0.032	0.078	-0.049	0.009
	[0.068]	[0.027]	[0.117]	[0.115]	[0.058]	[0.066]
>10 years total work experience	-0.038	0.028**	0.156***	0.065	0.009	-0.005
	[0.021]	[0.009]	[0.029]	[0.055]	[0.030]	[0.031]
3-10 years total work experience	-0.028	-0.002	0.029	-0.031	-0.034	-0.003
	[0.022]	[0.019]	[0.101]	[0.099]	[0.020]	[0.029]
Platform exp. >10 years	-0.116**	0.006	-0.033	-0.187	-0.152	-0.097
	[0.039]	[0.047]	[0.111]	[0.139]	[0.150]	[0.175]
Platform exp. 3-10 years	0.018	0.002	0.013	0.038	-0.057	-0.090***
	[0.050]	[0.013]	[0.036]	[0.082]	[0.030]	[0.016]
Platform exp. 2-3 years	0.031	0.003	-0.043	0.03	-0.01	-0.065**
	[0.049]	[0.029]	[0.082]	[0.129]	[0.017]	[0.018]
Platform exp. 1-2 years	0.047*	0.019	0.041	0.123**	0.002	-0.086*
	[0.022]	[0.018]	[0.039]	[0.042]	[0.040]	[0.040]
Platform exp. 7-12 months	0.011	0.056	0.114**	0.161*	-0.001	-0.042
	[0.025]	[0.031]	[0.032]	[0.081]	[0.050]	[0.029]
Platform exp. 0-6 months	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Finland	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
France	0.055*	-0.066**	-0.203	-0.122	-0.180***	-0.066***
	[0.024]	[0.022]	[0.113]	[0.113]	[0.023]	[0.013]
Germany	0.025*	-0.038***	-0.032	-0.035	-0.113***	-0.022
	[0.011]	[0.010]	[0.059]	[0.054]	[0.007]	[0.014]
Italy	0.100***	0.014**	0.051	0.203***	-0.111***	0.003
	[0.012]	[0.005]	[0.062]	[0.054]	[0.008]	[0.006]
Romania	-0.014	-0.024*	-0.024	-0.07	-0.044***	0.116***
	[0.015]	[0.012]	[0.031]	[0.037]	[0.009]	[0.015]
Spain	0.021	-0.039**	-0.085	-0.071	-0.140***	-0.056***
	[0.014]	[0.015]	[0.075]	[0.075]	[0.013]	[0.009]
United Kingdom	-0.014	-0.001	0.133**	0.045	-0.033**	-0.095***
	[0.010]	[0.007]	[0.052]	[0.035]	[0.012]	[0.016]
Constant	0.236***	0.039	-0.497***	-0.243**	0.737***	0.825***
	[0.007]	[0.036]	[0.074]	[0.072]	[0.051]	[0.053]
No. of Observations	*1,608*	*1,608*	*1,608*	*1,608*	*1,608*	*1,608*

From a policy perspective, Table 4-8 directly motivates why classification and protection debates should not rely solely on income dependence. The results imply that a large share of microworkers may combine platform work with other income sources (hence lower high-dependence rates), yet still face a work organisation characterised by routine execution and constrained discretion, conditions closely aligned with “worker-like” governance. This strengthens the case for a dual diagnostic approach in policy: dependence-based metrics capture economic reliance, while exposure-based metrics capture organisational control. For targeting upskilling and mobility policies, it suggests that microworkers may need interventions that explicitly address task constraints and progression pathways (e.g., routes into higher-complexity tasks, credentialing, and structured learning supports) even if they are not classified as highly income dependent platform workers.

4.3 Discussion and Implications

To summarize, this section first developed a framework in which the Joint CrowdLearn platform economy operated through two segments, i.e., freelancing and microwork, characterised by different task regimes, autonomy, and governance. Workers were assumed to bring occupational skill portfolios S_i(proxied by ESCO profiles assigned via their primary ISCO occupation), and segment productivity depended on how these portfolios complemented the segment’s task regime T_s. Because freelancing involved more complex, multi-step projects with higher discretion, it was expected to reward cognitive, social, and diversified/transferable bundles more strongly. Microwork, defined by fragmented and standardised tasks with lower discretion, was expected to be more compatible with routine execution and less complementary to complex transferable bundles. Segment membership was modelled as endogenous, with sorting driven by expected returns, entry frictions, autonomy preferences, non-monetary motives, and constraints in standard labour markets. This generated three sets of predictions: (i) sorting across segments in occupational portfolios and motivations, (ii) segment-specific assignment and learning mechanisms once active on the platform, and (iii) a policy-relevant divergence between organisational control and income dependence, captured by worker-like exposure.

Then, it translated these predictions into a block-by-block set of testable hypotheses and estimated them using conditional comparisons between microworkers and freelancers (with worker controls and country fixed effects). Block A tested the selection-and-regime implications. H1 predicted occupational portfolio segmentation; H2 predicted motivational segmentation; and H3 predicted task-regime differentiation. Block B tested the mechanism layer: H4 examined whether occupational skill composition mapped into the type of platform tasks performed (skill-task alignment), and H5 examined whether occupational transferability converted into upgrading differently by segment. Block C tested segment-specific learning and upgrading implications: H6 focused on learning activities, H7 on self-regulated learning strategies and transfer beliefs, and H8 on differences in the type of skill upgrading reported. Block D tested the regulatory implications: H9 predicted higher worker-like exposure in microwork, and H10 predicted that exposure could diverge from income dependence.

The empirical evidence in Tables 4-1 to 4-3 strongly supported the Block A predictions. Table 4-1 confirmed H1: microworkers were anchored in primary occupations with systematically weaker ESCO portfolios, lower cognitive/thinking and social intensity, higher physical/manual intensity, and lower diversification and transferability. Table 4-2 confirmed H2: microworkers were much less likely to cite autonomy, passion, and task choice, and much more likely to cite time-filling, enjoyment, and "fruitful activity," consistent with different participation logics across segments. Table 4-3 confirmed H3: microwork was more routine and repeatable and involved lower discretion, and was significantly less likely to involve creativity, skill variety, and complex skills. Together, these results established a clear segmented-regime baseline in endowments, motives, and work organisation.

Table 4-4 then assessed whether the model's mechanism channels operated as predicted. The evidence for H4 (skill-task alignment) was strongest for the cognitive channel: occupational thinking intensity was strongly associated with complex task content, while microworkers nonetheless operated in a substantially lower-complexity environment overall. The physical-to-routine and social-to-collaboration mappings were weaker once controls and segment interactions were included, suggesting that routineness and collaboration were driven primarily by segment-level task design and governance rather than by primary-occupation composition. The evidence for H5 (transferability conversion) was clearer: occupational transferability predicted technical upgrading for freelancers, but this relationship was significantly attenuated for microworkers, indicating weaker conversion of portable occupational bundles into technical upgrading in the microwork regime. This pattern aligned with a constrained-mobility interpretation in which task design and governance restrict how far transferable endowments can be turned into specialised upgrading within microwork.

Tables 4-5 to 4-7 evaluated the model's learning-return implications. Table 4-5 supported H6 in a nuanced way: microworkers reported weaker engagement in deliberate learning activities (following developments, reading, deep reflection, free online courses, collaboration) yet reported more frequent "new tasks," consistent with novelty without deeper cumulative investment. Table 4-6 strongly supported H7: microworkers exhibited large deficits across self-regulated learning strategies and transfer beliefs. Table 4-7 supported H8 by showing that upgrading differed in type rather than uniformly in level: microworkers were less likely to report technical and communication upgrading but more likely to report improvements in learning, analytical, computer, and language skills. This evidence was consistent with a hybrid human-capital profile in which microwork generates more general or foundational improvements while freelancing supports more specialised and market-facing skill formation.

Finally, Table 4-8 brought the evidence into direct contact with the model's regulatory logic. It supported H9 and H10 by showing a sharp divergence between dependence and control: microworkers were less likely to be highly income dependent, yet they reported substantially lower autonomy, substantially higher routineness, and a markedly higher composite worker-like exposure index. This confirmed the model's central policy implication that organisational exposure is distinct from income dependence and that reliance-based criteria alone can miss an important dimension of vulnerability rooted in work organisation. Taken together, the block-by-block pattern is difficult to reconcile with a fully competitive, integrated platform labour market in which segment labels primarily reflect transitory task choice and differences fade once controls are applied. Instead, the evidence is most consistent with a segmented platform economy that nonetheless contains hybrid elements: a cognitive alignment channel operates, but microworkers remain in a lower-complexity, higher-control environment and the conversion of transferability into specialised upgrading is weaker, motivating policy approaches that distinguish occupational endowments, organisational exposure, and progression pathways rather than treating platform work as a single homogeneous category.

Finally, Table 4-9 below summarises the full “model-to-evidence” chain developed in previous sections. It maps each model prediction to its corresponding testable hypothesis, the key empirical finding from Tables 4-1 to 4-8, and the interpretation for how the Joint CrowdLearn platform economy operates. This is meant to make the logic transparent: the model does not only predict average differences between microworkers and freelancers, but also mechanism differences (how skills map into tasks and how transferability converts into upgrading) and a policy-relevant distinction between organisational control and income dependence.

Taken together, the evidence points most strongly to a segmented platform labour market with hybrid elements. Segmentation is strongly supported by consistent differences in (i) occupational ESCO portfolios, (ii) motivations, and (iii) task regimes, as well as by the concentration of worker-like exposure in microwork despite lower income dependence. The “hybrid” element is that some skill-based channels operate, most notably the cognitive alignment channel (thinking intensity predicting complex tasks) and the presence of non-trivial upgrading among microworkers, but these channels function under constraints: microwork remains structurally more routine and low-autonomy, and the conversion of occupational transferability into specialised technical upgrading is weaker. This combination implies that the two segments are not merely different labels within one competitive market; they are distinct regimes with different learning environments and different pathways for mobility, which is central for both upskilling policy design and regulatory classification debates.

Overall, the evidence supports the following interpretation. The Joint CrowdLearn platform economy is segmented in who participates, why they participate, and how work is organised, with microwork systematically characterised by more routine tasks, lower autonomy, weaker occupational portfolios, and higher worker-like exposure. Yet the market is not “closed” in a strict sense: certain skill-task links exist, and microworkers do report forms of learning and upgrading, primarily of a more general or foundational type. This is the most coherent “hybrid” element: microwork may function as a supplementary, low-autonomy regime that generates some basic human-capital accumulation, but it provides weaker pathways toward specialised upgrading and mobility compared to freelancing.

Table 4-9: Summary of findings

Model prediction	Hypothesis	Key empirical finding (Tables)	Interpretation
A_1 : Sorting on occupational portfolios	H_1	Microworkers' primary occupations have lower thinking & social shares, higher physical share, and lower diversification/transferability/portfolio index (Table 4-1).	Strong segmentation in underlying occupational endowments.
A_2 : Motivational sorting	H_2	Microworkers are less autonomy/passion/choice motivated and more time-filling/fun/fruitful motivated (Table 4-2).	Distinct participation logics to segmented labour supply.
A_3 : Task-regime differentiation	H_3	Microwork is more routine/repeatable/low-autonomy and less creative/varied/complex (Table 4-3).	Distinct work organisation regimes to segmented market structure.
B_1 : Assignment: skills to tasks	H_4	Thinking share strongly predicts complex tasks; other channels (physical to routine, social to collaboration) are weaker; large baseline task gaps remain (Table 4-4 columns 1-3).	Hybrid mechanism: some skill-task alignment works, but microwork remains structurally constrained.
B_2 : Transferability conversion differs by segment	H_5	Transferability predicts technical upgrading for freelancers but is attenuated for microworkers (Table 4-4 columns 4-5).	Segmented mobility channel: weaker conversion of portable skills into specialised upgrading in microwork.
C_1 : Learning inputs differ	H_6	Microworkers report more "new tasks" but less deliberate learning (follow developments, reading, reflection, courses, collaboration) (Table 4-5).	Segmentation in learning environment: novelty without deep learning investment.
C_1 : Learning strategies differ	H_7	Microworkers score lower on all self-regulated learning strategies and transfer beliefs (Table 4-6).	Strong segmentation in learning capability/behaviour.
C_2 : Upgrading profiles differ	H_8	Microworkers: lower technical & communication upgrading, but higher learning/analytical/computer/language gains (Table 4-7).	Hybrid: different types of upgrading (general vs specialised) across segments.
D_1 : Worker-like exposure higher in microwork	H_9	Microworkers have higher low autonomy, higher routineness, higher exposure index (Table 4-8 columns 2-4).	Segmented governance/control concentrated in microwork.
D_2 : Control ≠ dependence	H_{10}	Microworkers are less likely to be highly income dependent, yet more worker-like exposed (Table 4-8 column 1 vs 2-4).	Policy-critical hybrid: vulnerability is multi-dimensional; dependence alone misses control-based exposure.

A first policy implication concerns classification and protection criteria. Findings show that high worker-like exposure is concentrated in microwork even when income dependence is lower. This suggests that policy frameworks relying heavily on earnings reliance (income dependence) risk missing workers who face employee-like control through routinised tasks and limited discretion. A more robust diagnostic approach would therefore treat organisational exposure indicators, routineness, standardisation, constrained autonomy, and governance intensity, as complementary to dependence measures when assessing vulnerability and designing protections. In practical terms, this supports regulatory attention to the structure of control (how work is organised and monitored) alongside pay reliance.

A second implication concerns targeting of upskilling and incentives. The evidence suggests that freelancing is more closely tied to specialised technical and communication upgrading (Table 4-7) and exhibits stronger learning activities and self-regulated learning strategies (Tables 4-5 and 4-6). This implies that incentives aimed at advanced upskilling, certification, and recognition of specialised competences are likely to be most effective in the freelancing segment, where the learning environment and task complexity provide higher returns to such investments. By contrast, microworkers exhibit weaker deliberate learning inputs and weaker self-regulated learning, while also facing a more routine, low-autonomy task regime. Policies aimed at microworkers should therefore be designed as low-friction, modular, and scaffolded interventions (short credentials, guided learning pathways, micro-credentials, embedded feedback), rather than assuming that workers will self-direct learning in a way that converts into specialised upgrading.

A third implication concerns mobility and progression within platforms and across segments. The model's conversion prediction is supported: occupational transferability converts into technical upgrading for freelancers but not for microworkers (Table 4-4). This implies that one route to reducing segmentation is to create mechanisms that improve conversion in microwork, namely, pathways that allow microworkers to access more complex tasks, accumulate credible signals of competence, and move toward task categories where transferable bundles can be utilised. Examples include structured progression ladders, verified skill badges linked to task access, and bridges from microtasks to longer project work. Without such progression mechanisms, microwork risks functioning as a "low-mobility" regime even when workers possess transferable occupational capabilities.

Finally, the cross-country dimension (captured by country fixed effects and the observed heterogeneity in coefficients) suggests that segmentation is embedded in national contexts. While the present analysis conditions on country effects rather than explaining them, the results still motivate policy coordination: segmentation patterns appear systematic across countries, implying that EU-level guidance on classification and upskilling may need to account for the fact that platform work is not uniform across segments and that the same regulatory instrument may have different impacts depending on whether it targets microwork-like governance structures or freelancing-like project work. The evidence therefore supports a segmented policy lens: treat platform work not as a single category, but as a set of regimes with different task structures, learning environments, and forms of vulnerability.

5. Primary data: Platform work in TRAILS-I survey

Section 5 begins with evidence from the TRAILS-I survey, which provides population-representative estimates of platform work participation and intensity across EU Member States and selected neighbouring countries. The TRAILS-I survey was implemented as a large-scale cross-country online survey of adults, using quota-based sampling to ensure national representativeness by key demographic and regional characteristics, and it captures both standard labour market positioning and engagement in multiple types of platform-mediated work over the preceding 12 months. It distinguishes between different platform work modalities (e.g., ride-hailing and delivery, freelance digital services, microwork/crowdwork, online selling, content creation and monetisation, local services, and accommodation sharing), and it further differentiates whether platform work is undertaken as a main source of income, a supplementary source, or an occasional activity. This structure enables a detailed mapping of how platform work is embedded in wider income and employment portfolios, and it supports analysis of socio-demographic gradients, reliance on platform income, and indicators of resilience and vulnerability. The TRAILS-I survey design, fieldwork implementation, and full questionnaire documentation have been presented in detail in Deliverable D2.4.

The present section therefore focuses on the survey measures and descriptive patterns that are directly relevant to platform work, skill portfolios, and subsequent analysis of segmentation and mobility. It introduces primary evidence from the TRAILS-I survey to document the prevalence, intensity, and socio-economic patterning of platform work across Europe and the EU's neighbourhood. Rather than treating platform work as a single, uniform phenomenon, the descriptive figures provide a structured overview that captures both the extensive margin (who participates at all) and the intensive margin (how strongly individuals engage and depend on platform work). In doing so, the section offers a consistent descriptive baseline for understanding platform work as an increasingly common, yet highly differentiated, form of labour-market participation across countries and regions.

The descriptive evidence is organised around three complementary dimensions. First, it documents incidence, measured as whether respondents report any platform work in the past 12 months. Second, it examines intensity and dependence, including whether individuals engage in one or multiple types of platform work, how frequently they participate, and whether platform earnings constitute a main, supplementary, or occasional source of income. Third, it explores socio-demographic stratification, describing how both participation and intensity vary across age, gender, education, and indicators of economic resources such as net disposable income and wealth. Together, these descriptive patterns establish a consistent baseline for interpreting platform work as both a geographically uneven phenomenon and a heterogeneous set of labour-market strategies, ranging from sporadic engagement to more systematic reliance.

The section proceeds in three steps. It begins by mapping the geography of recent platform work, first at the country level and then at a regional level, in order to capture both cross-country differences and within-country heterogeneity that may be masked by national averages. This spatial overview is intended to establish where platform work is more and less prevalent, and to provide an empirical baseline for interpreting subsequent results on intensity and worker profiles in light of differing institutional settings and local labour-market conditions.

The section then shifts from incidence to the intensive margin of platform work, focusing on how platform work is organised in practice. Specifically, it shows how often individuals engage in one or more types of platform work, and the extent to which income from platform work is a primary, supplementary or occasional source of income. By distinguishing between occasional engagement and more sustained reliance, this part of the analysis highlights the heterogeneity of platform work primarily functions as a core livelihood, a secondary income stream, or an intermittent activity, and thus helps to differentiate between casual participation and forms of engagement that may carry stronger implications for economic security and labour-market attachment.

Moreover, the section examines how both participation and intensity are patterned across key socio-demographic and economic characteristics, including age, gender, education, and indicators of net disposable income and wealth. This distributional perspective helps identify which groups are more likely to enter platform work to enter platform work in the first place and which are more likely to depend on it. In turn, it provides an initial basis for assessing whether platform work is concentrated among specific population segments, such as younger cohorts, individuals with fewer economic resources, or those in particular educational groups, or whether it is more broadly spread across the workforce.

Finally, it closes by linking these descriptive participation patterns to a harmonised skills framework. Specifically, the section outlines how respondents' self-reported main job titles and task descriptions are translated into individual-level ISCO-08 4-digit (ISCO-4) occupational profiles and subsequently merged to the ESCO 2022 skills taxonomy. This mapping enables the construction of comparable skill portfolios at the individual level, expressed in a common European language of skills, competences, and occupations, and provides the basis for assessing skill breadth, skill composition, and the presence of transferable skill bundles associated with different types of work. By combining a distributional perspective on who enters and relies on platform work with an ESCO-based skills mapping, the section establishes a descriptive benchmark for the later analysis of whether platform work is associated with segmentation or mobility, and whether observed differences reflect distinct skill endowments, different work regimes, or both.

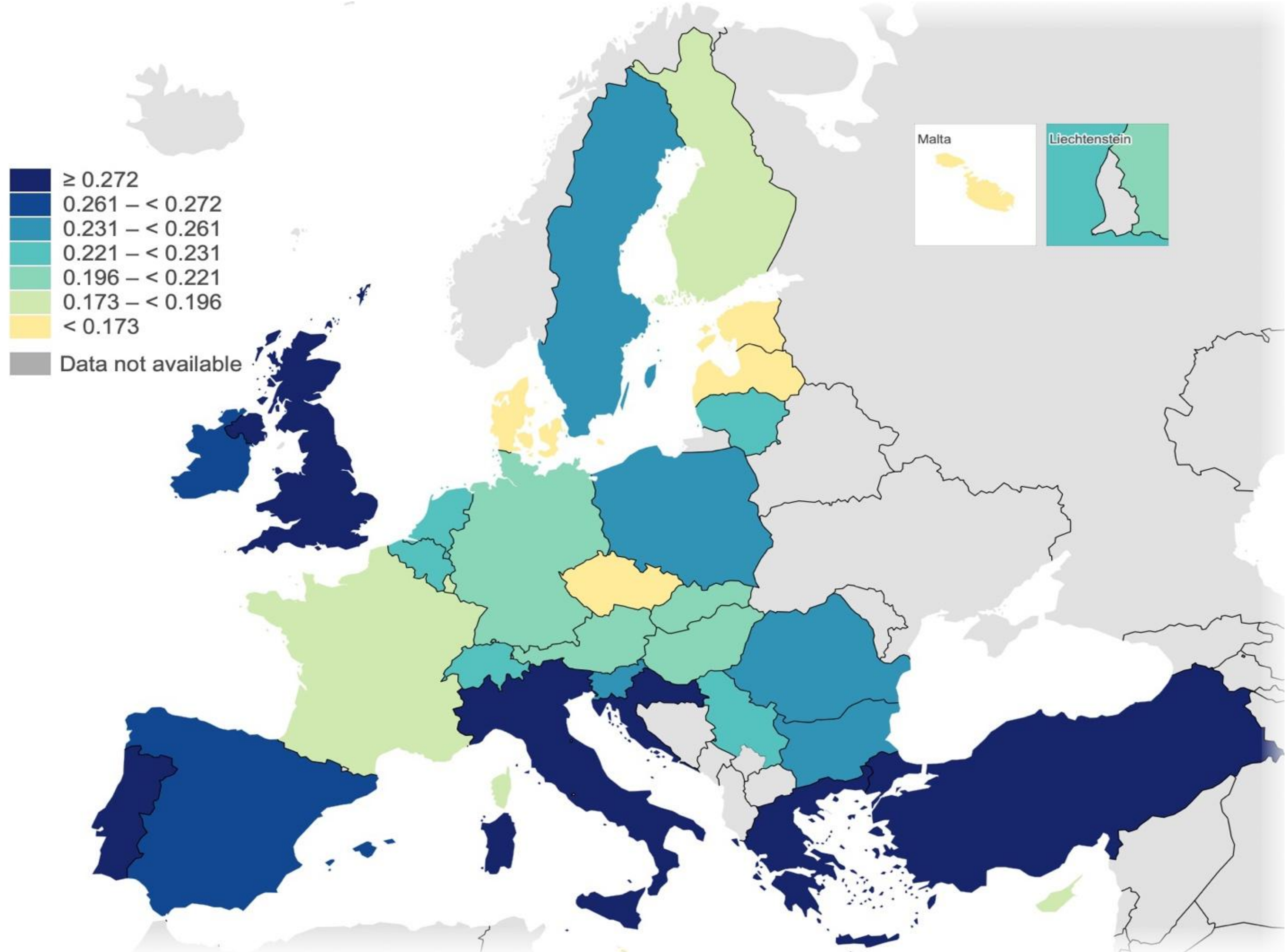
5.1 Platform Work in the EU and Beyond

In all maps presented in this section, both at the country and regional level, data are grouped using a quintile classification, which splits the distribution into seven classes with an equal number of values, ensuring a balanced comparison across categories (the corresponding cut-offs are reported in the legend). At the regional level, the underlying data are reported primarily at the NUTS-2 level for most countries, while regional figures are available at the NUTS-1 level for the United Kingdom, Germany, and Türkiye.

Figure 5-1 maps the share of respondents reporting any platform work in the past 12 months by country in the TRAILS-I survey, offering a first, country-level distribution of platform work exposure across Europe and the EU's neighbourhood. The map makes clear that recent platform work is far from evenly distributed across national contexts. Shares of platform workers spans from below 17.3% in the lowest-incidence group (e.g., Denmark, Estonia, Latvia, Czechia, and Malta) to above 27% in the highest-incidence group, e.g., Greece, Croatia, Italy, Portugal, Ireland, the United Kingdom and Türkiye. In between these extremes, most countries fall in the middle of the distribution (around 19-23%), including much of Western and Central Europe (e.g., Germany, Austria, Belgium, and the Netherlands) and parts of South-Eastern Europe. Taken together, these groupings suggest that platform work is widespread rather than marginal, yet national prevalence differs markedly, pointing to the relevance of country-specific labour-market conditions, institutional settings, and the diffusion of platform-mediated services in shaping participation.

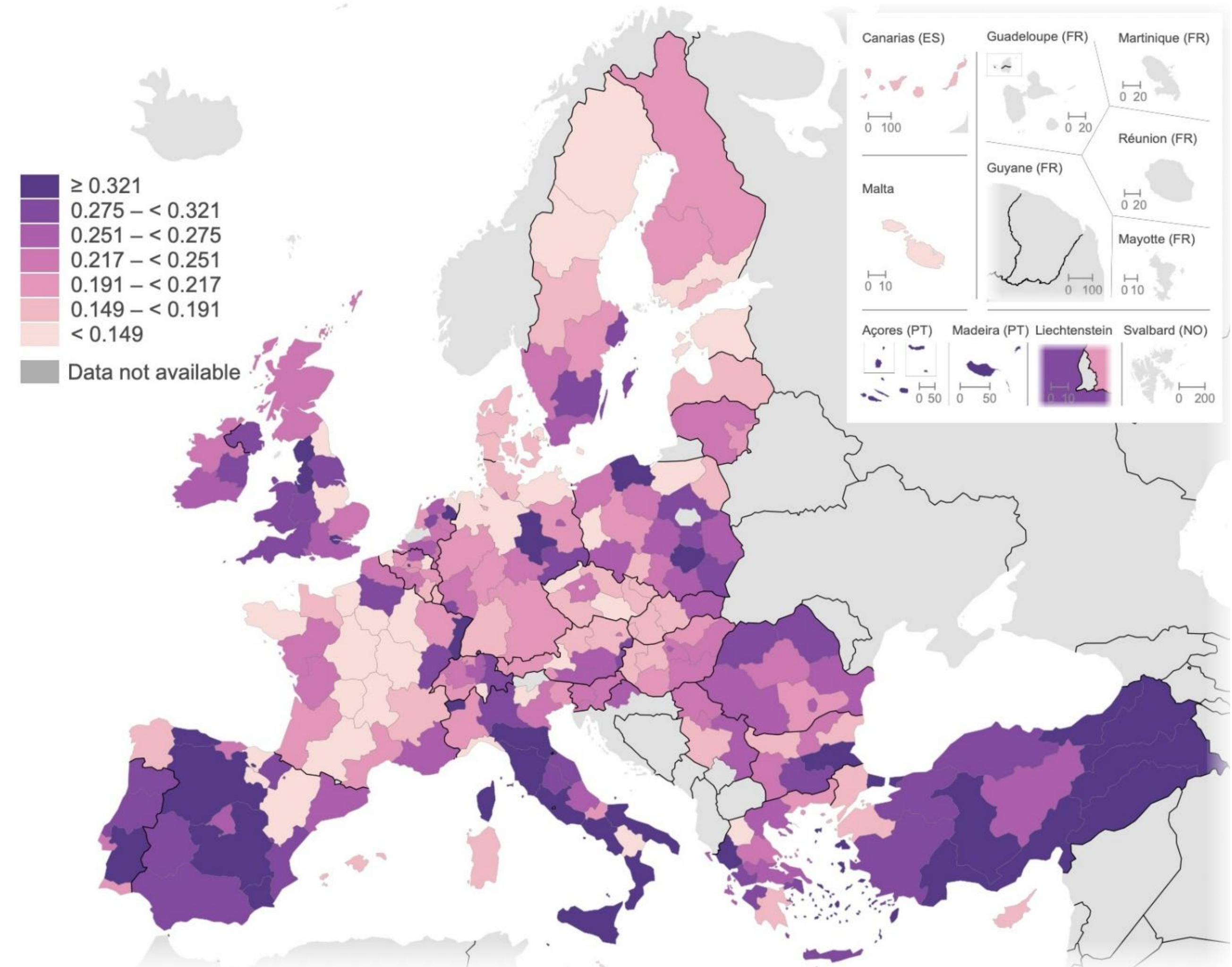
Figure 5-2 complements the country picture by mapping the share of individuals reporting platform work in the last 12 months at a regional level, thereby revealing how much geographic variation can exist within countries. The shading intensity captures the prevalence of recent platform engagement, darker shades indicate higher shares, and a broad spatial pattern emerges. Specifically, Southern and parts of Eastern Europe show comparatively higher shares of platform workers, whereas many regions in Central and Western Europe display more moderate shares. Particularly high concentrations are visible in parts of Spain, Italy, Greece, Romania, and Türkiye, suggesting that in these areas platform work represents a relatively salient component of regional labour-market activity. Conversely, several regions in France, Germany, and parts of Central Europe appear in lighter shades, indicating comparatively lower engagement, while Northern Europe presents a more mixed configuration with pockets of moderate participation alongside lower-prevalence areas. Crucially, the regional map underscores that national averages can mask substantial regional heterogeneity even within the same national context, where regions may differ sharply in exposure to platform work. This spatial unevenness is consistent with the view that platform work participation is shaped by regional economic structures, local labour-market conditions, urbanisation patterns, and the development of digital ecosystems that support platform matching and service delivery.

Figure 5-1: Platform work experience in the last 12 months by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-2: Platform work experience in the last 12 months by region



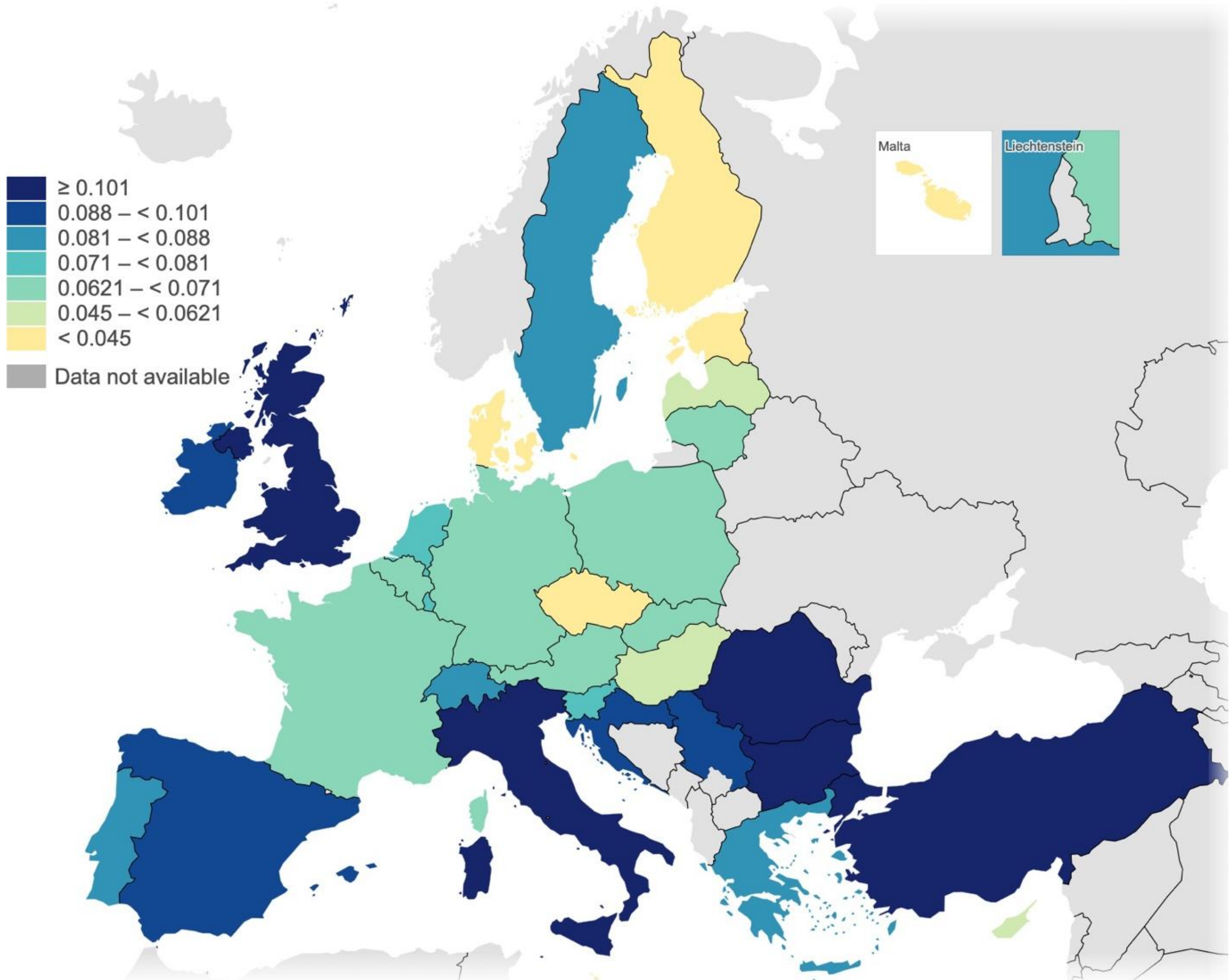
Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-3 maps, at the country level, the share of TRAILS-I respondents who report working in more than one type of platform work during the reference period, i.e., engaging across multiple platform categories such as transportation/delivery, digital/online work, e-commerce/asset-based activities, local services, or care-related tasks. This indicator captures a more intensive and diversified form of platform engagement than the overall “any platform work” measure, because it reflects not only participation but also breadth across segments of the platform economy. As expected, levels are therefore lower across all countries. The map’s classification shows that the national shares range from below 4.5% in the lowest group to 10.1% or more in the highest group, revealing substantial cross-country heterogeneity in the extent to which platform workers diversify across task types. Countries with higher rates of multi-type platform work cluster in the United Kingdom and in parts of Southern and South-Eastern Europe, including Italy, Romania, Bulgaria, and Türkiye. Conversely, lower rates are visible in several Nordic and Central European countries, including Finland, Denmark, Estonia, Czechia, and Malta. Taken together, the country map suggests that diversified platform engagement is geographically uneven, and that in some national contexts platform work is more likely to be organised as a portfolio of activities across multiple platform segments, rather than being confined to a single platform type

Figure 5-4 extends this analysis to the regional level by mapping the share of respondents reporting experience in multiple platform work types across European regions with darker shades indicating higher prevalence. The regional view reveals a more granular, and often sharper, picture than national averages, highlighting that multi-platform engagement tends to concentrate in specific subnational labour markets. A clear spatial pattern emerges, with particularly high concentrations in Southern Europe and parts of Eastern Europe, where several regions appear in the darkest categories. Regions in Spain, Italy, Greece, Romania, and Türkiye stand out, suggesting that diversified platform participation is especially salient in these areas. This regional clustering is consistent with the interpretation that multi-type platform engagement may be more common where platform activity spans multiple sectors simultaneously (e.g., online tasks alongside local services) and where workers’ income strategies may involve switching between platform categories or combining them in parallel. At the other end of the distribution, many regions in France, Germany, Austria, and parts of Central Europe appear in lighter shades, indicating comparatively lower levels of multi-platform experience. Northern Europe again shows a mixed configuration: some regions exhibit moderate engagement, but the strongest concentrations remain less prominent than in Southern and Eastern parts of the map.

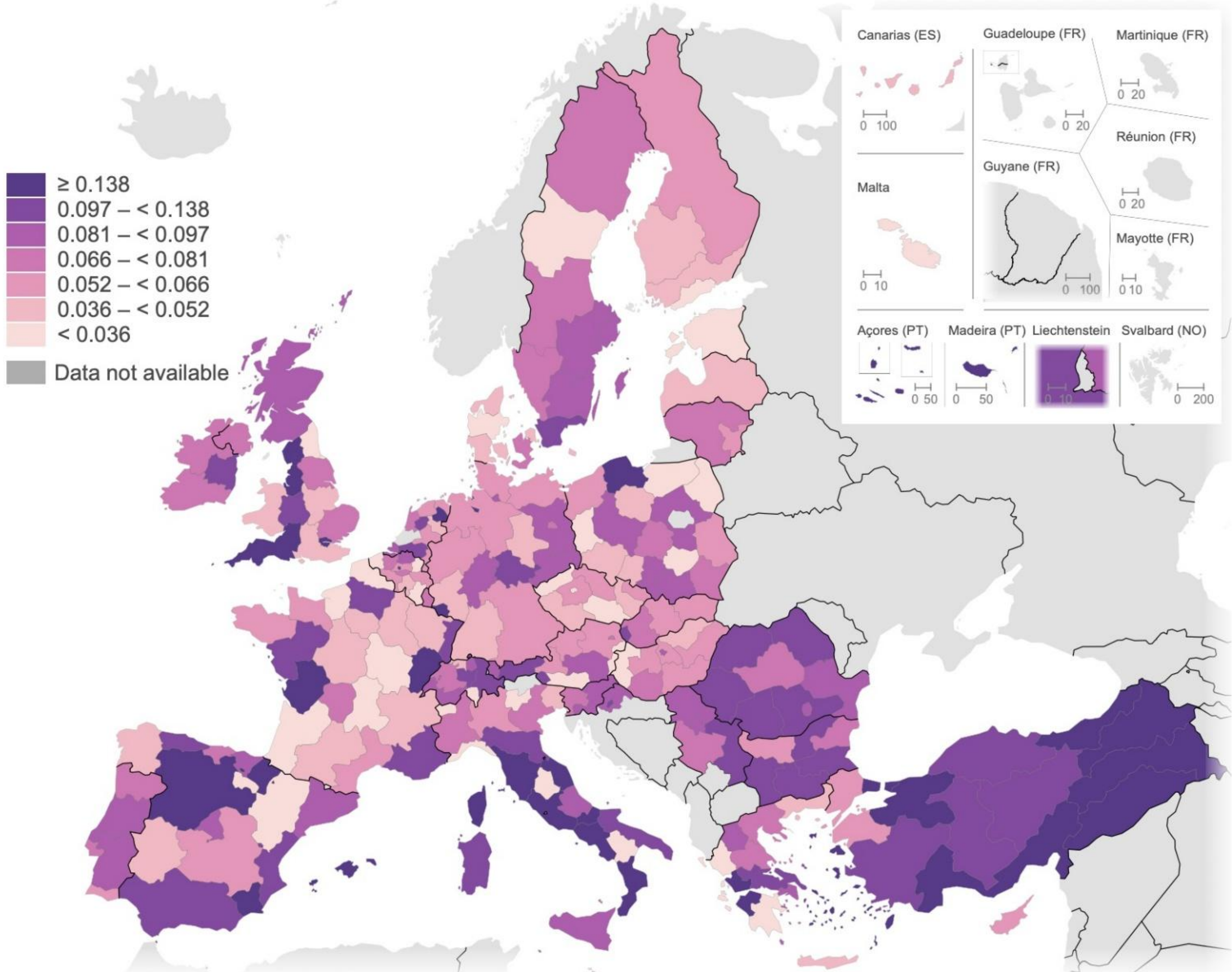
Importantly, the regional map also makes visible substantial within-country heterogeneity: countries with moderate national averages may still include regions with relatively high multi-type platform work, while high-scoring countries may contain pockets where diversified engagement is less prevalent. This within-country variation reinforces that multi-platform participation is not merely a national attribute but is likely shaped by regional economic structures, local labour-market dynamics, and the degree to which different platform segments have diffused within regional economies. Overall, Figures 5-3 and 5-4 jointly underscore that diversification across platform work types, an indicator of more intensive and complex engagement with platform work, is unevenly distributed across Europe and is concentrated in specific national and regional contexts.

Figure 5-3 : Experience in multiple platform work types by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-4: Experience in multiple platform work types by region



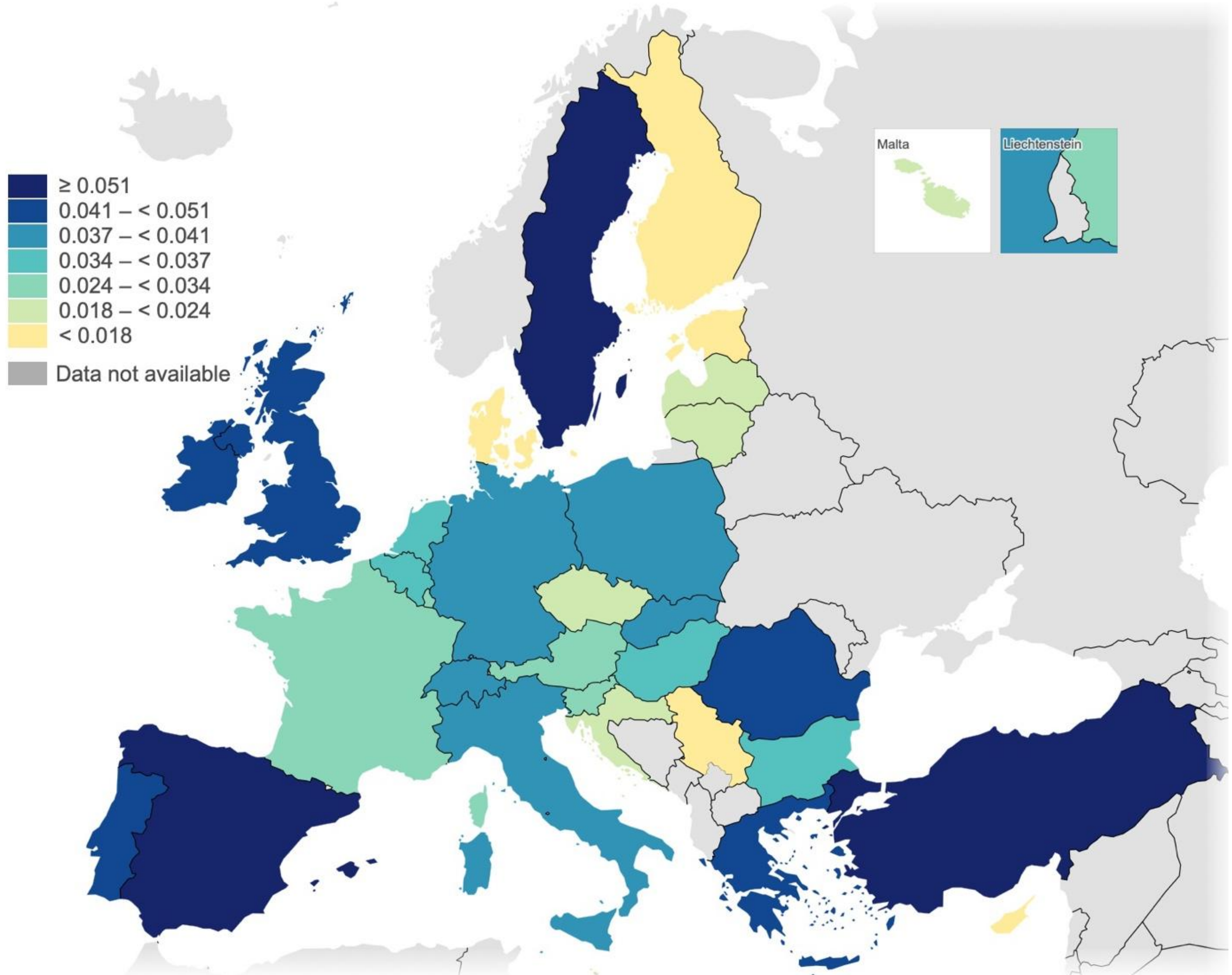
Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-5 maps, at the country level, the share of TRAILS-I respondents who report that platform work constitutes their main source of income. As an indicator, "main income" captures a high-threshold form of platform engagement and identifies respondents for whom platform earnings are not merely an add-on, but the primary basis of livelihood. Unsurprisingly, the shares are therefore much lower than the broader measure of "any platform work experience," reinforcing that for most respondents who participate in platform work, it is typically combined with other income sources rather than replacing them. The country distribution nevertheless shows meaningful variation: the mapped values range from below 1.8% in the lowest group to 5.1% or more in the highest group. This implies that, even though primary reliance on platform work is generally uncommon, it is not negligible everywhere and can reach visibly higher levels in some national contexts. The highest values are concentrated in a small set of countries, such as Sweden, Spain, and Türkiye, where the map suggests that platform work more often functions as a principal income activity for a non-trivial minority of respondents. A second group with relatively elevated shares includes parts of South-Eastern Europe (e.g., Portugal, Greece and Romania), as well as Ireland and the United Kingdom. At the other end, very low shares are observed in countries, such as Finland, Denmark, Estonia, Serbia and Cyprus, indicating that in these settings platform work is much less frequently reported as the main livelihood source. Taken together, the country map highlights two simultaneous features of platform work: primary dependence is rare overall, but where it does occur, it tends to be geographically clustered, pointing to systematic cross-country differences in the role platform work plays within national income portfolios.

Figure 5-6 complements the national picture by mapping, at the regional level, the share of respondents for whom platform work represents the main source of income. Moving from countries to regions is particularly informative for this high-dependence indicator because it can reveal whether primary reliance on platform income is diffuse within a country or instead concentrated in specific subnational labour markets. The spatial distribution shows a visible concentration of darker-shaded regions in Southern and parts of Eastern Europe, such as regions in Spain, Italy, Greece, Romania, and Türkiye. In these areas, the map suggests a comparatively stronger integration of platform work into regional labour-market structures, consistent with the idea that, for some regions, platform work may be closer to a primary occupation rather than only a supplementary activity. By contrast, many regions in Northern and Western Europe, including parts of France, Germany, the Netherlands, and the Nordic countries, appear in lighter shades, indicating lower reliance on platform work as the main income source. While pockets of higher intensity may still be visible within these countries, the overall pattern implies that platform work is less commonly reported as a primary livelihood basis in these regional labour markets. The regional map also suggests that even where national prevalence is moderate, regions can differ sharply, suggesting that local economic conditions, employment opportunities, and the availability (and maturity) of platform markets may shape whether platform work can become a main income source.

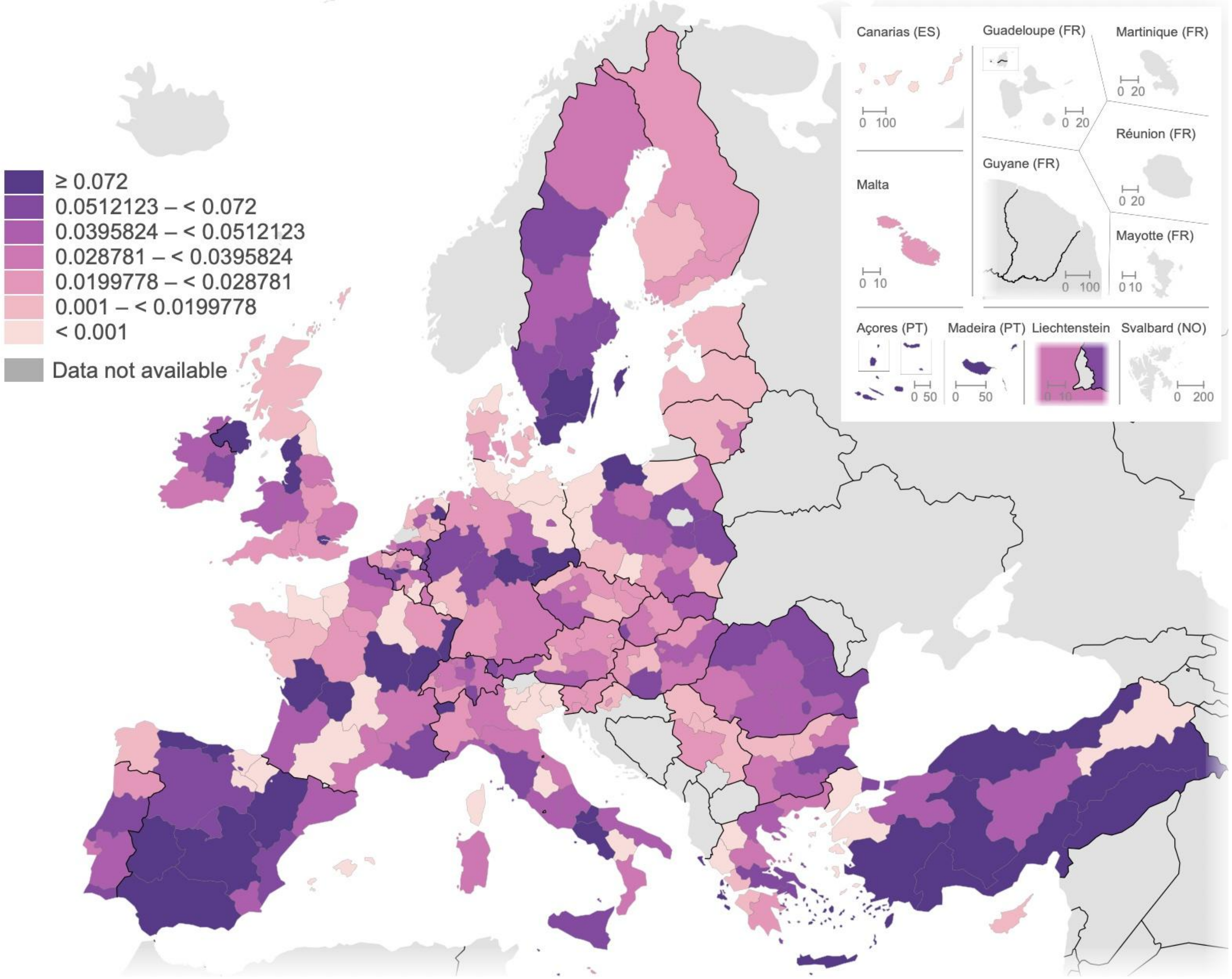
Overall, the combined evidence from the country and regional maps indicates that primary dependence on platform work is structurally limited in aggregate, but where it emerges, it tends to do so unevenly across space, with higher concentrations in specific Southern and Eastern regional clusters.

Figure 5-5: Platform work as the main source of income by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-6: Platform work as the main source of income by region



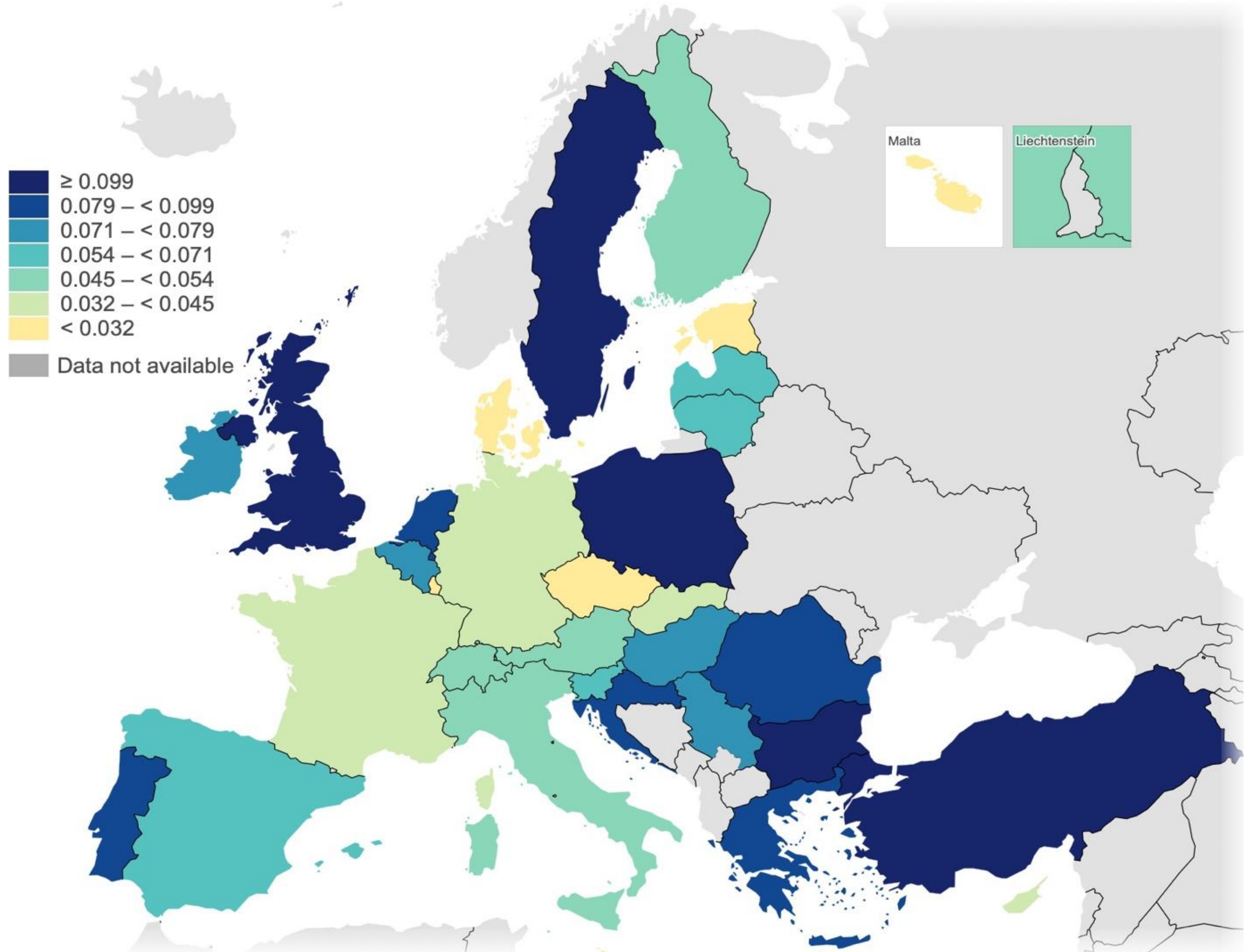
Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-7 maps, at the country level, the share of TRAILS-I respondents who report that platform work provides a supplementary source of income. Compared to the “main income source” measure, this indicator is expected to be more prevalent because it captures platform work used alongside another primary income source (e.g., wages, self-employment income, pensions, study-related support). Even so, the map shows that supplementary platform work remains highly uneven across national contexts. Specifically, country scores span from below 3.2% in the lowest group to 9.9% or more in the highest group (as indicated by the legend cut-offs). This range signals that, while supplementary platform work is present across Europe and the EU’s neighbourhood, the extent to which it is used as a common income-complement varies substantially. The highest shares are concentrated in a set of countries where platform work appears to play a comparatively widespread “top-up” role, most notably in Sweden, Poland, Bulgaria, Greece, Romania, the United Kingdom, and Türkiye. In these contexts, the map suggests that platform work does not only appear as a labour-market phenomenon but is also more frequently integrated into household income portfolios as an additional stream. At the opposite end, very low shares are clustered in countries such as Denmark, Czechia, Estonia, and Malta, indicating that within these national settings supplementary platform work is reported much less often and may be more marginal as a routine income-complement. Most other countries fall into intermediate bands, suggesting that supplementary platform work is present across Europe but with markedly different intensity.

Figure 5-8 maps the share of individuals who engage in platform work as a supplementary income source across European regions. Because respondents can be concentrated in particular local labour markets, the regional view is especially informative about whether supplementary platform work is diffuse within countries or instead clusters in specific subnational areas. The map shows a broader spread than at the country level, with the lowest group falling below 2.4% and the highest group reaching 11.9% or more, highlighting that some regions exhibit very high prevalence even when national averages are more moderate. The darkest shades, indicating the highest regional prevalence, are particularly visible across parts of Southern and Eastern Europe, with notable concentrations in regions of Spain, Italy, Greece, Romania, Bulgaria, and Türkiye. This spatial clustering is consistent with supplementary platform work functioning as a meaningful mechanism for income diversification in these regional labour markets: rather than replacing primary earnings, platform work appears more often to complement them, potentially reflecting seasonal work patterns, fragmented employment structures, or broader reliance on mixed income sources. By contrast, many regions in France, Germany, Austria, and parts of Central Europe appear in lighter shades, indicating comparatively lower prevalence of supplementary platform work, while Northern Europe presents a more mixed share. Finally, the regional map highlights that supplementary platform work is geographically uneven and appears closely linked to regional labour market structures, income volatility, and the availability of alternative employment opportunities.

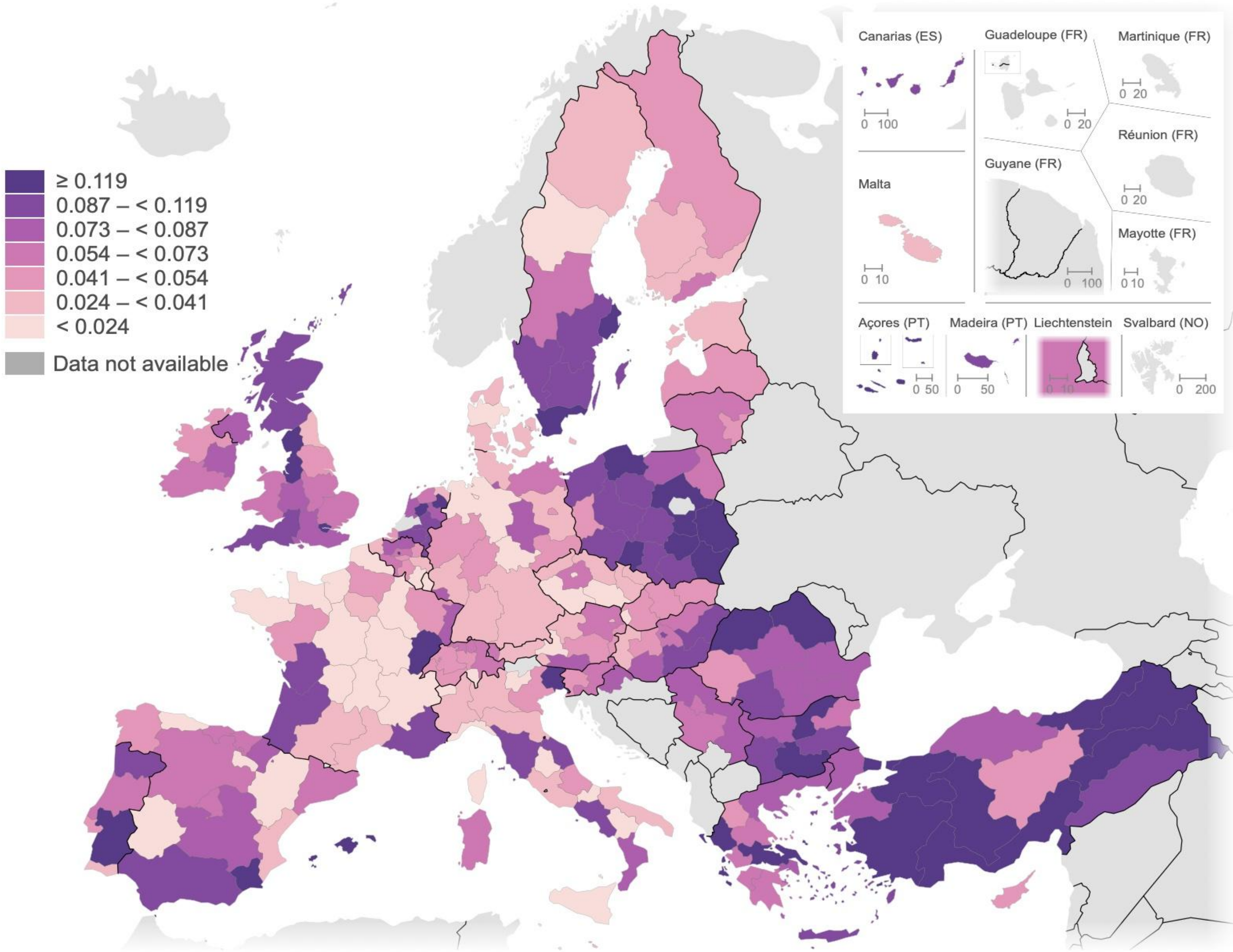
Overall, the two maps together indicate that supplementary platform work is geographically uneven at both levels of aggregation and appears closely linked to regional labour-market structures, differences in economic opportunity, and the local diffusion and maturity of platform-based work opportunities.

Figure 5-7: Platform work as a supplementary source of income by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-8: Platform work as a supplementary source of income by region



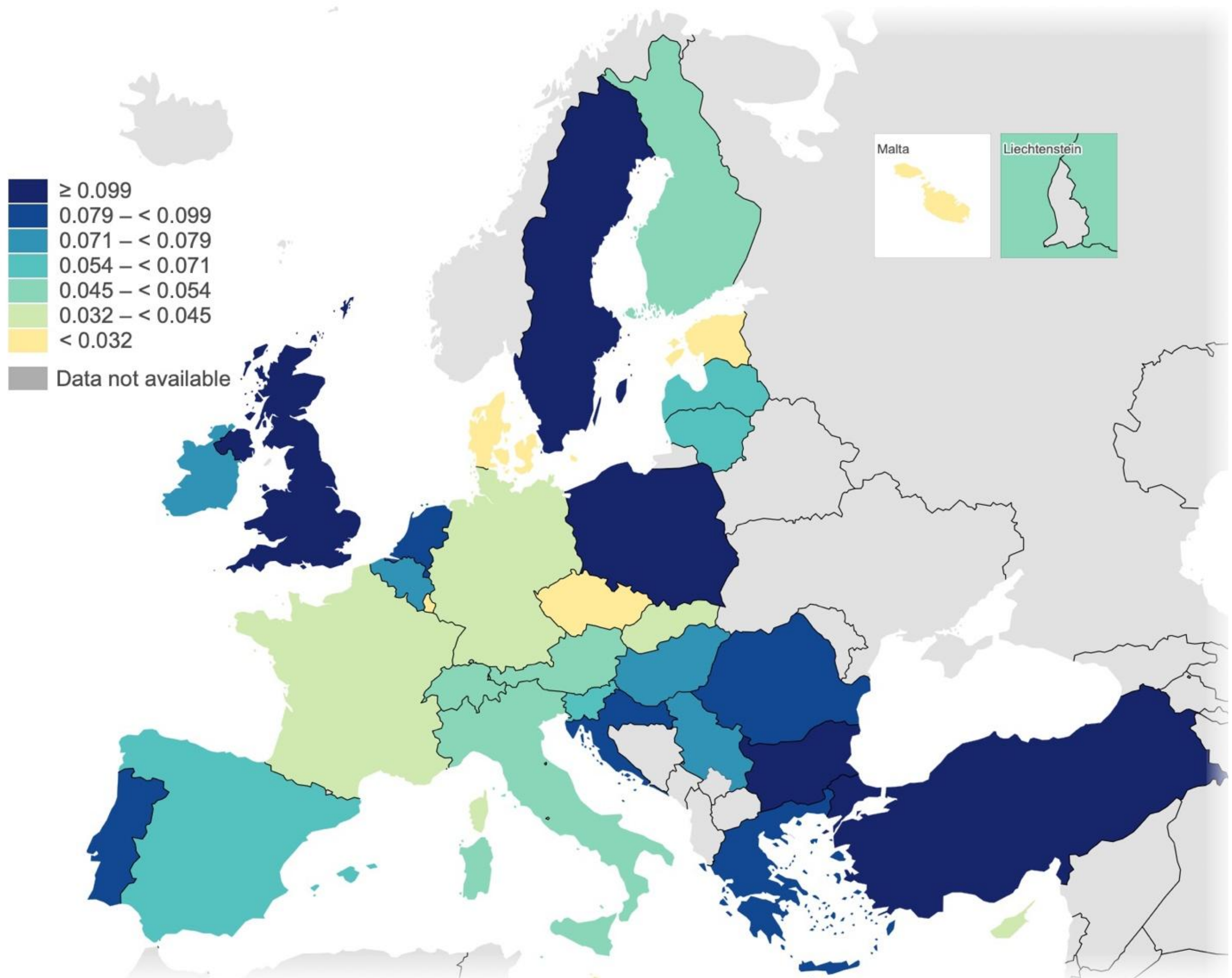
Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-9 maps the share of TRAILS-I respondents by country who report that platform work is an occasional activity. This indicator captures the "light-touch" end of platform engagement and, as expected, it is slightly more prevalent than cases where platform work is the main income source. Across countries, the shares range from below 7.2% to 13.6% or more, indicating that occasional platform work is widespread but varies noticeably in intensity across national contexts. The map shows that occasional platform work is particularly common in several countries in Western and Southern Europe, such as the United Kingdom, Italy, Portugal, Spain, Ireland, Croatia, and Slovenia, suggesting that in these settings platform work is often used as a flexible, intermittent complement to other forms of employment or income. In contrast, lower shares are visible in a number of Nordic and Central/Eastern European countries, including Sweden, Poland, Estonia, Latvia, and Malta. Most other countries fall into intermediate bands, underscoring that occasional platform participation is a broadly observed pattern across Europe and the EU's neighbourhood, even though varies markedly in intensity.

Figure 5-10 extends the analysis to the regional level by mapping the share of individuals who engage in platform work as an occasional activity across European regions. Darker shades indicate higher levels of participation in platform work undertaken on a non-regular basis, and the resulting spatial pattern again highlights pronounced geographic unevenness. Relatively strong concentrations are visible in Southern Europe and parts of Eastern Europe, particularly in regions of Spain, Italy, Greece, Romania, and Türkiye, suggesting that occasional platform work constitutes a common labour-market strategy in these areas. Several regions in the United Kingdom and parts of Central Europe also appear in darker categories, indicating that intermittent platform engagement is not limited to one part of Europe but can be prominent where platforms are well diffused and where workers combine multiple income sources. At the other end, lighter shades dominate in parts of Northern Europe and in some regions of France and Germany, pointing to comparatively lower prevalence of occasional platform work in these regional labour markets. Importantly, the regional map reveals substantial within-country heterogeneity, indicating that occasional platform work is geographically uneven and appears closely linked to regional labour market flexibility, economic volatility, and the diffusion of digital platform ecosystems across Europe.

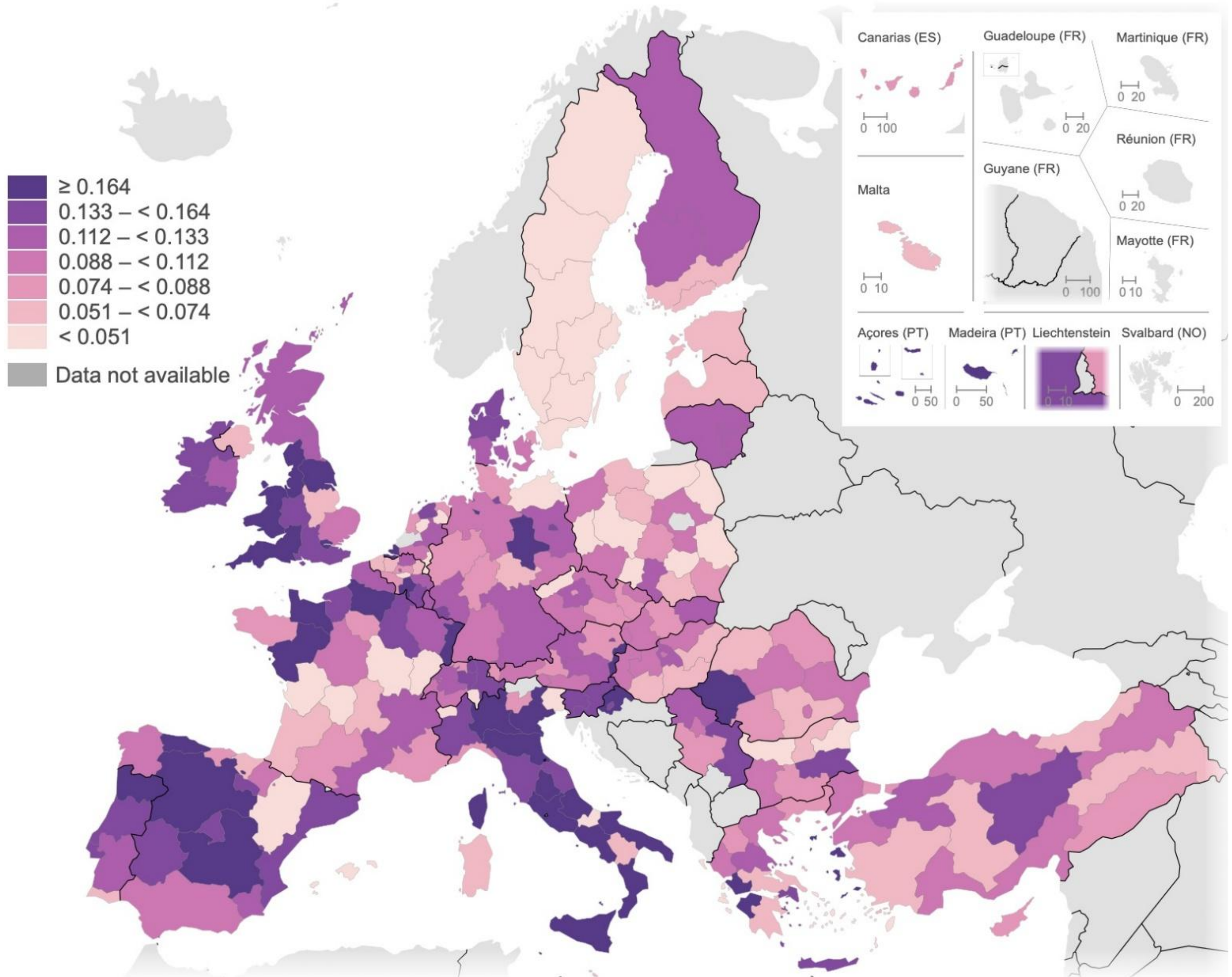
Overall, these two maps shows that the most common form of platform engagement is often intermittent rather than primary, but that the incidence of occasional platform work remains strongly place-dependent, plausibly reflecting differences in regional labour-market flexibility, economic volatility, and the maturity of local digital platform ecosystems.

Figure 5-9: Platform work as an occasional activity by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5-10: Platform work as an occasional activity by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 5.11 disaggregates reported platform work by country into three categories: i) platform skill-intensive (freelance/creative services, content creation and monetisation, microwork/crowdwork), ii) platform routine (ride-hailing/transport and food/goods delivery), and iii) platform intermediation (online selling and gig commerce, local services/household tasks, accommodation/property sharing, and other).

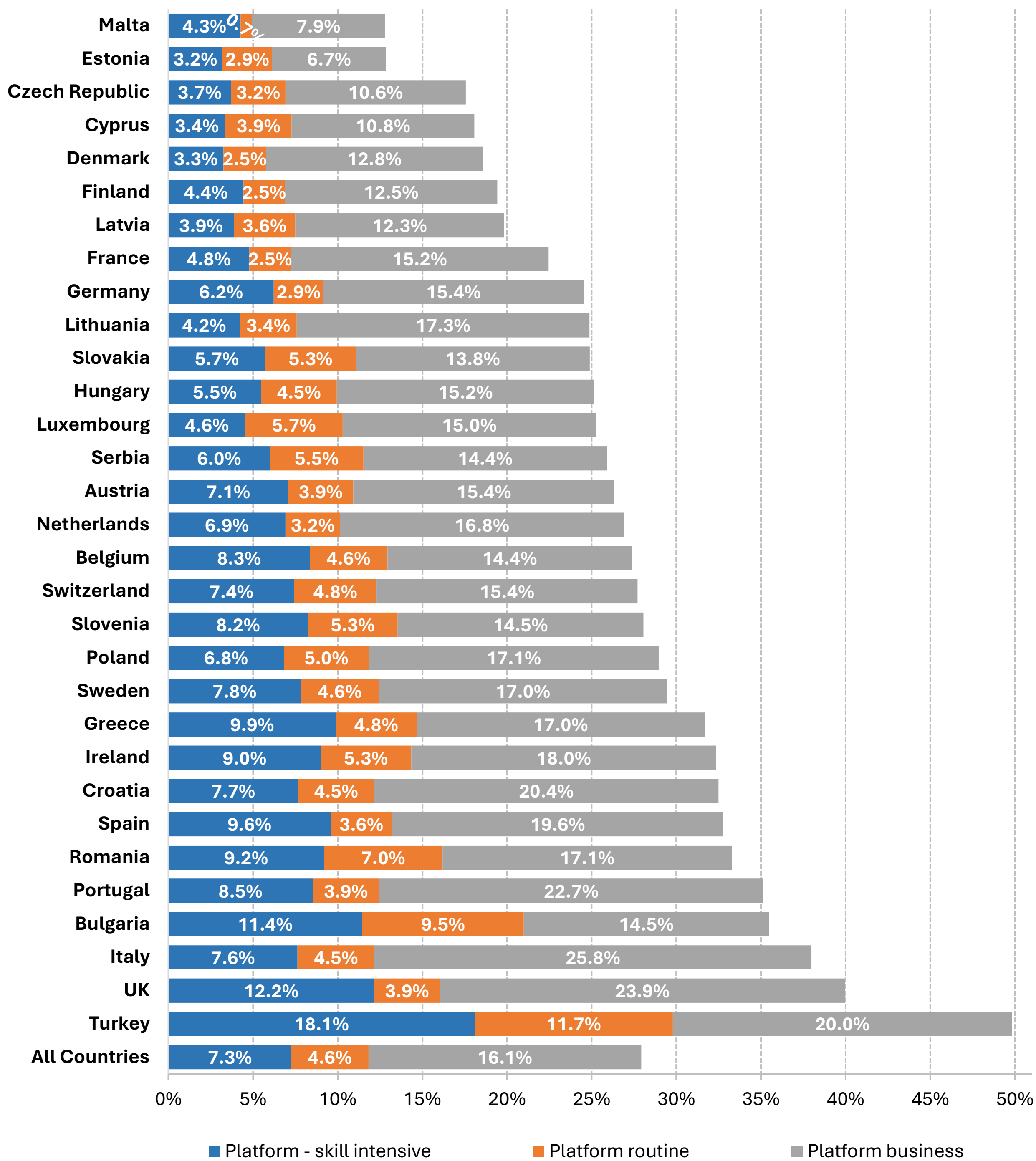
Figure shows a general pattern where platform intermediation is the dominant type of platform work in every country, with substantially higher reported incidence than either skill-intensive or routine platform work. At the aggregate ("All Countries") level, around 16.1% of respondents report a intermediation-type of platform work, compared with about 7.3% in skill-intensive activities and 4.6% in routine transport/delivery. This aggregate pattern indicates that platform work is most commonly anchored in transaction and matching activities such as online selling, local services, and accommodation or property sharing, rather than being driven primarily by delivery or ride-hailing or exclusively digital task-based work

However, cross-country differences are evident. At the upper end, countries such as Italy and the United Kingdom stand out with particularly high intermediation platform work (around 25.8% and 23.9%, respectively), alongside sizeable skill-intensive components (about 7.6% in Italy and 12.2% in the UK). Portugal has around 22.7% intermediation platform work and Croatia around 20.4% form a second tier of high intermediation, while Türkiye combines very high levels across all three segments (around 20.0% intermediation; 18.1% skill-intensive; 11.7% routine), making it the clearest example of a broad and intensive platform ecosystem in the figure.

These patterns suggest that in high-scoring countries, platform work is not confined to a single "gig" type. It often spans marketplaces for goods/services and, in some cases, is paired with a stronger digital-labour component (freelance/creative or microwork/crowdwork). The routine type of platform work is consistently the smallest, but it also shows meaningful clustering. The highest routine shares are concentrated in Türkiye (11.7%) and Bulgaria (9.5%), followed by Romania (7.0%) and a group of countries around the 5-6% range (e.g., Luxembourg, Serbia, Ireland, Slovakia, Slovenia). By contrast, routine platform work is very low in countries such as Malta (below 1%) and remains comparatively low in parts of Northern and Western Europe, such as Finland, France, Denmark where it is around 2.5%. This suggests that ride-hailing/delivery is an important platform channel in specific national contexts, but it is not the main driver of overall platform work prevalence in the TRAILS-I data.

Finally, the skill-intensive type of platform work, while always below intermediation, varies substantially, from low levels in countries such as Denmark, Estonia, Cyprus, Czechia (roughly 3-4%) to much higher levels in Türkiye (18.1%), the UK (12.2%), and Bulgaria (11.4%), while Greece, Spain, Romania, Ireland, and Portugal also relatively elevated (about 8.5-9.9%). This suggests that cross-country differences in "platform work" are driven primarily by variation in the prevalence of intermediation-type activities, while cross-national differences in the routine and skill-intensive segments add an important second dimension. Taken together, this indicates that the concrete form platform work takes can differ markedly across countries, even when captured using the same survey instrument, ranging from platform economies centred on marketplaces and household services to contexts where delivery/transport or digital skill-based work plays a more prominent role.

Figure 5-11: Types of platform work by country



5.2 Demographic decomposition of platform work

Figure 5-12 presents the share of individuals reporting platform work experience in the last 12 months, disaggregated by age group and by country. At the aggregate ("All Countries") level, participation is clearly graded downward by age. The highest rates are observed among younger individuals, particularly those aged 18-24 and 25-34 while participation declines steadily across older age groups. Individuals aged 45-54 show markedly lower engagement, and rates are lowest among those aged 55 and above. This pattern highlights the strong association between platform work and younger cohorts, likely reflecting greater digital familiarity, labour market entry dynamics, and the appeal of flexible or transitional employment forms.

Cross-country variation is nevertheless substantial. In countries such as Türkiye, Italy, Portugal, Spain, Greece, and the United Kingdom, platform work experience is particularly high among younger age groups, often exceeding levels observed elsewhere. In contrast, countries such as Malta, Estonia, and Denmark display comparatively lower participation across all age categories. In several Central and Eastern European countries, including Poland, Romania, Bulgaria, and Croatia, participation in platform work remains strong among both younger and older age groups, although it continues to decline gradually at older ages. Overall, while age seems to be related to platform work participation, national labour market structures and digital ecosystem maturity shape the intensity of engagement across countries.

Figure 5-13 presents the share of individuals reporting experience in multiple platform work types, disaggregated by age group and by country. At the aggregate ("All Countries") level, multi-platform engagement is again concentrated among younger cohorts. Individuals aged 18-24 and 25-34 exhibit the highest shares, while participation in multiple platform work types declines progressively among those aged 35-44 and 45-54, and is lowest among older age groups. This pattern suggests that diversification across platform work types is closely associated with younger individuals, who may be more digitally adept, more flexible in their labour market strategies, or more inclined to experiment with multiple income-generating channels.

Cross-country variation is also marked. In countries such as Türkiye, Romania, Italy, Spain, and Bulgaria, younger age groups display particularly high levels of multi-platform participation, often substantially exceeding those observed in Northern European countries. In contrast, countries such as Malta, Czechia, Finland, and Denmark show lower overall shares and a more compressed age gradient. In several Western European countries, including Germany, the Netherlands, Belgium, and Austria, participation remains higher among younger and prime-age groups but declines steadily with age. Overall, the figure highlights age as a strong and consistent correlate of multi-platform engagement, while national labour market structures and digital ecosystem development shape the intensity of participation across countries.

Figure 5-12: Platform work experience in the last 12 months by age group and by country

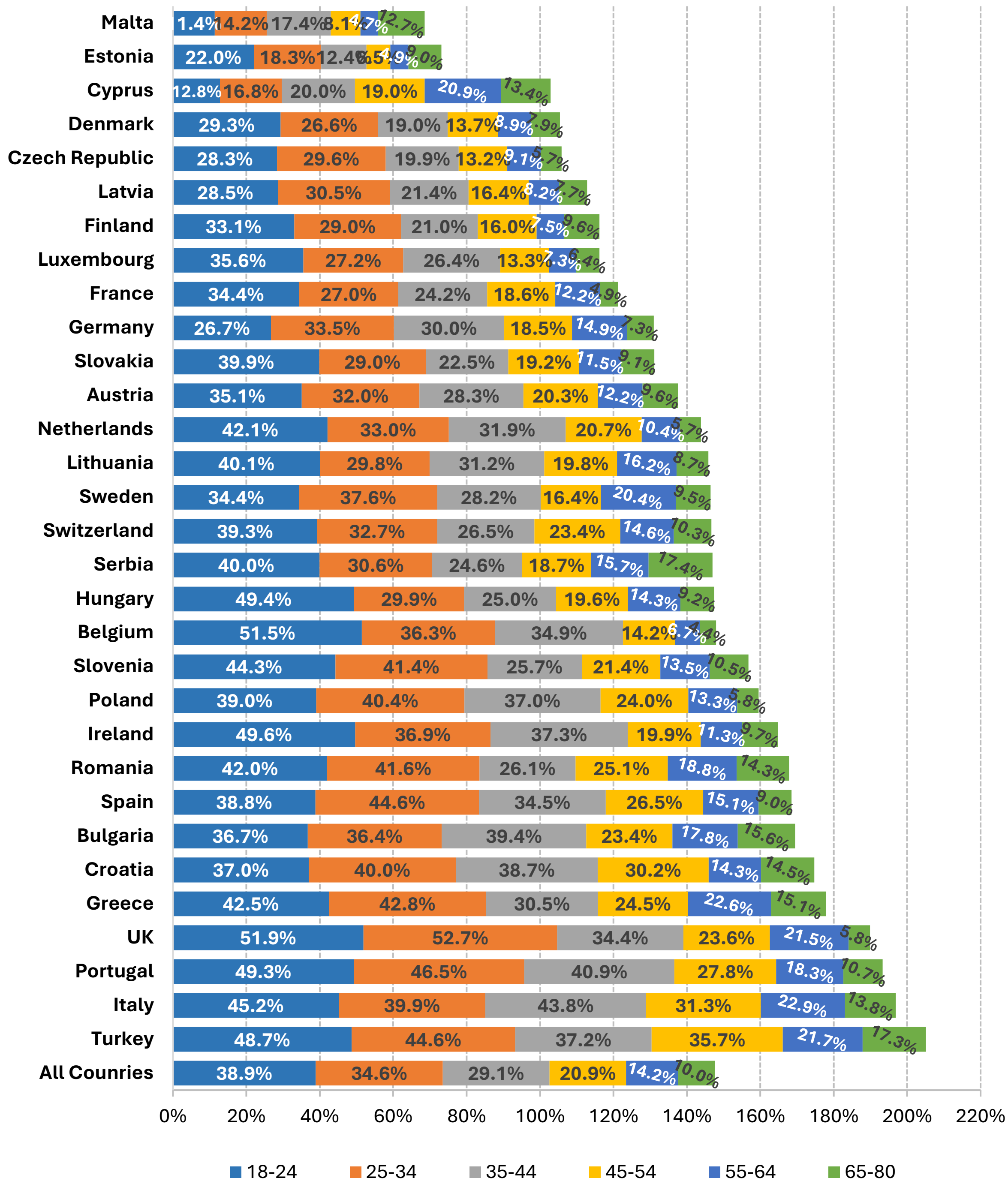


Figure 5-13: Experience in multiple platform work types by age group and by country

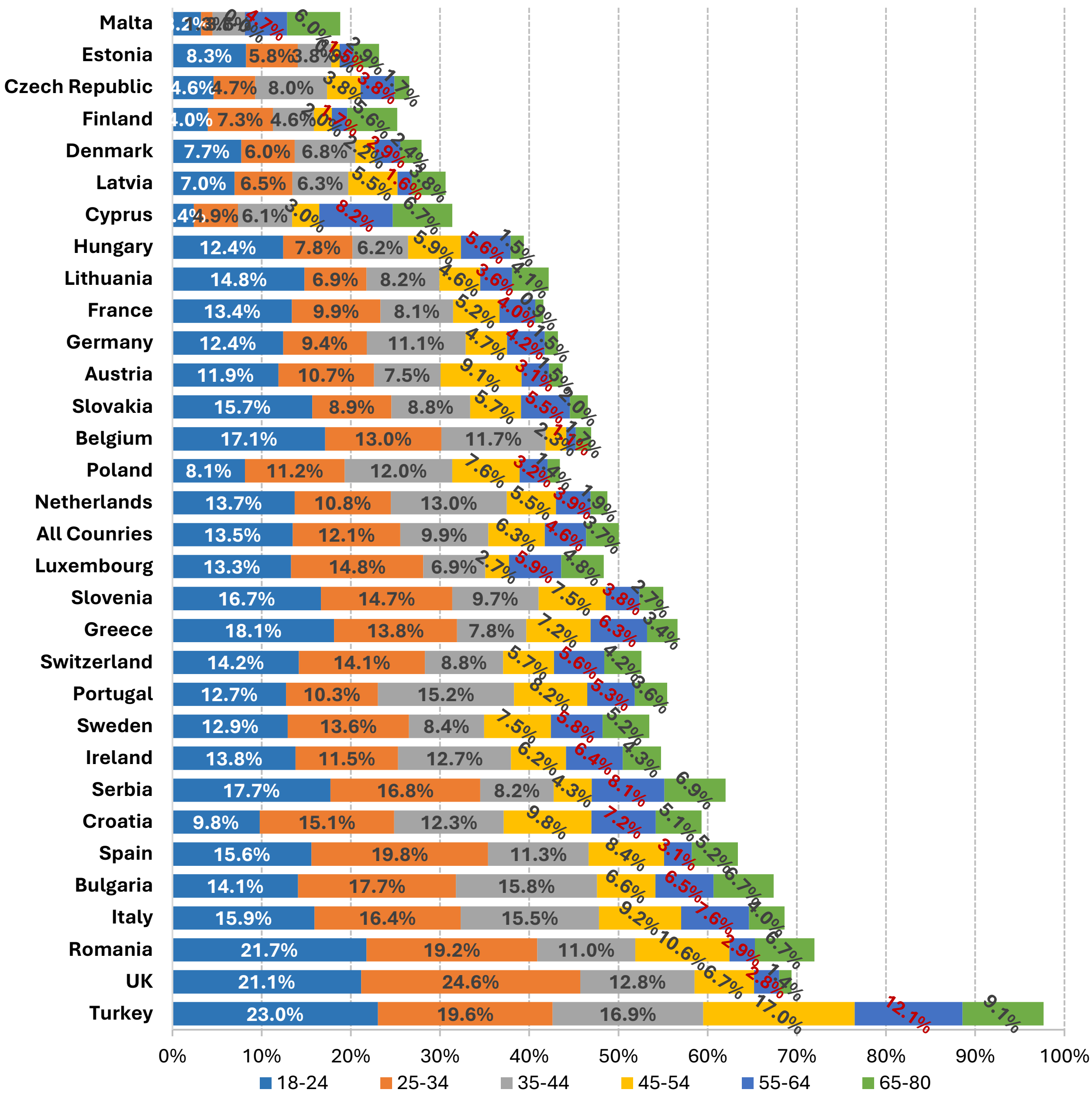


Figure 5-14 presents the share of individuals for whom platform work constitutes the main source of income, disaggregated by age group and by country. At the aggregate ("All Countries") level, reliance on platform work as a primary income source is relatively limited across all age categories, especially in older age groups. Young ages (18-24 and 25-34) show slightly higher shares compared to older cohorts, but the differences are less pronounced than for overall platform participation. Engagement declines gradually among individuals aged 45-54 and is lowest among the oldest group. This pattern suggests that while younger individuals are more active in platform work generally, dependence on it as a main income source is not overwhelmingly concentrated in any age group.

Cross-country variation, however, is considerable. In countries such as Türkiye, Spain, Romania, Portugal, and Italy, reliance on platform work as a primary occupation is comparatively higher, particularly among younger and early prime-age groups. In contrast, countries such as Denmark, Estonia, Finland, and Cyprus exhibit very low shares across all age groups, indicating that platform work plays only a marginal role as a main source of income. In several Western and Central European countries, including Germany, the Netherlands, and Belgium, differences between age groups are moderate, with somewhat higher shares among those aged 25-34. Overall, while age influences primary reliance on platform work to some extent, cross-country institutional and labour market factors appear more decisive in explaining variation.

Figure 5-14: Platform work as the main source of income by age group and by country

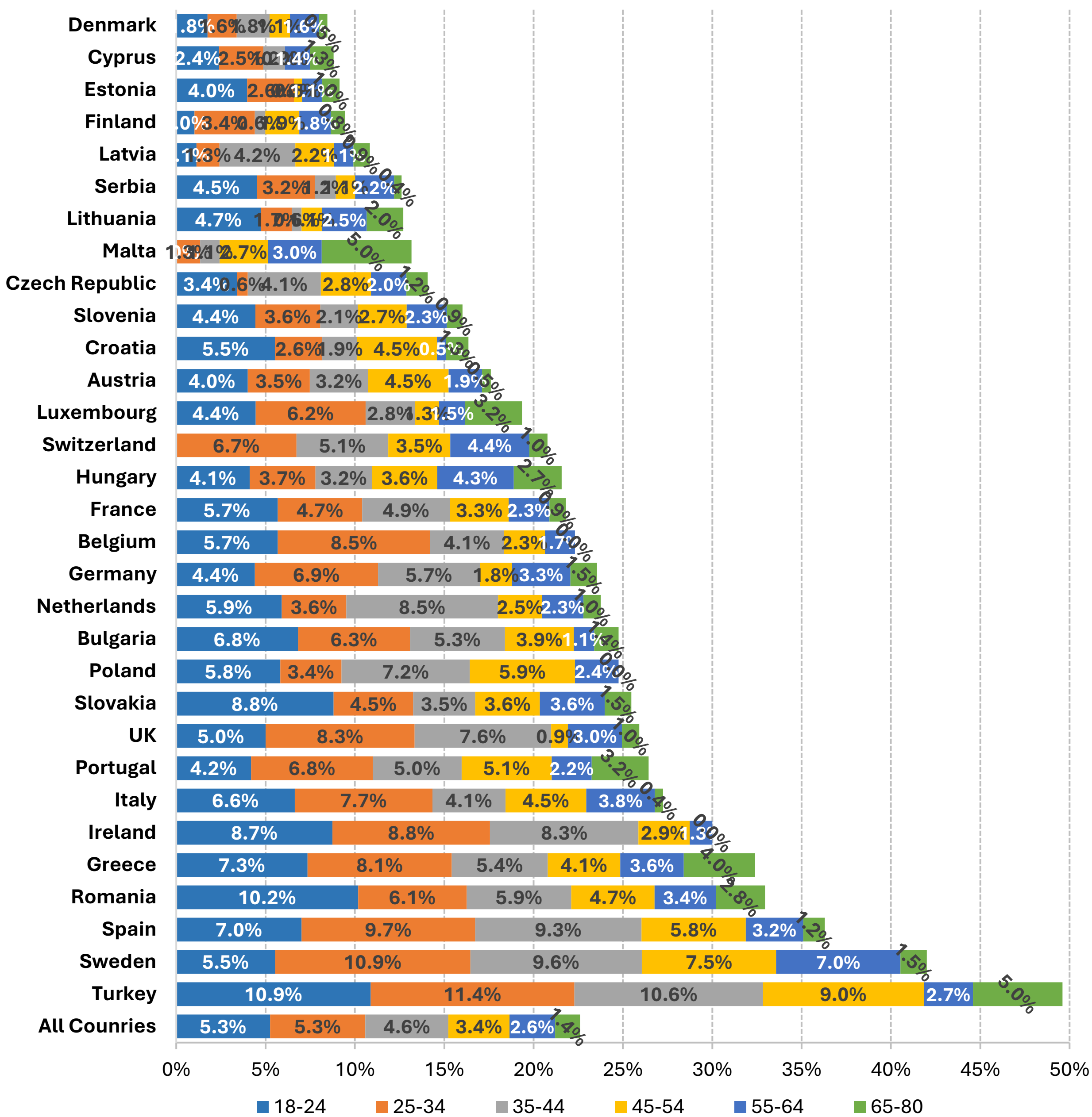


Figure 5-15 presents the share of individuals engaging in platform work as a supplementary source of income, disaggregated by age group and by country. At the aggregate (“All Countries”) level, supplementary platform work is clearly more prevalent among younger age groups. Individuals aged 18-24 and 25-34 report the highest participation rates, while engagement declines steadily among those aged 35-44 and 45-54, and is lowest among older cohorts. This age gradient suggests that younger individuals are more likely to use platform work to complement their primary earnings, possibly due to greater digital fluency, transitional labour market positions, or a stronger preference for flexible income arrangements.

Cross-country differences are also pronounced. In countries such as Türkiye, Bulgaria, the United Kingdom, Romania, and Portugal, supplementary platform work reaches comparatively high levels among younger and prime-age groups. In contrast, countries such as Luxembourg, Malta, and Denmark exhibit lower participation across all age categories. In several Southern and Eastern European countries, including Greece, Poland, and Croatia, engagement is particularly strong among younger cohorts but remains visible among middle-aged groups as well. Overall, the figure highlights age as a consistent determinant of supplementary platform engagement, while national labour market structures and digital ecosystem development shape the intensity of participation across countries.

Figure 5-16 presents the share of individuals engaging in platform work as an occasional activity, disaggregated by age group and by country. At the aggregate (“All Countries”) level, occasional platform work is clearly concentrated among younger cohorts. Individuals aged 18-24 report the highest participation rates, followed closely by those aged 25-34, while engagement declines progressively among older age groups. Participation among individuals aged 45-54 and especially 55+ is substantially lower. This consistent age gradient indicates that occasional platform work is particularly aligned with younger individuals, likely reflecting its flexibility, compatibility with studies or early career stages, and greater digital familiarity.

Cross-country variation, however, remains pronounced. In countries such as Türkiye, Bulgaria, Poland, the United Kingdom, and Romania, occasional platform work is especially high among younger and prime-age groups. In contrast, countries such as Luxembourg, Malta, and Estonia show lower participation rates across all age categories. In Southern European countries, including Italy, Spain, Greece, and Portugal, engagement is comparatively strong among younger and middle-aged cohorts but drops among older groups. Overall, the figure underscores age as a robust and consistent determinant of occasional platform participation, while national labour market structures and digital ecosystem development shape the overall intensity of engagement across countries.

Figure 5-15: Platform work as a supplementary source of income by age group and by country

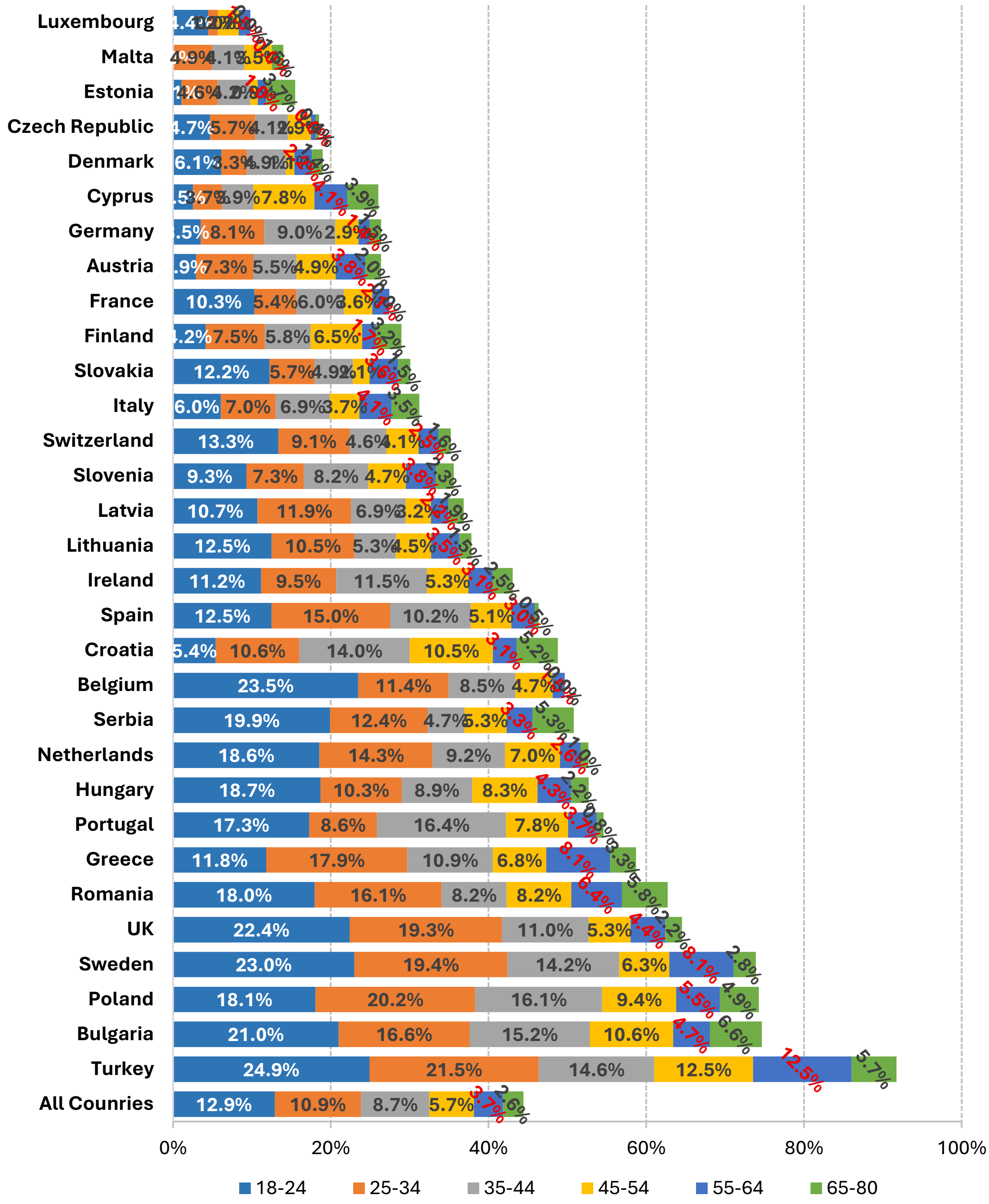


Figure 5-16: Platform work as an occasional activity by age group and by country

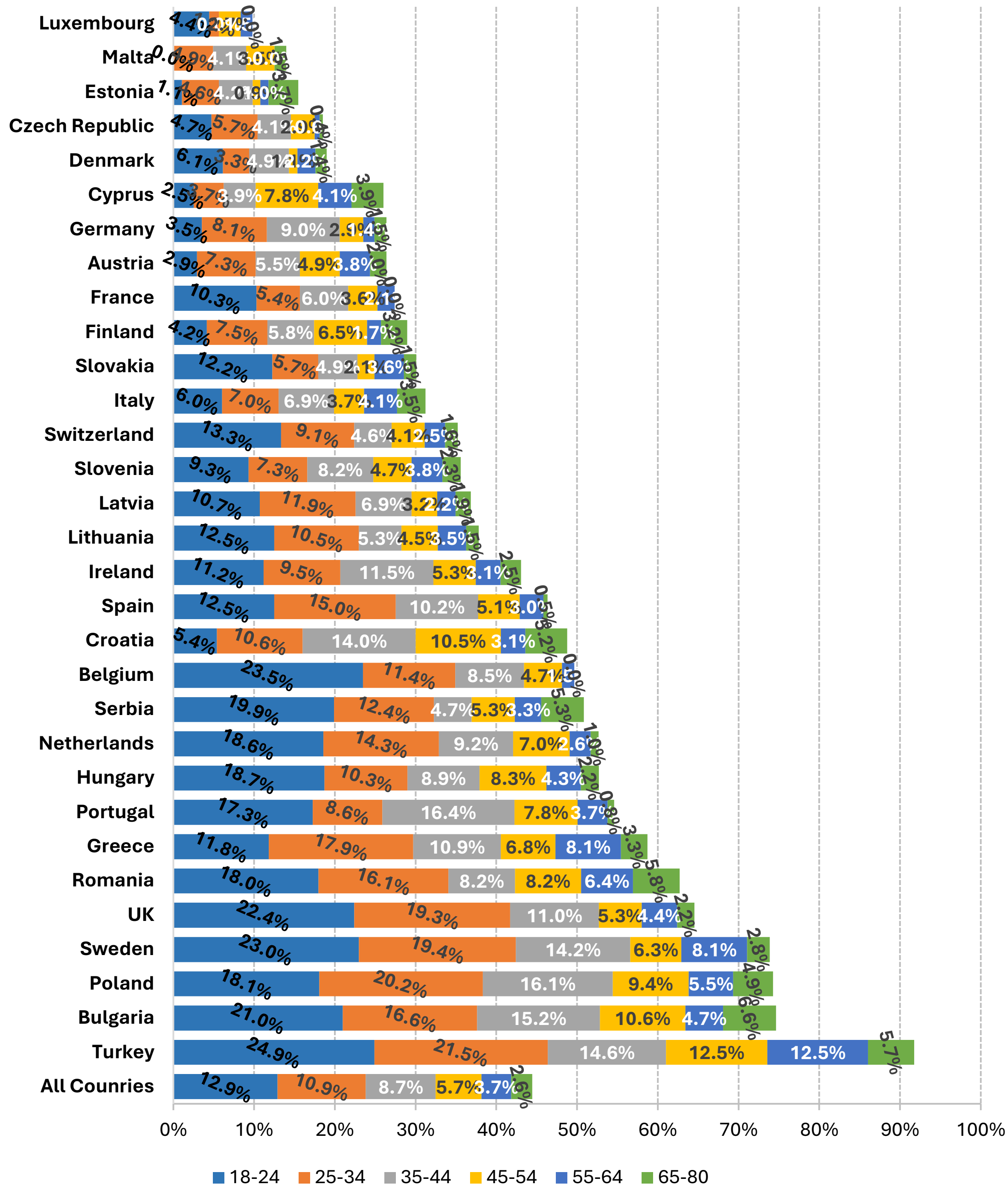


Figure 5-17 presents the share of individuals reporting platform work experience in the last 12 months, disaggregated by gender and by country. At the aggregate ("All Countries") level, women report slightly higher participation rates than men, indicating that recent engagement in platform work is not male-dominated and may even be somewhat more prevalent among women overall. The gender gap, however, is generally moderate rather than extreme, suggesting broad participation across both groups. This pattern highlights the inclusive nature of platform work in terms of recent engagement, potentially reflecting its flexibility and compatibility with diverse employment arrangements.

Cross-country variation is nevertheless substantial. In countries such as Türkiye, the United Kingdom, Italy, Portugal, Greece, and Romania, participation rates are relatively high for both genders, with women often displaying equal or higher engagement compared to men. In contrast, countries such as Estonia, Malta, Czechia, and Denmark exhibit lower overall shares for both genders. In several Northern and Western European countries, including Germany, the Netherlands, Belgium, and Sweden, gender differences are relatively small, pointing to more balanced participation patterns. Overall, while gender shapes participation to some extent, national labour market conditions and digital ecosystem development appear to play a more decisive role in explaining cross-country differences in recent platform work experience.

Figure 5-18 presents the share of individuals reporting experience in multiple platform types, disaggregated by gender and by country. At the aggregate ("All Countries") level, men display slightly higher rates of multi-platform engagement than women, suggesting that diversification across platform types is somewhat more common among male participants. However, the overall gender gap is moderate, indicating that both men and women participate in multiple platform activities to a meaningful extent. This pattern may reflect differences in occupational segmentation within platform work, with men potentially more concentrated in activities that facilitate cross-platform engagement.

Cross-country variation is nevertheless pronounced. In countries such as Türkiye, the United Kingdom, Romania, Bulgaria, and Italy, multi-platform participation is relatively high for both genders, though men often exhibit higher shares. In contrast, countries such as Malta, Estonia, Czechia, and Finland show comparatively low levels of engagement across both groups. In several Western and Northern European countries, including Germany, Austria, the Netherlands, and Belgium, gender differences are present but not large, pointing to relatively balanced patterns of diversification. Overall, while gender influences the likelihood of engaging in multiple platform types, national labour market structures and the organization of platform sectors appear to be more decisive in shaping cross-country differences.

Figure 5-17: Platform work experience in the last 12 months by gender and by country

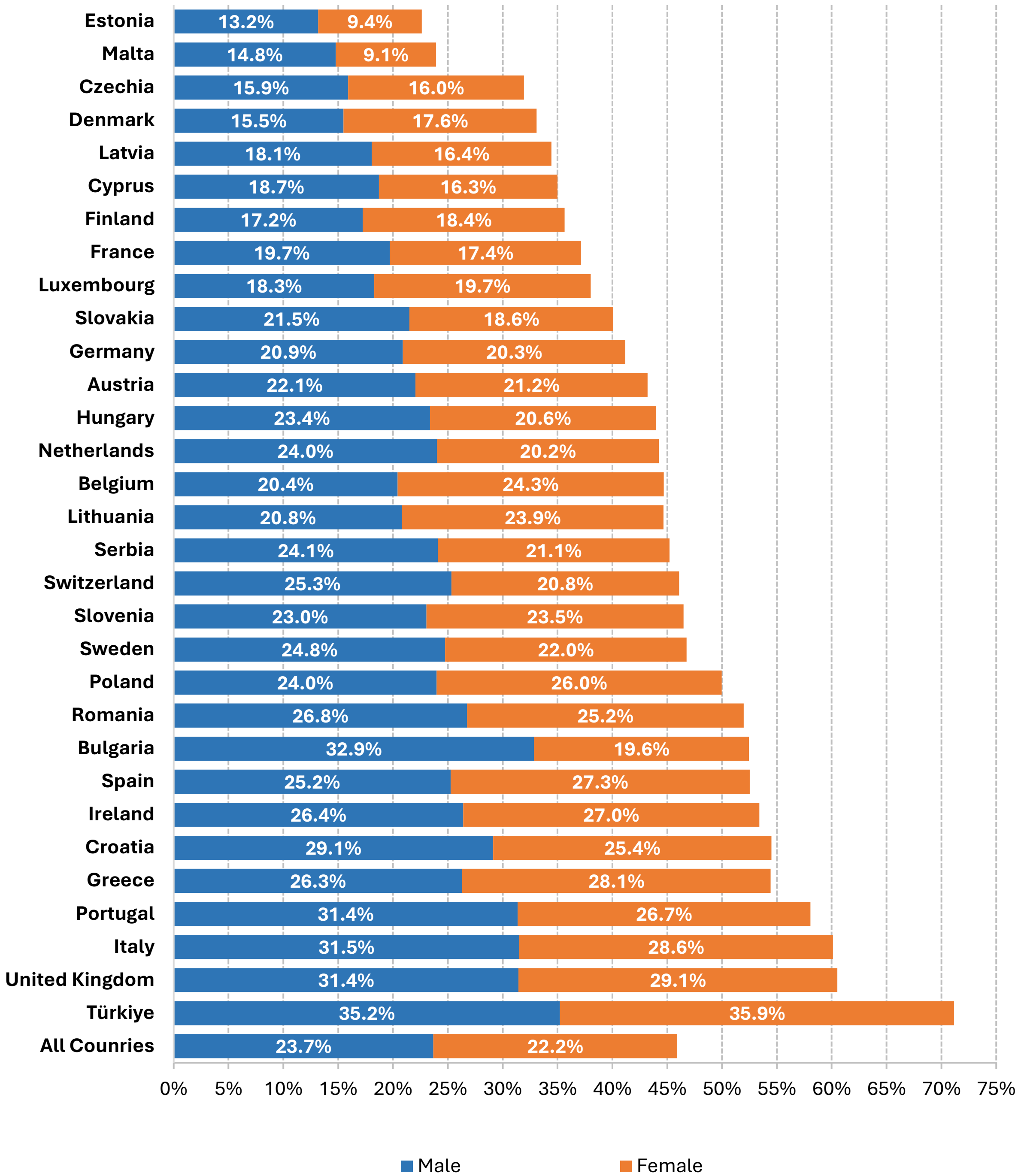


Figure 5-18: Experience in multiple platform types by gender and by country

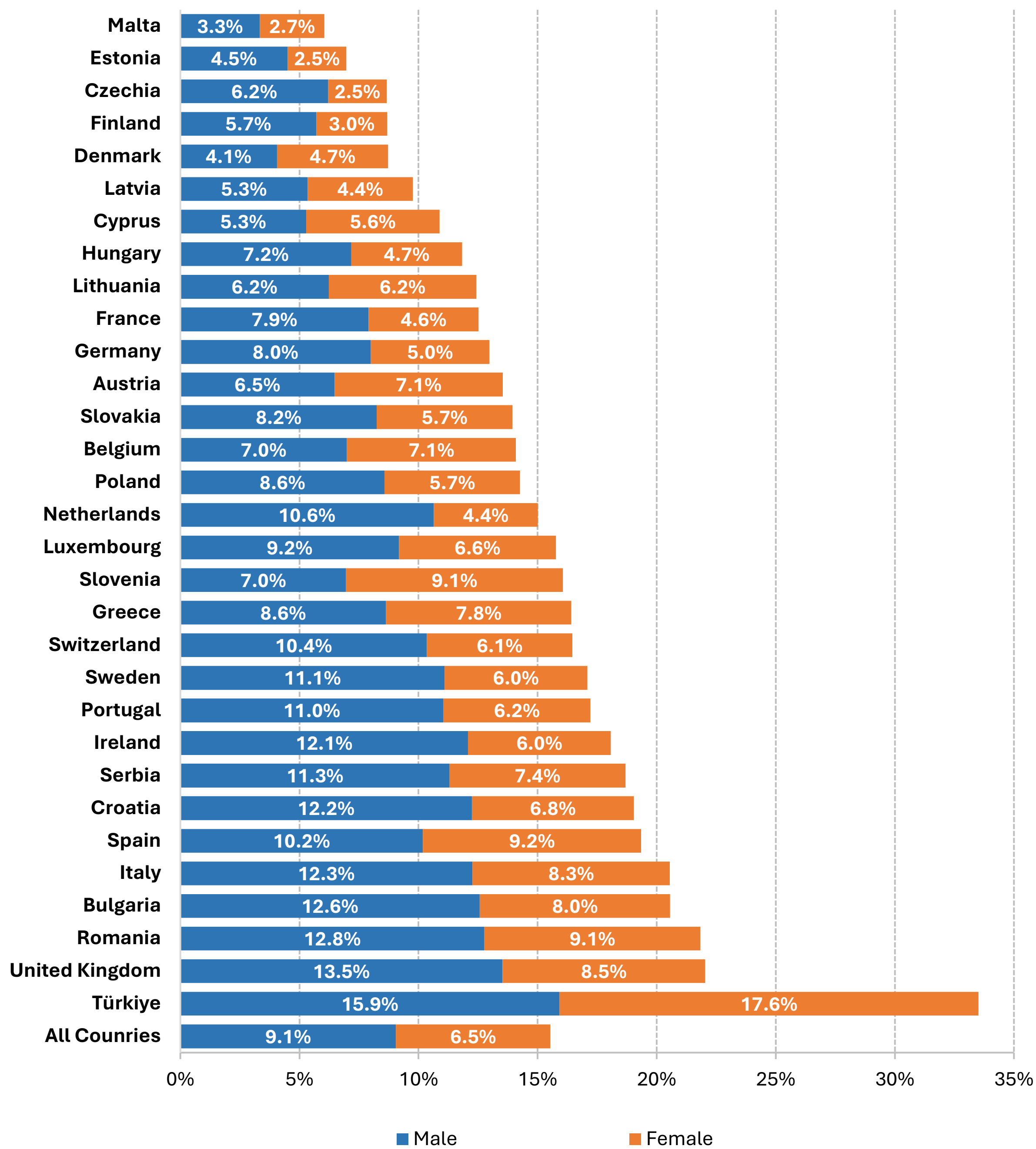


Figure 5-19 presents the share of individuals for whom platform work constitutes the main source of income, disaggregated by gender and by country. At the aggregate ("All Countries") level, reliance on platform work as a primary income source is relatively limited for both genders. Men display slightly higher shares than women overall, indicating a modest gender gap in dependence on platform work as a main occupation. However, the differences are not large, suggesting that primary reliance on platform income remains a minority phenomenon across both groups.

Cross-country variation is nevertheless substantial. In countries such as Türkiye, Spain, Romania, Portugal, and the United Kingdom, the share of individuals depending primarily on platform work is comparatively higher, with notable gender gaps in some cases. In Türkiye and Spain, for instance, female participation as a main source of income stands out as particularly elevated relative to many other countries. In contrast, Northern and Western European countries, including Estonia, Denmark, Finland, and Cyprus, exhibit very low shares for both men and women, indicating that platform work plays only a marginal role as a principal occupation. Overall, while gender differences exist, national labour market structures and institutional contexts appear to be more decisive in shaping cross-country patterns of reliance on platform work as a main source of income.

Figure 5-19: Platform work as the main source of income by gender and by country

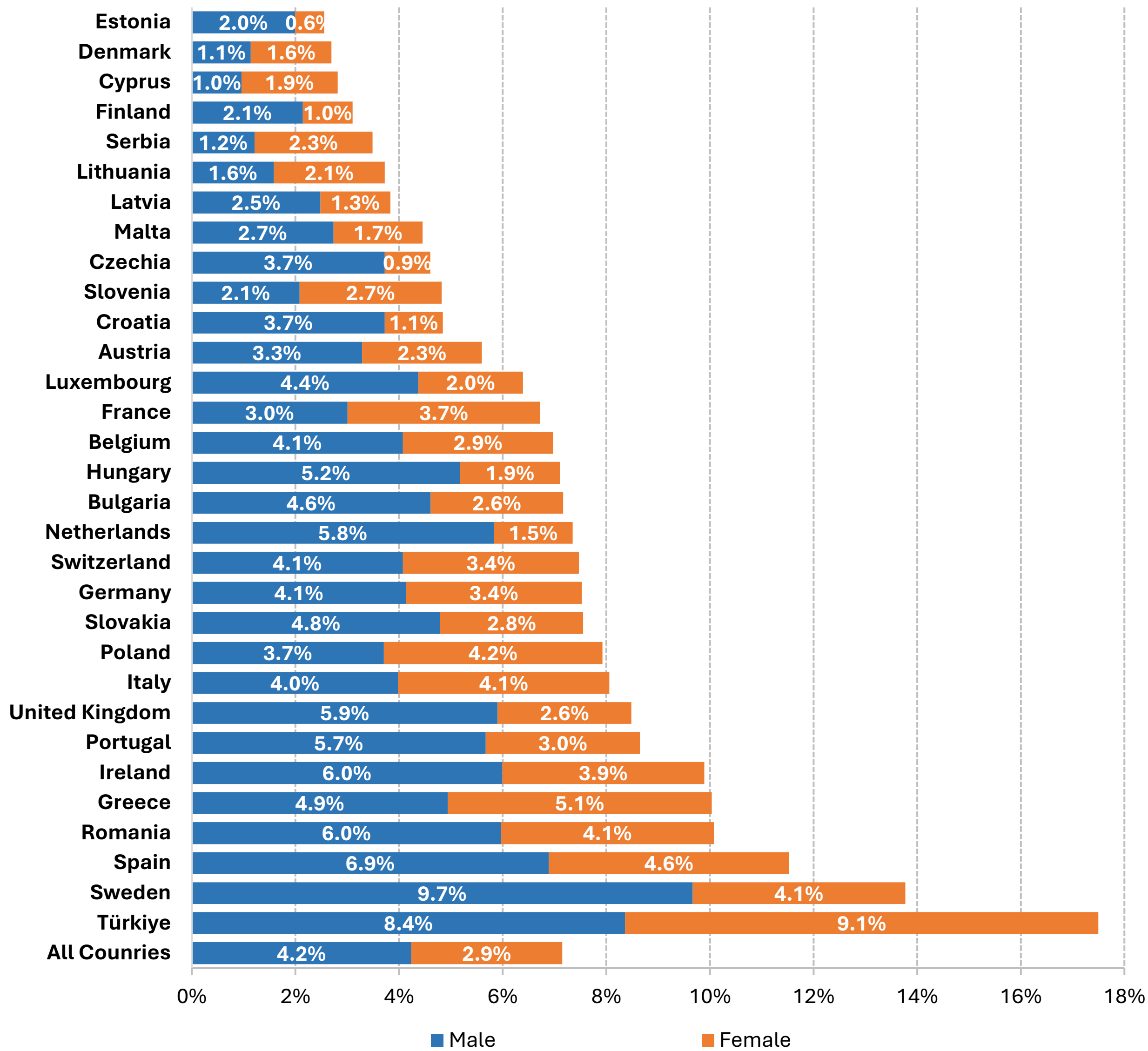


Figure 5-20 presents the share of individuals engaging in platform work as a supplementary source of income, disaggregated by gender and by country. At the aggregate ("All Countries") level, men report slightly higher participation than women, indicating a modest gender gap in using platform work to complement primary earnings. Nevertheless, the difference remains limited, suggesting that supplementary platform engagement is relatively widespread among both genders. Compared to platform work as a main source of income, supplementary participation appears more common overall, reinforcing the view that platforms are frequently used as an additional rather than primary income stream.

Cross-country variation is again pronounced. In countries such as Türkiye, Poland, Sweden, Bulgaria, and the United Kingdom, supplementary platform work reaches comparatively high levels for both genders, with men often showing somewhat higher shares. In contrast, countries such as Luxembourg, Malta, Estonia, and Czechia display lower and more compressed participation rates. In Southern and Eastern European countries, including Romania, Greece, Portugal, and Croatia, shares are moderate to high, with gender gaps varying across contexts. Overall, while men tend to engage slightly more in supplementary platform work, national labour market structures and institutional environments appear more influential than gender alone in explaining cross-country differences.

Figure 5-21 presents the share of individuals engaging in platform work as an occasional activity, disaggregated by gender and by country. At the aggregate ("All Countries") level, women report higher participation rates than men, indicating a noticeable gender gap in occasional platform engagement. This suggests that platform work as a flexible, non-regular activity may be particularly attractive or accessible to women, potentially reflecting its compatibility with other employment arrangements or care responsibilities. Compared to platform work as a main source of income, occasional participation is more widespread and exhibits clearer gender differentiation. Cross-country variation is substantial.

In countries such as Italy, Croatia, the United Kingdom, Slovenia, and Ireland, occasional platform work reaches comparatively high levels for both genders, with women often showing significantly higher shares than men. In contrast, countries such as Sweden, Estonia, Malta, and Poland display lower participation rates and smaller gender gaps. In several Southern and Eastern European countries, including Greece, Romania, Türkiye, and Spain, participation is moderate to high, again frequently with women exhibiting stronger engagement. Overall, while gender plays a more visible role in occasional platform work than in other forms of engagement, national labour market conditions and institutional contexts remain central in shaping cross-country patterns.

Figure 5-20: Platform work as a supplementary source of income by gender and by country

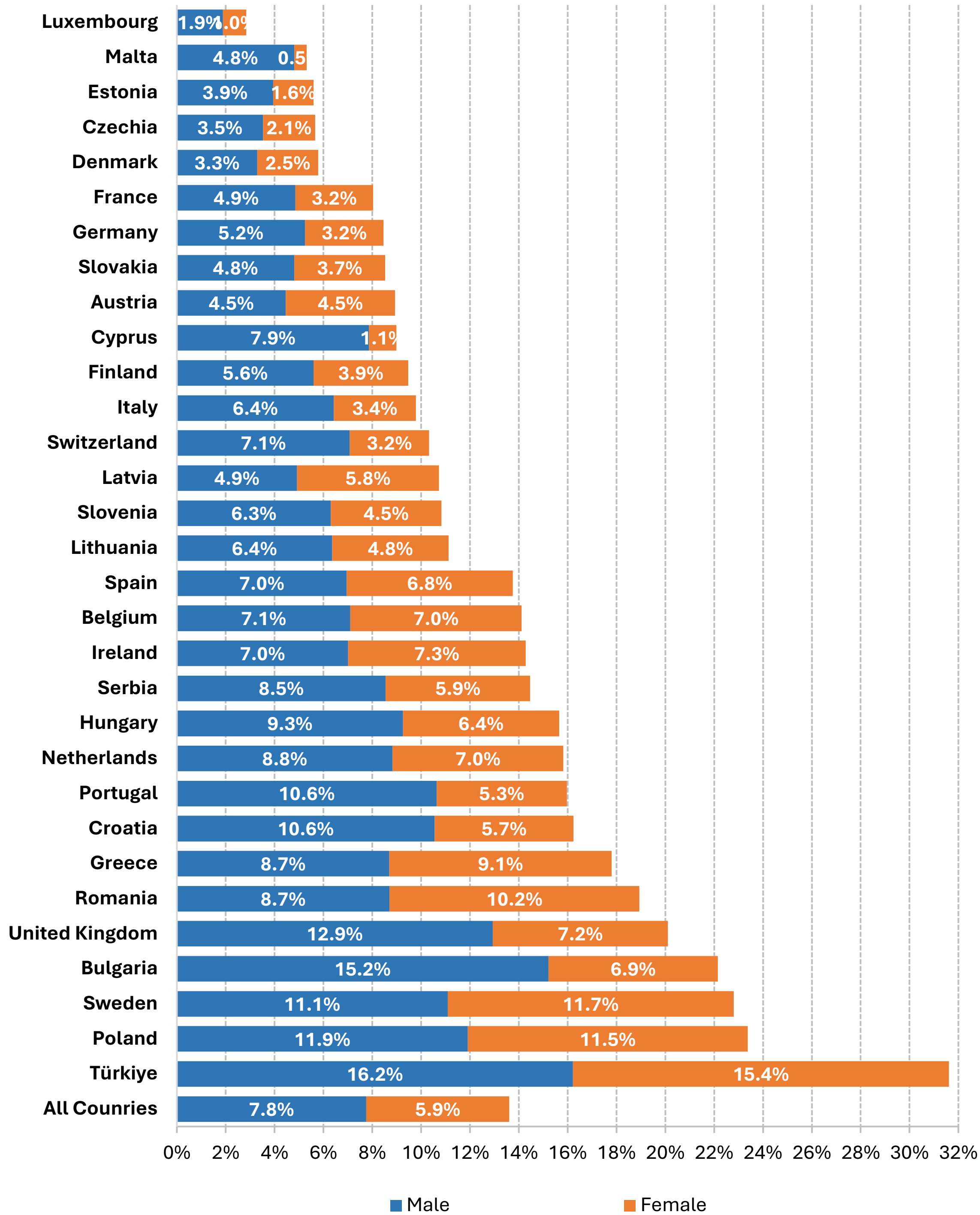


Figure 5-21: Platform work as an occasional activity by gender and by country

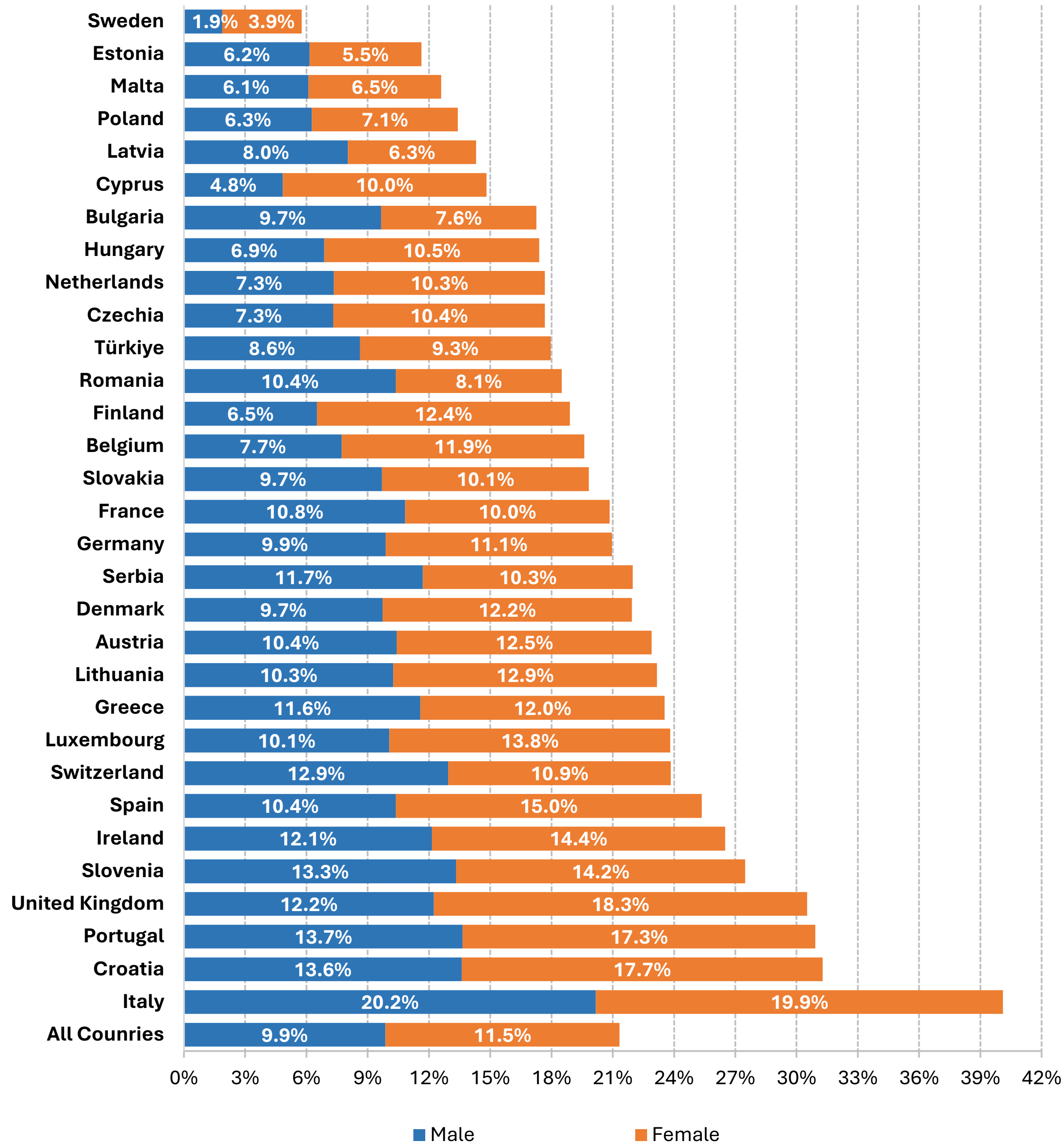


Figure 5-22 presents the share of individuals reporting platform work experience in the last 12 months, disaggregated by educational attainment (low, medium, high) and by country. At the aggregate ("All Countries") level, recent platform engagement is fairly evenly distributed across education groups, though individuals with medium and high education levels display slightly higher participation rates than those with low education. This pattern suggests that platform work is not confined to lower-skilled segments of the labour market; rather, it attracts individuals across the educational spectrum, with a modest tilt toward those with at least medium qualifications.

Cross-country differences are nonetheless substantial. In countries such as Türkiye, Croatia, Hungary, Romania, and Portugal, participation rates are relatively high across all education groups, with particularly strong engagement among medium-educated individuals. In contrast, countries such as Malta, France, Denmark, and Estonia show lower overall shares, especially among the low-educated group. In several Western and Northern European countries, including Germany, the Netherlands, Switzerland, and the United Kingdom, higher-educated individuals often exhibit comparatively strong participation, indicating that platform work may complement professional or skilled activities. Overall, the figure highlights that while education level shapes recent platform engagement to some degree, national labour market structures and institutional contexts remain central in explaining cross-country variation.

Figure 5-23 presents the share of individuals reporting experience in multiple platform types, disaggregated by educational attainment (low, medium, high) and by country. At the aggregate ("All Countries") level, engagement across multiple platform types is relatively balanced across education groups, with only modest differences between low-, medium-, and high-educated individuals. While medium-educated individuals display slightly higher participation than the low-educated group, the overall variation is limited. This suggests that diversification across platform types is not strongly stratified by education and is accessible across skill levels.

Cross-country differences, however, are pronounced. In countries such as Türkiye, Croatia, Romania, and Slovakia, participation in multiple platform types is substantially higher across all education groups, with particularly strong engagement among low- and medium-educated individuals in some cases. In contrast, Northern and smaller economies, including Estonia, Cyprus, Finland, and Malta, show comparatively low and more compressed levels across education categories. In Western European countries such as Germany, the Netherlands, Belgium, and Austria, differences between education groups are moderate, often with slightly higher shares among medium- or high-educated individuals. Overall, the figure indicates that while education plays some role in shaping the breadth of platform engagement, national labour market conditions and digital ecosystem development appear to be more decisive in explaining cross-country variation.

Figure 5-22: Platform work experience in the last 12 months by education and by country

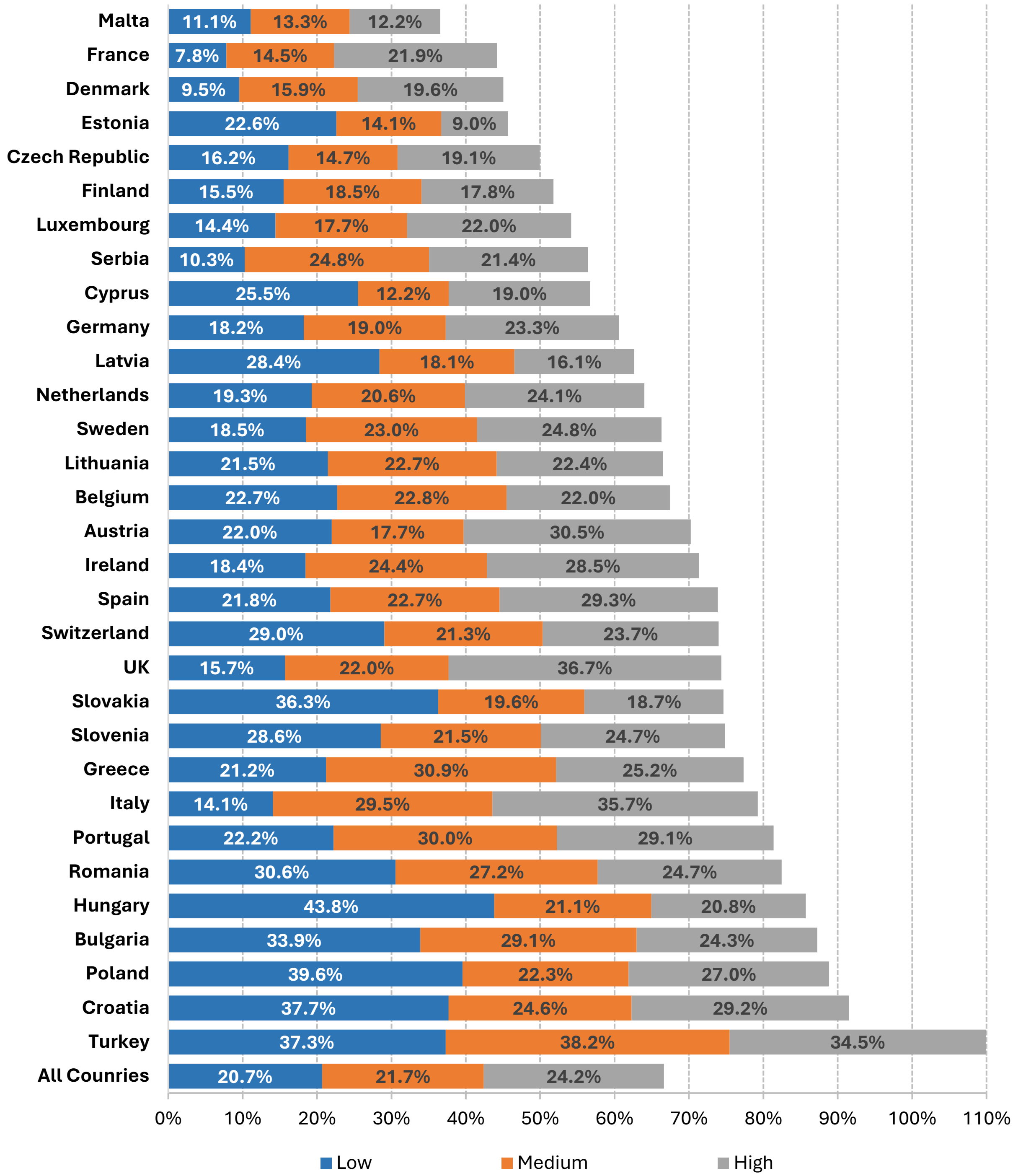


Figure 5-23: Experience in multiple platform types by education and by country

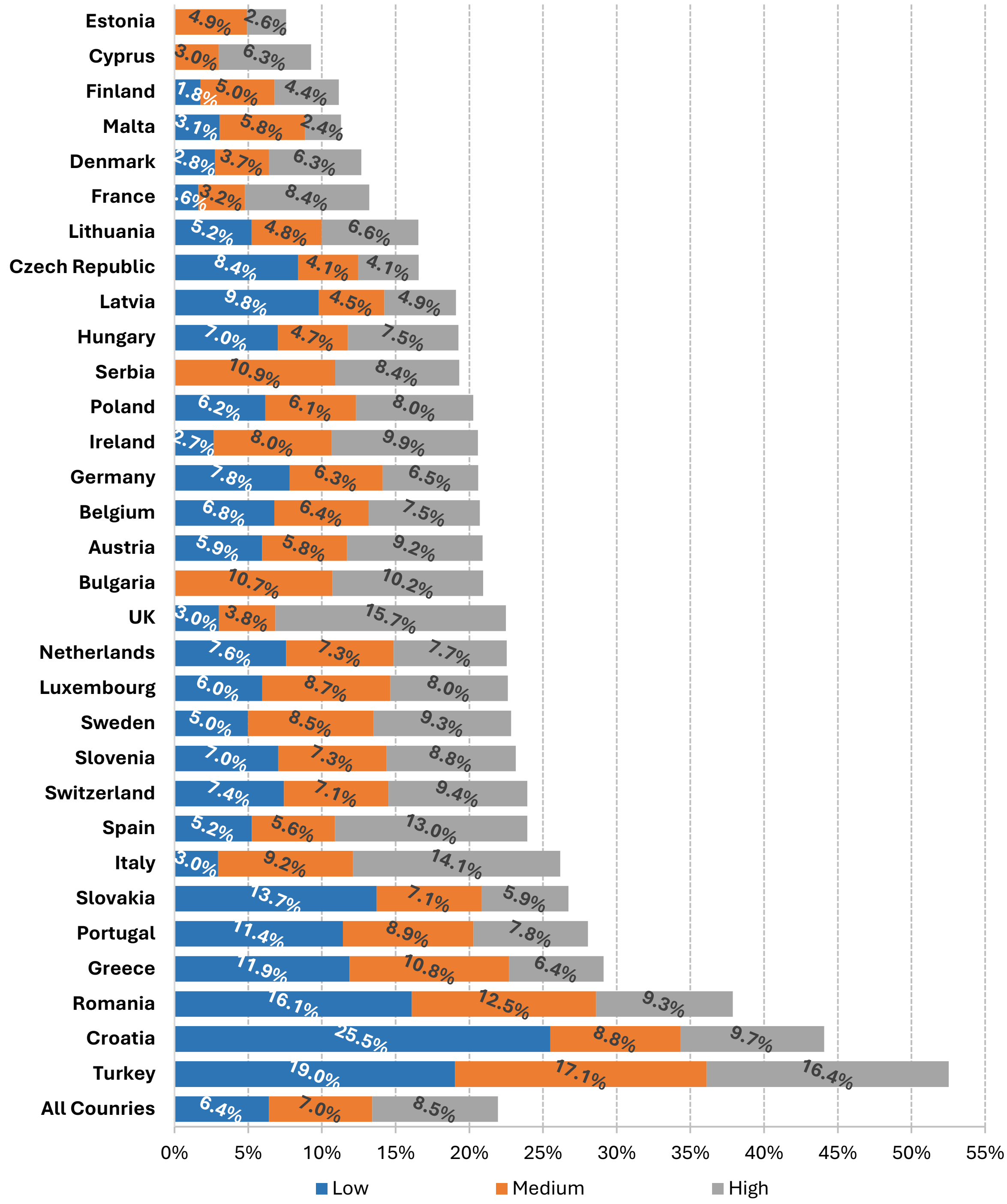


Figure 5-24 presents the share of individuals for whom platform work constitutes the main source of income, disaggregated by educational attainment (low, medium, high) and by country. At the aggregate ("All Countries") level, reliance on platform work as a primary income source remains relatively limited across all education groups. Individuals with low education display slightly higher shares compared to medium- and high-educated groups, but overall differences are modest. This pattern suggests that while platform work as a main occupation is somewhat more prevalent among lower-educated individuals, it is not overwhelmingly concentrated in this group and remains a minority form of employment overall.

Cross-country variation is nonetheless substantial. In countries such as Türkiye, Spain, Slovakia, Romania, and Croatia, platform work as a main income source reaches comparatively higher levels across education groups, with particularly notable shares among low- and medium-educated individuals. In contrast, Northern and Western European countries, including Denmark, Finland, Cyprus, and the Czech Republic, exhibit very low shares across all education categories, indicating that platform work plays only a marginal role as a primary occupation. In countries such as Germany, Belgium, and the Netherlands, differences between education groups are relatively small, reflecting a more even distribution. Overall, the figure highlights that although education level shapes the likelihood of depending primarily on platform work to some extent, national labour market structures and institutional contexts appear to be the more decisive drivers of cross-country differences.

Figure 5-25 presents the share of individuals engaging in platform work as a supplementary source of income, disaggregated by educational attainment (low, medium, high) and by country. At the aggregate ("All Countries") level, supplementary platform work is more prevalent among individuals with higher education, followed by those with medium education, while the lowest participation is observed among the low-educated group. This indicates a clearer educational gradient compared to platform work as a main income source. Supplementary engagement appears particularly attractive to higher-educated individuals, possibly reflecting greater access to digital skills, professional networks, or opportunities to monetize specialized competencies through platform-based activities.

Cross-country variation, however, remains substantial. In countries such as Poland, Türkiye, Sweden, and Cyprus, participation is notably high, especially among medium- and high-educated individuals. In several Southern and Eastern European countries, including Romania, Bulgaria, Croatia, and Greece, shares are also relatively elevated, though the distribution across education groups is more mixed. By contrast, Northern and smaller economies such as Luxembourg, Estonia, Denmark, and France display comparatively low levels across all education categories. Overall, the figure suggests that supplementary platform work is more strongly associated with higher educational attainment than primary platform work, while still being shaped decisively by national labour market structures and institutional contexts

Figure 5-24: Platform work as the main source of income by education and by country

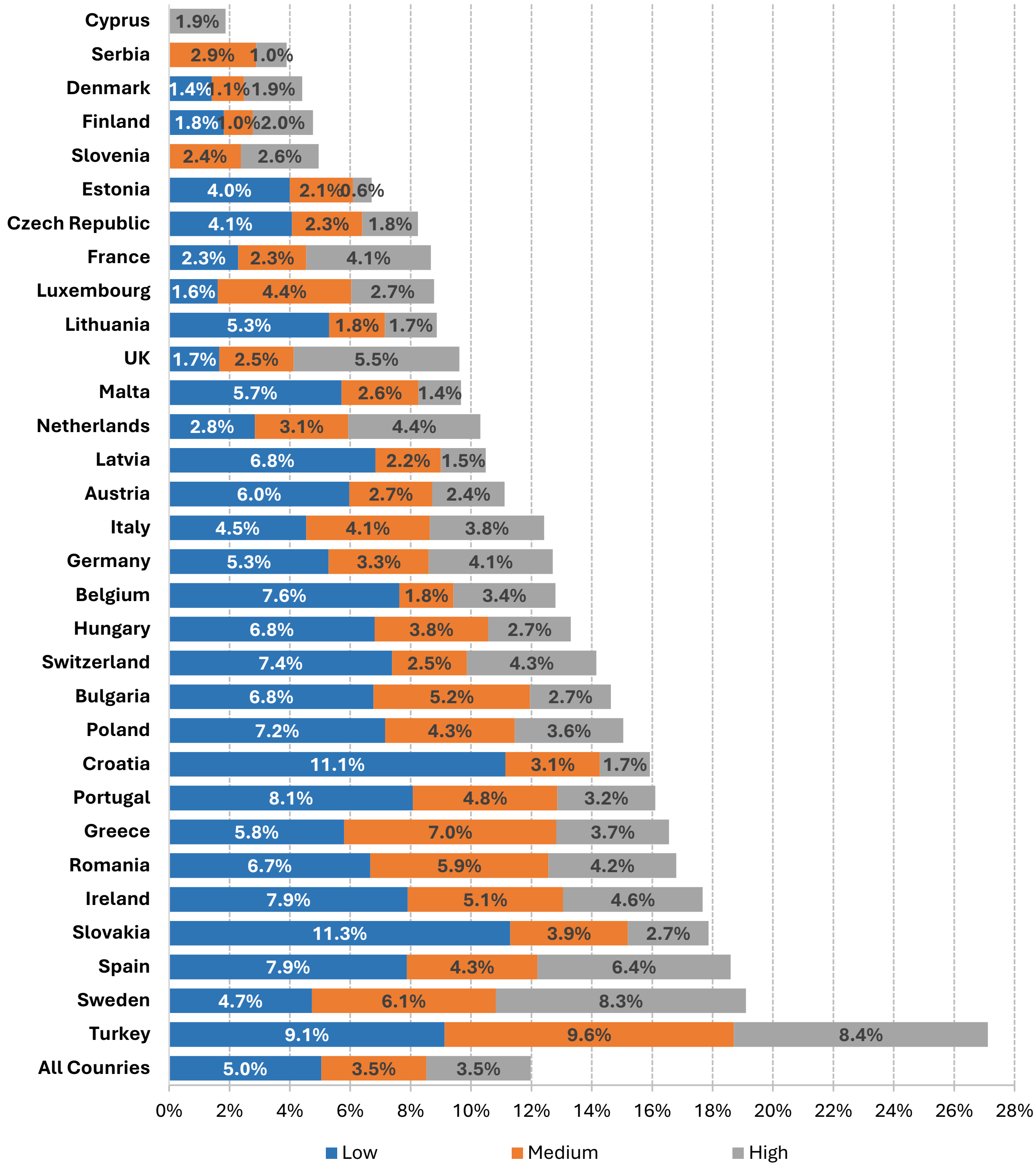


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Figure 5-25: Platform work as a supplementary source of income by education and by country

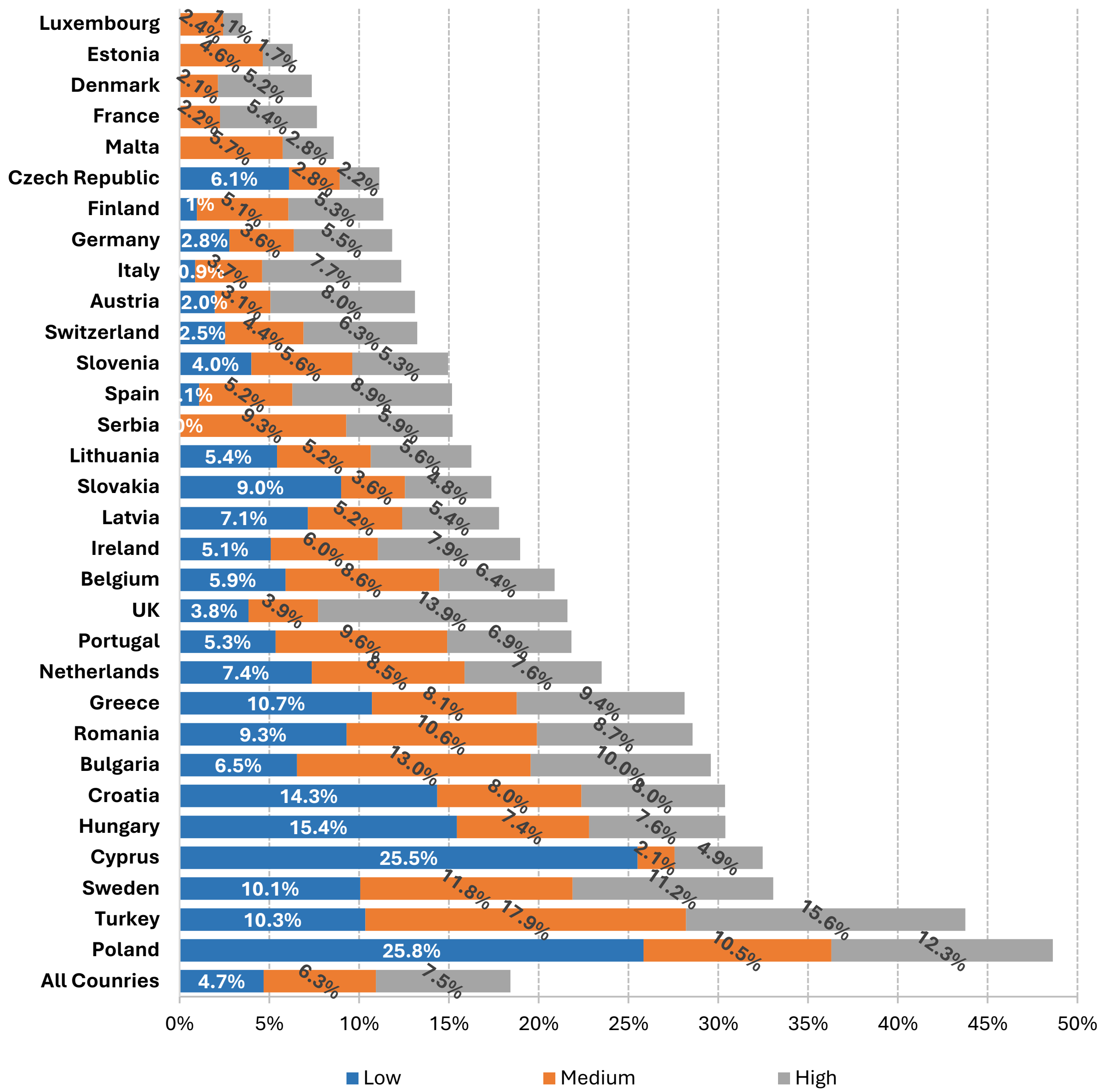


Figure 5-26 presents the share of individuals engaging in platform work as an occasional activity, disaggregated by educational attainment (low, medium, high) and by country. At the aggregate ("All Countries") level, occasional platform work is most prevalent among individuals with higher education, followed by those with medium education, while participation among the low-educated group is comparatively lower. This indicates a clear educational gradient, with occasional engagement appearing particularly compatible with higher skill levels, possibly reflecting greater flexibility, digital competencies, or the use of platforms for project-based or complementary professional activities.

Cross-country differences are also marked. In countries such as Italy, Croatia, the United Kingdom, Slovenia, and Portugal, shares are relatively high across all education groups, with especially large shares among medium- and high-educated individuals. In contrast, countries such as Sweden, Cyprus, Poland, and Malta display lower and more compressed levels across education categories. In several Central and Eastern European countries, such as Slovakia, Romania, Lithuania, and Bulgaria, shares are more evenly spread but still tends to peak among medium- or high-educated groups. Overall, the figure suggests that occasional platform work is more strongly associated with higher educational attainment than primary reliance on platform income, while national labour market structures and institutional contexts remain key in explaining cross-country variation.

Figure 5-26: Platform work as an occasional activity by education and by country

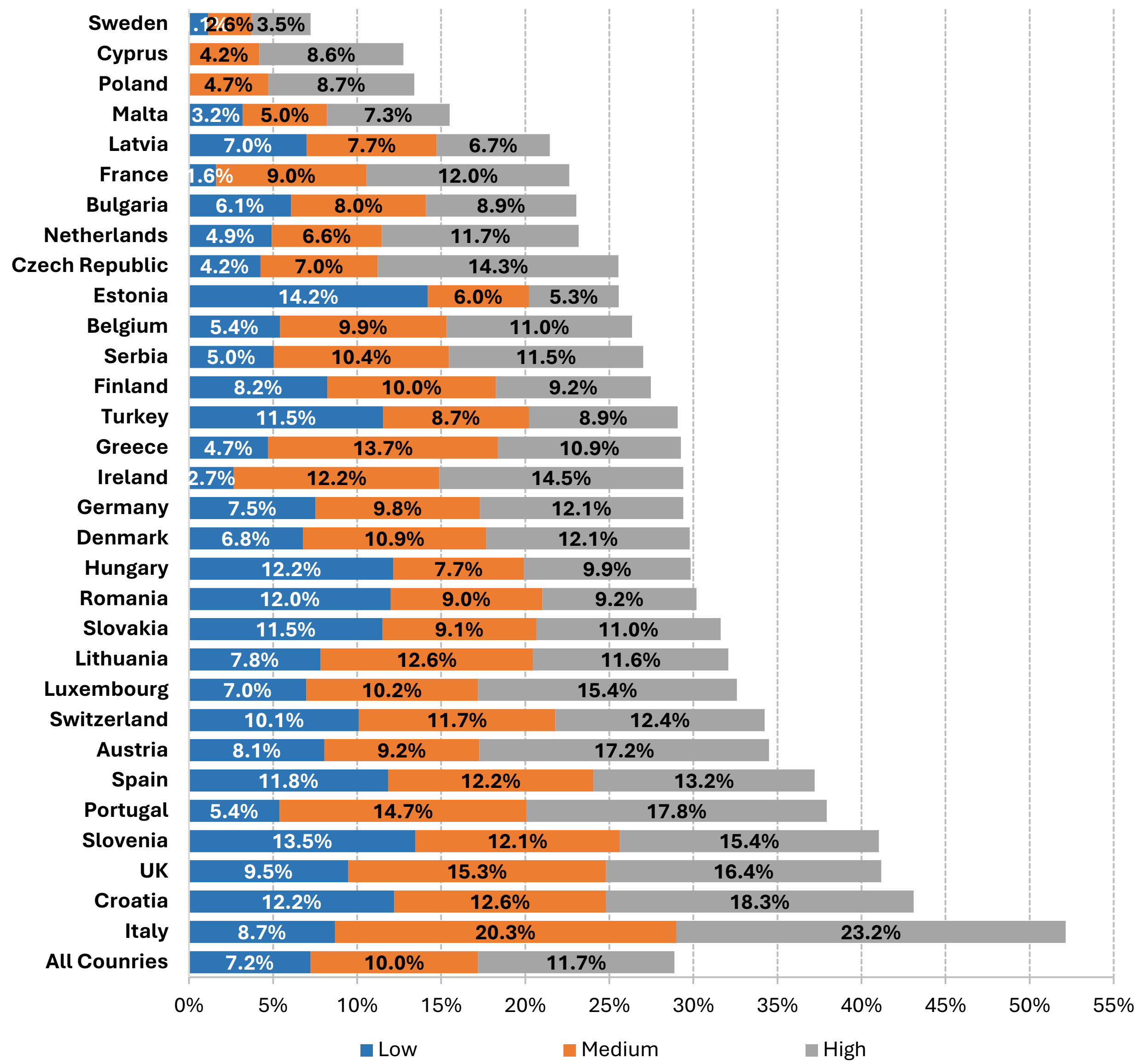


Figure 5-27 presents the share of individuals reporting platform work experience in the last 12 months, disaggregated by income decile and country. At the aggregate ("All Countries") level, recent platform engagement is relatively evenly distributed across income groups, with percentages clustering within a narrow range across deciles. There is no clear monotonic income gradient; instead, participation appears broadly diffused across low-, middle-, and high-income groups. Middle-income deciles (approximately the 4th to 7th) show slightly elevated shares, suggesting that platform work in the past year is not exclusively driven by income necessity at the bottom of the distribution, nor confined to higher-income individuals, but rather reflects a widespread and cross-cutting form of labour market participation.

Cross-country variation, however, is substantial. In countries such as Türkiye, Portugal, Italy, the United Kingdom, and Croatia, higher income deciles, particularly the 7th to 10th, often display markedly higher participation rates, indicating strong engagement among better-off groups. In contrast, several Northern and smaller economies (e.g., Estonia, Malta, Denmark, and Czechia) show more moderate and evenly distributed patterns across income levels. In parts of Southern and Eastern Europe, including Greece, Romania, Poland, and Bulgaria, participation is robust across multiple income deciles, with peaks sometimes observed in both middle and upper segments. Overall, the figure suggests that recent platform work experience is shaped less by income position alone and more by country-specific institutional, labour market, and digital ecosystem factors.

Figure 5-28 presents the share of individuals reporting experience on multiple digital platforms, disaggregated by income decile and country. At the aggregate ("All Countries") level, multi-platform engagement is fairly evenly distributed across income groups, with only moderate variation between the lowest and highest deciles. While the top income decile shows a slightly higher share compared to the lower deciles, the overall pattern does not reveal a strong monotonic income gradient. This suggests that diversifying across platforms is not exclusively a strategy of high-income earners but is observed across the income distribution, potentially reflecting broader labour market flexibility and the modular nature of platform work.

Country-level patterns, however, reveal notable heterogeneity. In countries such as Türkiye, Italy, the United Kingdom, and Romania, higher income deciles, especially the 8th to 10th, display markedly elevated shares, indicating more intensive or diversified platform use among better-off individuals. In contrast, several Northern and smaller economies (e.g., Malta, Estonia, Denmark, and Finland) exhibit lower and more evenly spread levels of multi-platform experience across income groups. In parts of Southern and Eastern Europe, including Spain, Portugal, Croatia, and Bulgaria, participation is more dispersed, with some peaks in middle-income deciles, suggesting that multi-platform engagement may serve as a strategy for income smoothing or risk diversification. Overall, the figure highlights that while income plays a role in shaping the intensity of platform engagement, national institutional and labour market contexts remain crucial determinants of multi-platform participation.

Figure 5-27: Platform work experience in the last 12 months by income decile and by country

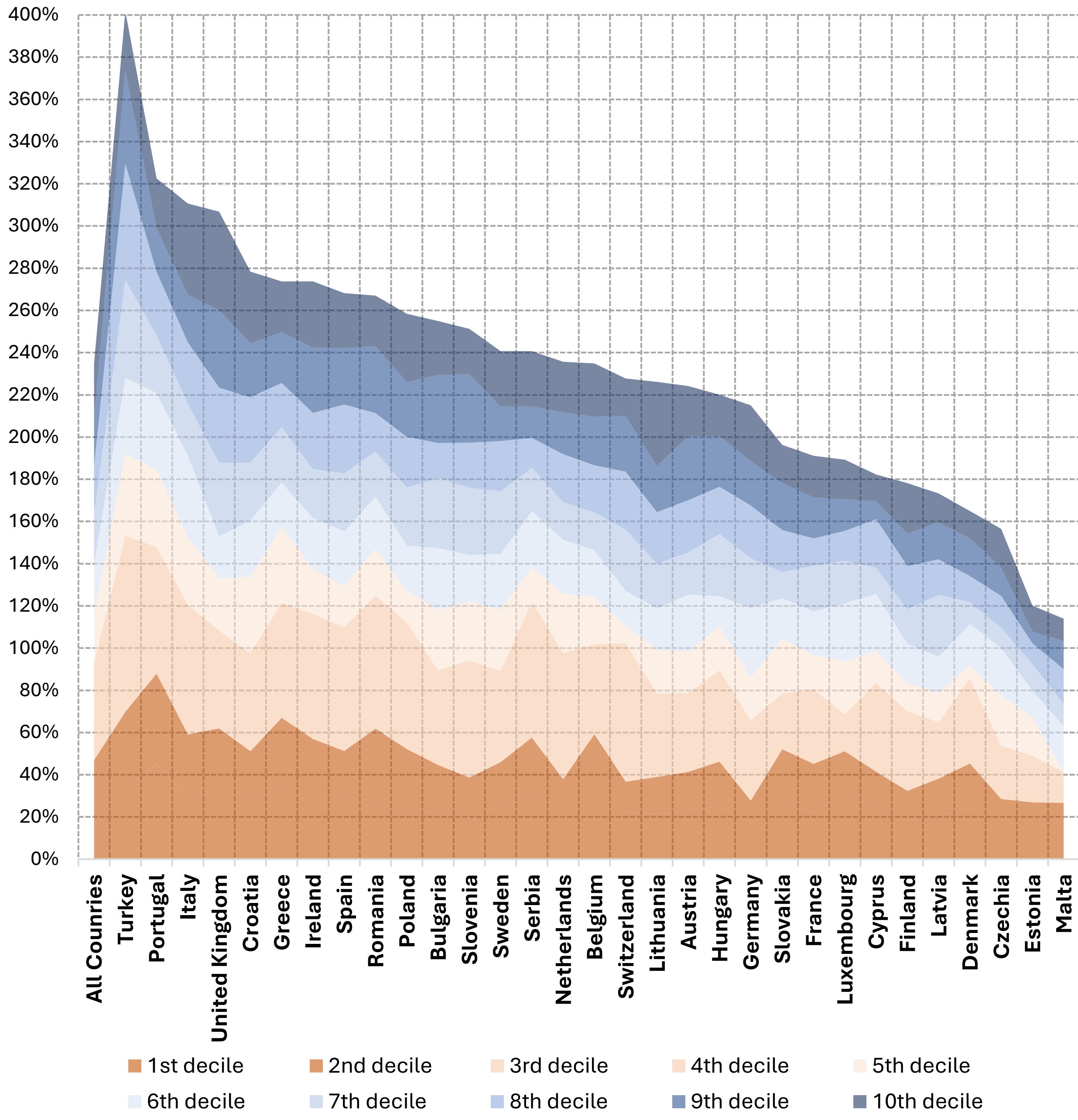


Figure 5-28: Experience in multiple platforms by income and by country

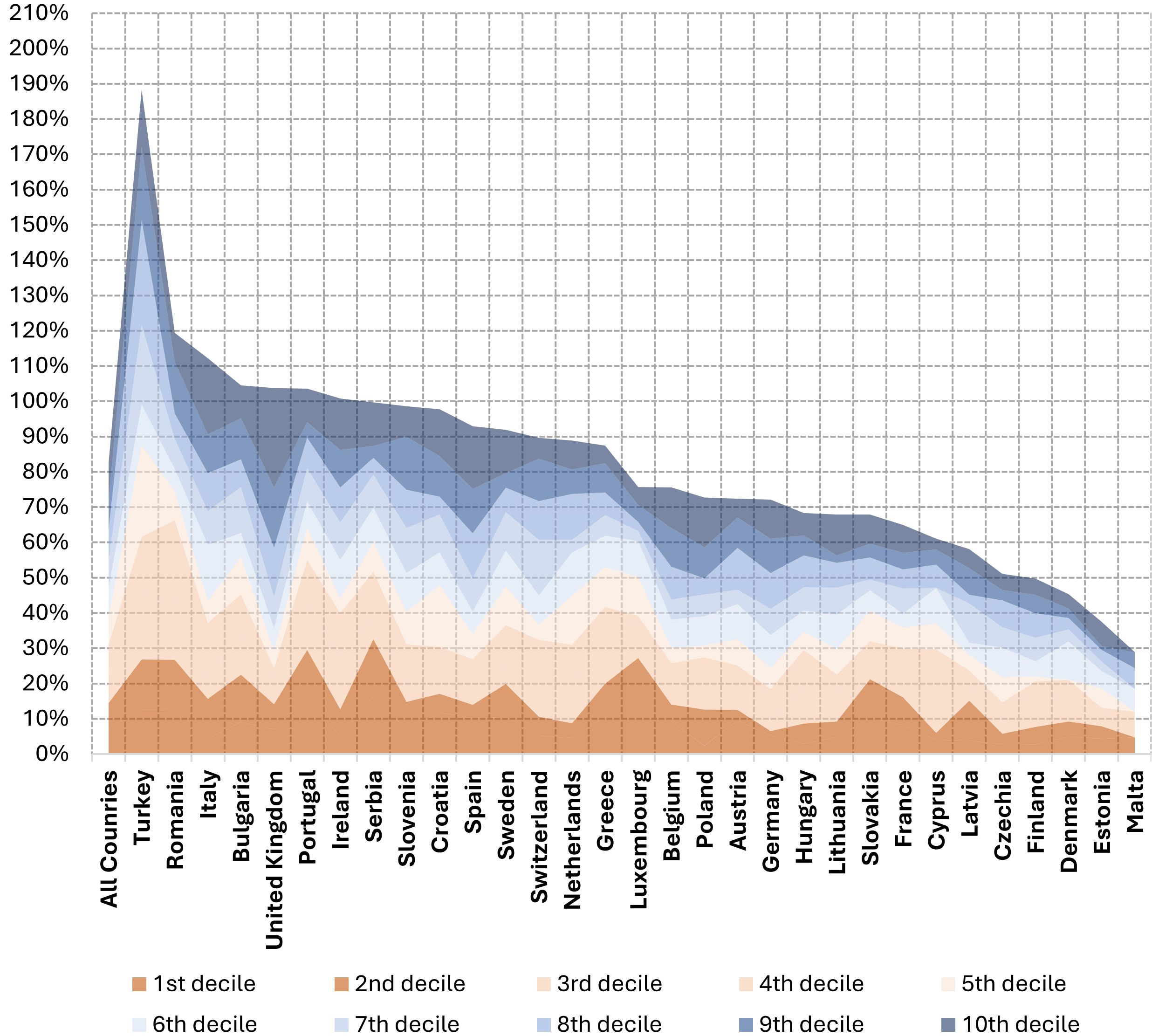


Figure 5-29 presents the share of individuals for whom platform work constitutes the main source of income, disaggregated by income decile and country. At the aggregate ("All Countries") level, reliance on platform work as a primary income source remains limited across the income distribution, with relatively low percentages in all deciles. There is no pronounced linear income gradient; instead, participation appears slightly more visible in lower and middle income deciles, while remaining modest even at the top of the distribution. This pattern suggests that depending primarily on platform work is not a widespread phenomenon and is somewhat more associated with individuals in comparatively lower income positions.

Cross-country differences, however, are significant. In most Northern and Western European countries, such as Denmark, Finland, the Netherlands, Belgium, and Germany, shares remain low and relatively evenly distributed across income groups, indicating that platform work plays only a marginal role as a main occupation. In contrast, countries such as Türkiye stand out, with particularly high shares in middle and upper-middle income deciles, pointing to a stronger reliance on platform work as a core income source. Southern and Eastern European countries, including Spain, Romania, Portugal, and Poland, display moderate but uneven patterns, with occasional peaks in specific income deciles. Overall, the figure underscores that while income position shapes the likelihood of depending primarily on platform work to some extent, national labour market structures and institutional contexts appear to be more decisive in explaining cross-country variation.

Figure 5-29: Platform work as the main source of income by income and by country

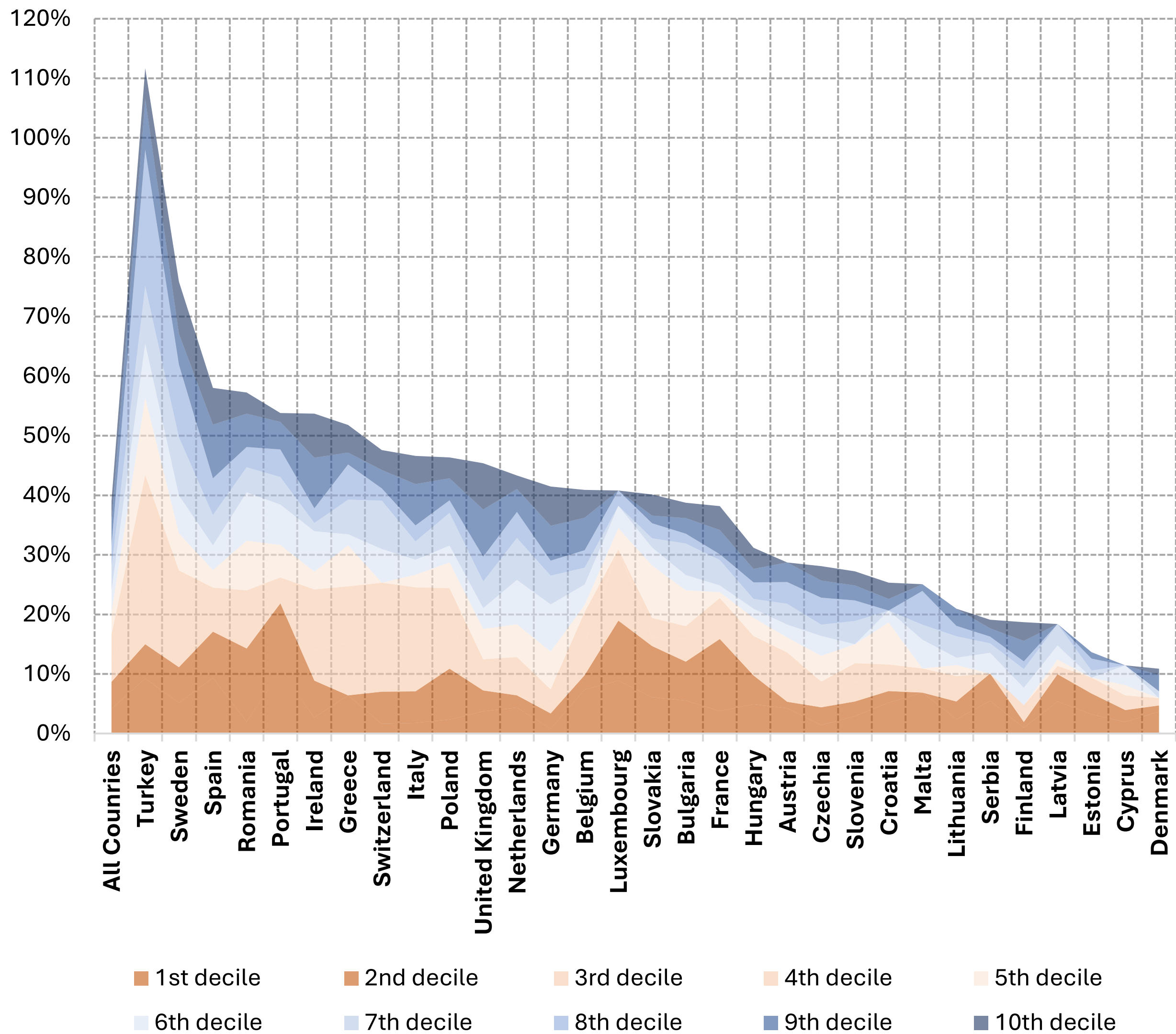


Figure 5-30 presents the share of individuals engaging in platform work as a supplementary source of income, disaggregated by income decile and country. At the aggregate (“All Countries”) level, supplementary platform work is relatively evenly distributed across income groups, with modest variation between the lowest and highest deciles. While the upper income deciles (particularly the 8th to 10th) display slightly higher shares, the overall pattern does not reveal a strong linear gradient. This suggests that using platform work to complement primary earnings is not confined to low-income individuals seeking financial support but is also common among middle- and higher-income groups as a strategy for income diversification.

At the country level, however, significant heterogeneity emerges. In countries such as the United Kingdom, Poland, Sweden, and especially Türkiye, higher income deciles exhibit markedly elevated shares, indicating a strong tendency among better-off individuals to use platform work as an additional income stream. Southern and Eastern European countries, including Romania, Bulgaria, and Greece, also show relatively high participation across several income deciles, though often with more pronounced peaks in upper-middle segments. In contrast, several Northern and smaller economies (e.g., Luxembourg, Malta, Denmark, and Estonia) display lower and more evenly distributed shares. Overall, the figure highlights that while income plays a role in shaping supplementary engagement, cross-country institutional and labour market differences remain central in explaining the observed variation.

Figure 5-31 presents the share of individuals engaging in platform work as an occasional activity, disaggregated by income decile and country. At the aggregate (“All Countries”) level, occasional platform work is broadly distributed across the income spectrum, with relatively similar shares across deciles and no pronounced linear gradient. Middle-income groups (approximately the 4th to 7th deciles) show slightly higher participation, but differences between lower- and upper-income groups remain moderate. This pattern suggests that occasional engagement in platform work functions as a flexible and accessible form of labour market participation, cutting across income levels rather than being concentrated among either the lowest or the highest earners.

At the country level, however, variation is substantial. In countries such as Italy, Portugal, Croatia, Slovenia, Ireland, and the United Kingdom, participation rates are particularly elevated in middle- and upper-income deciles, indicating that occasional platform work may serve as a complementary or discretionary activity among better-off groups. In contrast, several Northern and smaller economies (e.g., Sweden, Estonia, Malta, and Poland) display lower and more evenly distributed shares across income deciles. In Southern and Eastern European countries, including Greece, Lithuania, Serbia, and Romania, participation often peaks in specific middle or upper segments, reflecting heterogeneous national labour market conditions. Overall, the figure underscores that while income level influences occasional engagement to some extent, cross-country institutional and structural factors play a central role in shaping patterns of participation.

Figure 5-30: Platform work as a supplementary source of income by income and by country

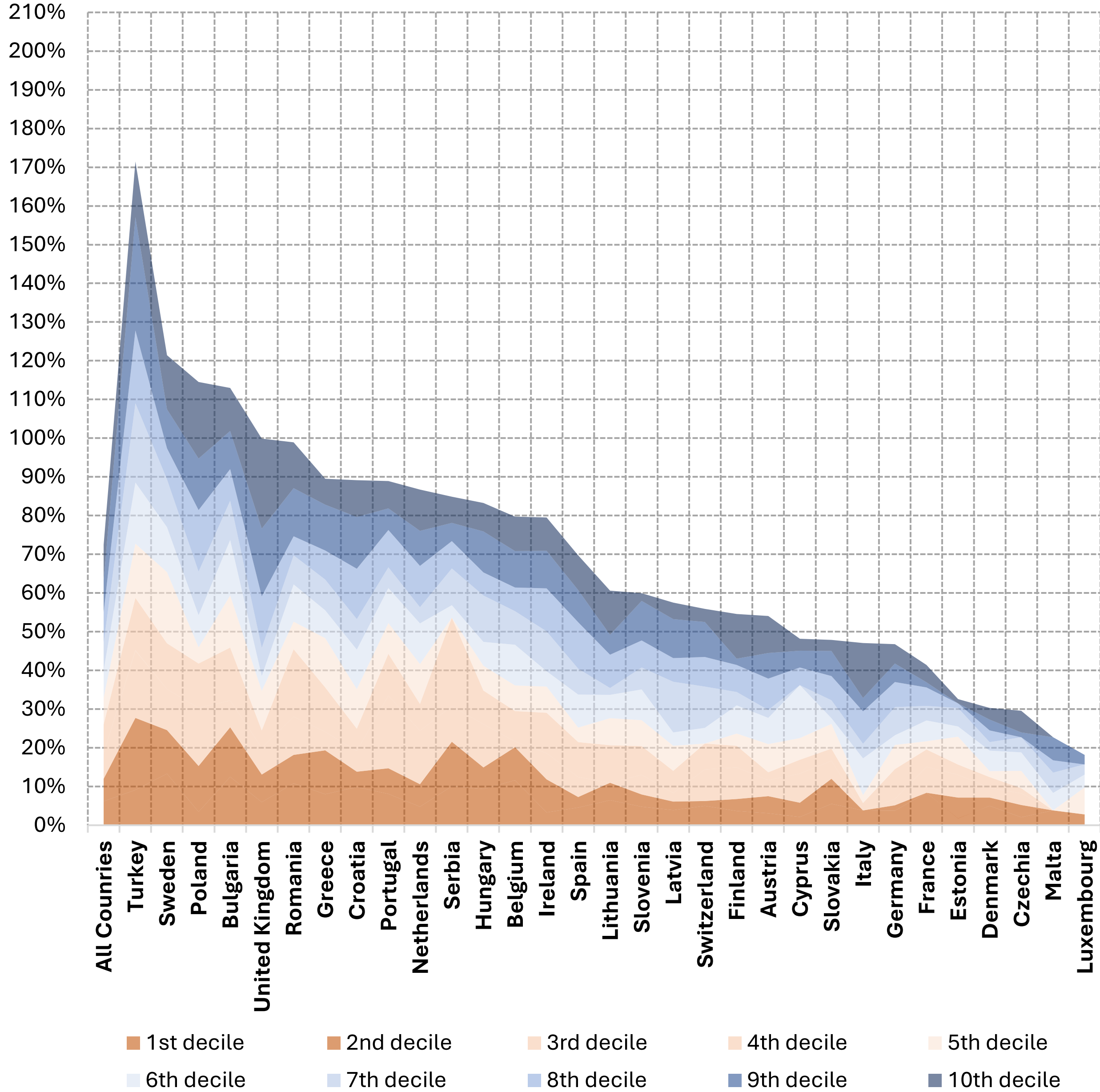


Figure 5-31: Platform work as an occasional activity by income and by country

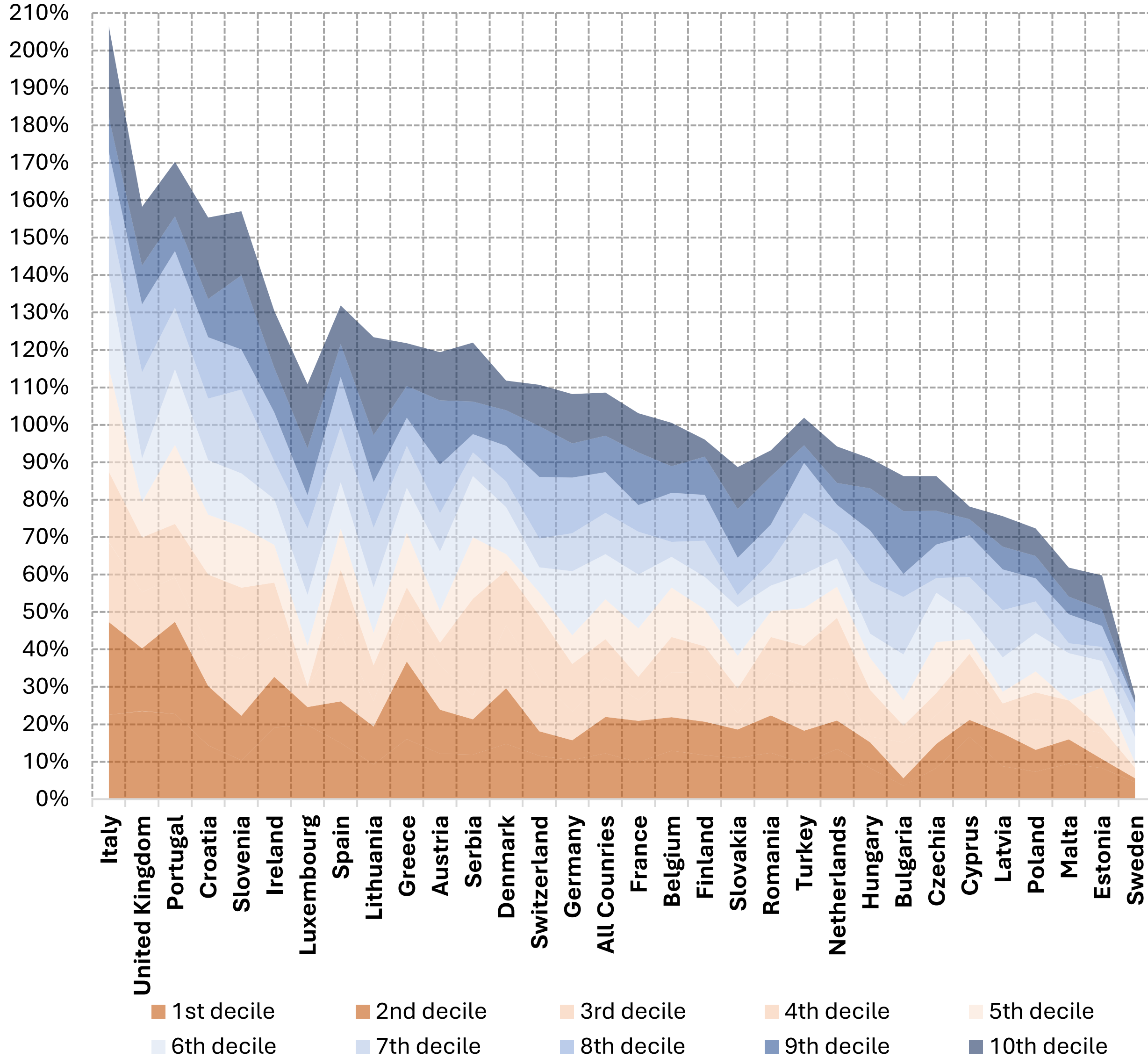


Figure 5-32 presents the share of individuals reporting platform work experience in the last 12 months, disaggregated by wealth decile and country. At the aggregate ("All Countries") level, recent platform engagement is widely distributed across the wealth spectrum, with relatively similar shares across deciles and only moderate variation between lower and upper wealth groups. Middle deciles (4th to 7th) tend to show slightly higher participation, indicating that recent platform activity is not confined to economically vulnerable households but is also prevalent among middle-wealth individuals. Overall, the absence of a strong monotonic gradient suggests that short-term engagement in platform work cuts across socioeconomic strata.

At the country level, however, patterns differ markedly. In countries such as the United Kingdom, Italy, Türkiye, Croatia, Germany, and Spain, higher wealth deciles, particularly the 7th to 10th, often display substantially elevated shares, pointing to more intensive or widespread recent participation among better-off groups. In contrast, several Northern and smaller economies (e.g., Estonia, Denmark, Finland, and Malta) exhibit lower and more evenly distributed rates across deciles. Southern and Eastern European countries, including Greece, Portugal, Romania, and Poland, frequently show strong engagement across multiple deciles, with notable peaks in both middle and upper segments. These differences likely reflect variation in labour market structures, digital platform penetration, and the broader institutional context shaping opportunities and incentives for recent platform work participation.

Figure 5-33 displays the share of individuals reporting experience on multiple digital labour platforms, broken down by wealth decile and country. At the aggregate ("All Countries") level, participation is relatively evenly distributed across wealth groups, with only modest differences between lower and upper deciles. There is a slight tendency for middle-to-upper deciles (5th to 8th) to report somewhat higher levels of multi-platform experience, suggesting that individuals with greater financial resources may be more likely to diversify their platform engagement. However, the absence of a steep wealth gradient indicates that multi-platform participation is not confined to a particular socioeconomic stratum but is a broadly accessible strategy within the platform economy.

Cross-country variation is nonetheless pronounced. In countries such as Germany, Spain, the United Kingdom, Italy, and Türkiye, higher deciles, particularly the 7th to 10th, often display elevated shares, pointing to more intensive or diversified platform engagement among wealthier groups. In contrast, Nordic and smaller economies such as Estonia, Denmark, and Finland show comparatively moderate and more evenly distributed levels across deciles. In several Southern and Eastern European countries (e.g., Romania, Croatia, Bulgaria, and Serbia), middle deciles frequently exhibit peaks, indicating that diversification across platforms may serve as a strategy for income smoothing among middle-wealth households. Overall, the figure highlights substantial institutional and labour market differences shaping the depth and diversification of platform work across Europe.

Figure 5-32: Platform work experience in the last 12 months by wealth and by country

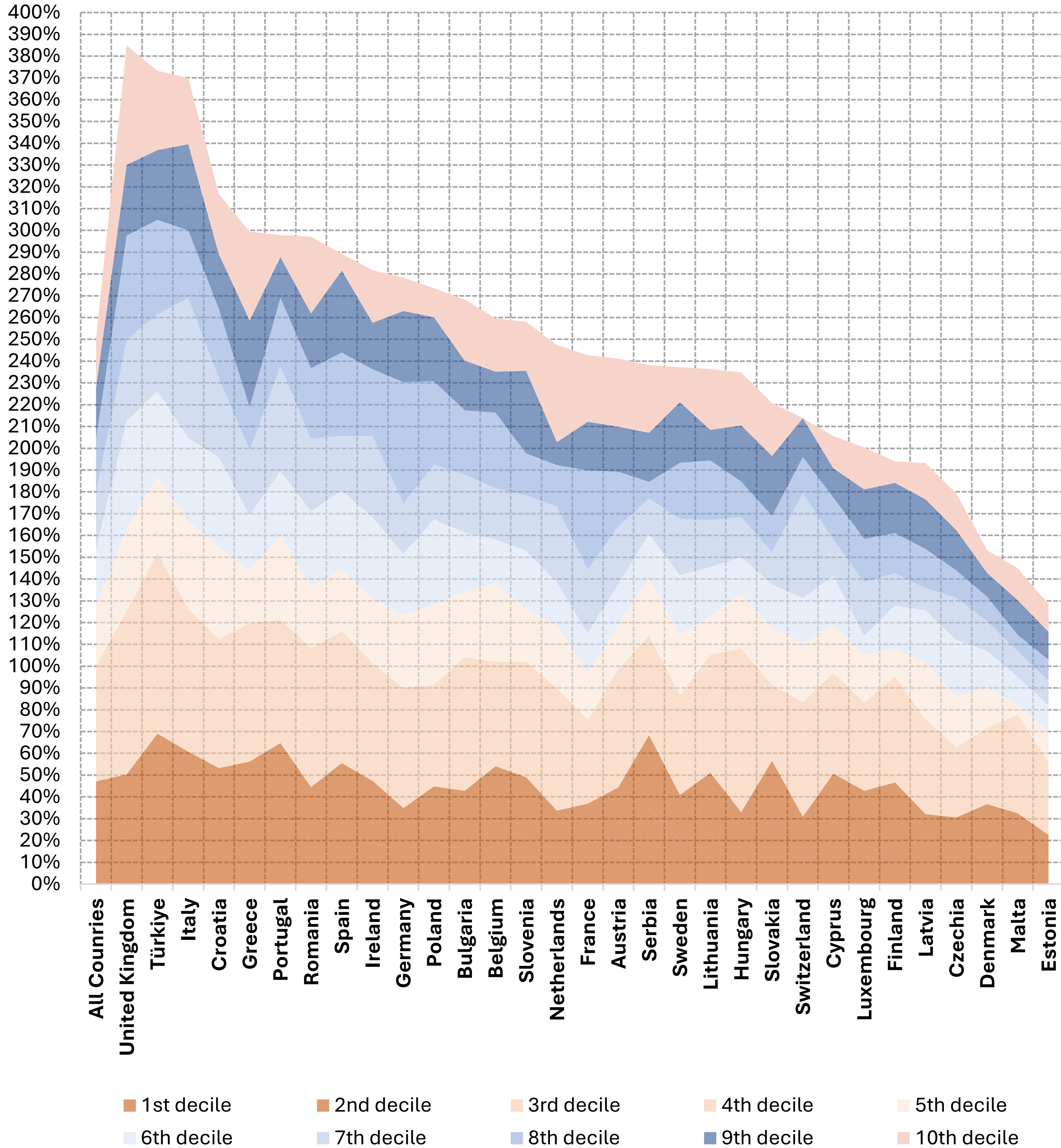


Figure 5-33: Experience in multiple platforms by wealth and by country

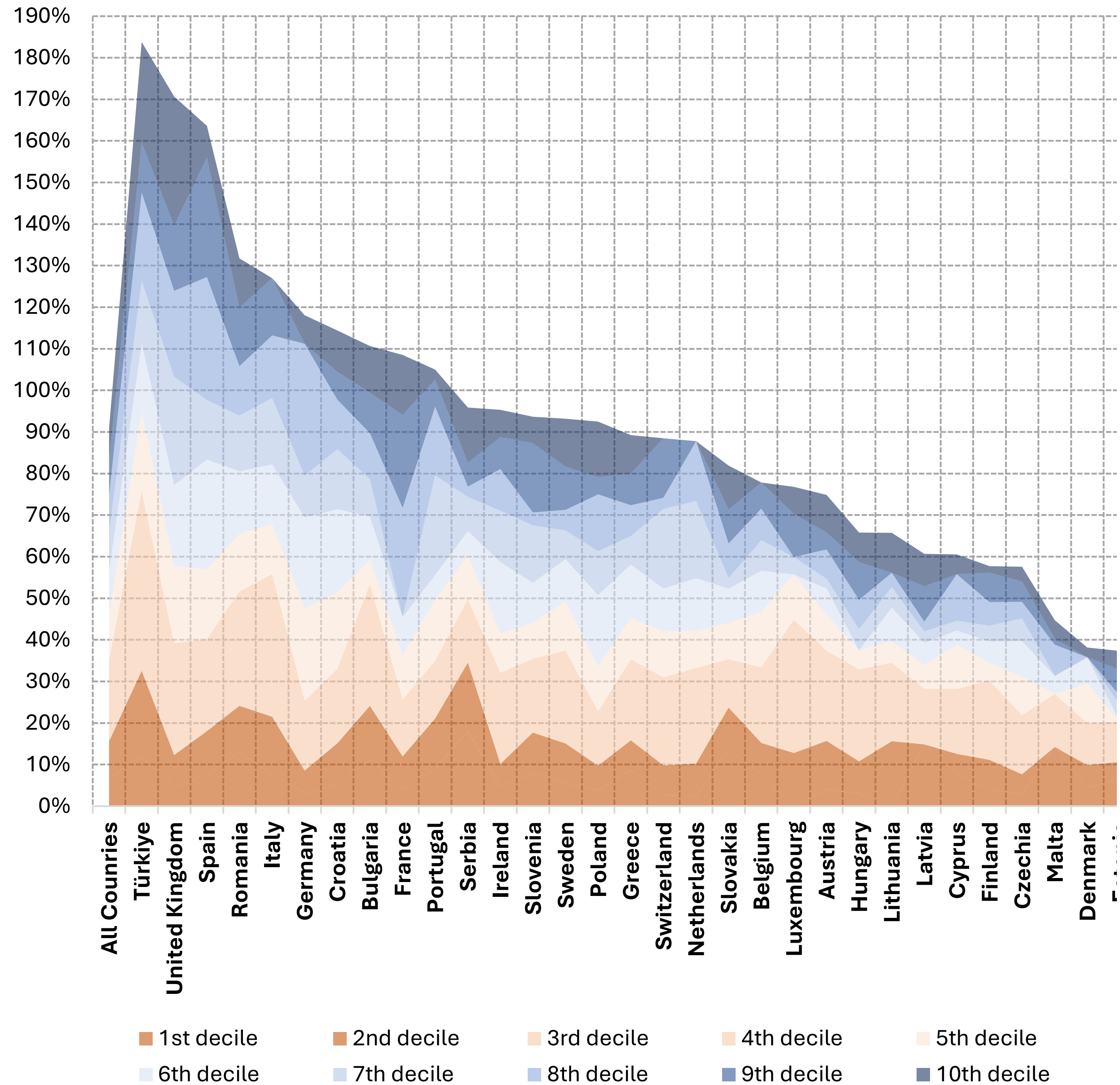


Figure 5-34 presents the share of individuals for whom platform work constitutes the main source of income, broken down by wealth decile and country. At the aggregate ("All Countries") level, reliance on platform work as a primary income source is relatively limited across all wealth groups, with percentages remaining low and fairly evenly distributed across deciles. Unlike supplementary or occasional platform work, there is no strong upward gradient toward the top wealth deciles. Instead, participation appears slightly more pronounced among lower and middle wealth groups, suggesting that when platform work becomes the main source of income, it is more closely associated with households that may have fewer alternative income opportunities.

Cross-country differences are nevertheless substantial. In several countries, including Spain, Germany, Hungary, and the United Kingdom, certain middle or upper-middle deciles show noticeable peaks, indicating that reliance on platform income is not confined exclusively to the least wealthy. In contrast, countries such as Denmark, Estonia, Finland, and Cyprus display comparatively low shares across all deciles, pointing to a more marginal role of platform work as a primary occupation. In Southern and some Eastern European countries (e.g., Greece, Italy, Romania, and Türkiye), the distribution is more dispersed, with some concentration in middle deciles and occasional spikes in higher deciles. Overall, the figure suggests that platform work as a main income source remains a minority phenomenon, with its socioeconomic profile varying considerably depending on national labour market conditions and institutional settings.

Figure 5-34: Platform work as the main source of income by wealth and by country

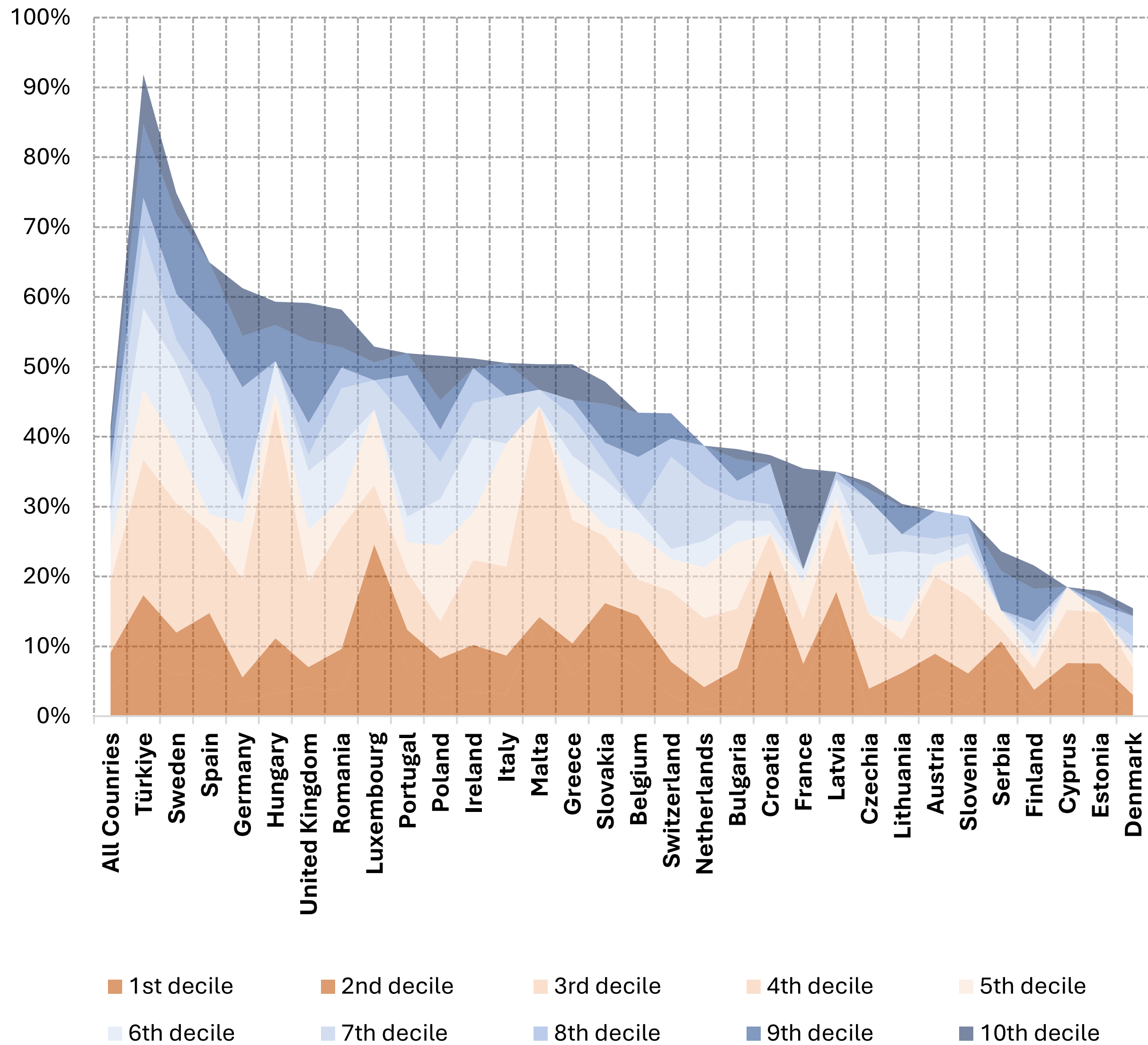


Figure 5-35 presents the share of individuals engaged in platform work as a supplementary source of income, disaggregated by wealth decile within each country. Overall, participation tends to be higher among individuals in the upper wealth deciles, particularly the 8th to 10th deciles, suggesting that platform work is not exclusively a coping mechanism for lower-wealth groups but also an income diversification strategy for more affluent households. In many countries, the distribution follows a gradual upward pattern across deciles, although the gradient is not always linear. The "All Countries" aggregate shows relatively balanced participation across deciles, with slightly higher shares in the middle-to-upper segments, indicating that platform work as a secondary income source cuts across wealth strata.

At the country level, substantial heterogeneity emerges. Countries such as the United Kingdom, Poland, Romania, Türkiye, Italy, Spain, and Greece display particularly high participation rates in the top wealth deciles, pointing to a strong engagement of wealthier individuals in supplementary platform activities. In contrast, several smaller or Northern European countries (e.g., Luxembourg, Estonia, Denmark, and Malta) exhibit lower overall shares and a flatter distribution across deciles. In some cases, middle deciles (4^{th}-7th) show notable peaks, suggesting that platform work may be especially attractive to middle-wealth households seeking income smoothing. These cross-country differences likely reflect variations in labour market structures, digital platform penetration, and the broader institutional and economic context shaping incentives for supplementary earnings.

Figure 5-36 illustrates the share of individuals engaging in platform work as an occasional activity, disaggregated by wealth decile across countries. In contrast to supplementary platform work, occasional participation appears more evenly distributed across the wealth spectrum in the aggregate results. The "All Countries" average shows relatively similar percentages across deciles, with only modest variation between lower and upper wealth groups. This suggests that occasional platform work functions as a flexible and accessible activity that cuts across socioeconomic strata, rather than being concentrated among either the least or the most affluent households. The middle deciles (4th to 7th) often display slightly elevated shares, indicating that occasional engagement may serve as a complementary or experimental income source for middle-wealth individuals.

At the country level, however, notable heterogeneity persists. In several Southern and Western European countries, such as Italy, Portugal, France, and the United Kingdom, higher wealth deciles (particularly the 8th to 10th) exhibit comparatively strong participation, pointing to the use of platforms for flexible, non-primary earnings among more affluent groups. In some cases (e.g., Italy and France), specific upper deciles stand out with markedly high shares, creating a pronounced skew toward wealthier individuals. Conversely, in countries such as Poland, Latvia, Estonia, and Hungary, participation is more evenly spread or slightly more prominent among lower-to-middle deciles. These cross-country differences likely reflect variations in digital adoption, labour market flexibility, and the institutional environment shaping the role of platform work as an occasional, rather than regular, form of economic activity.

Figure 5-35: Platform work as a supplementary source of income by wealth and by country

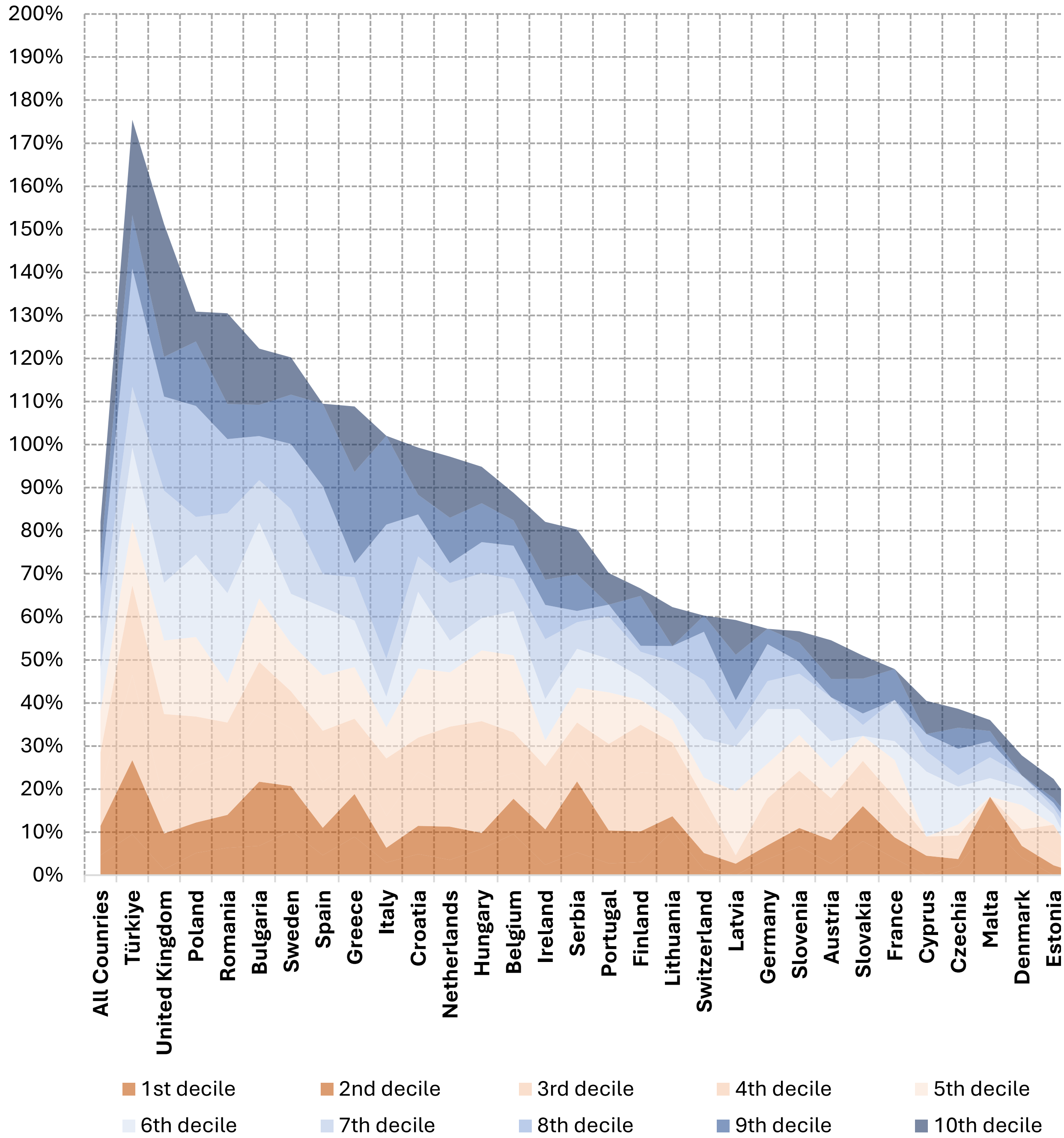
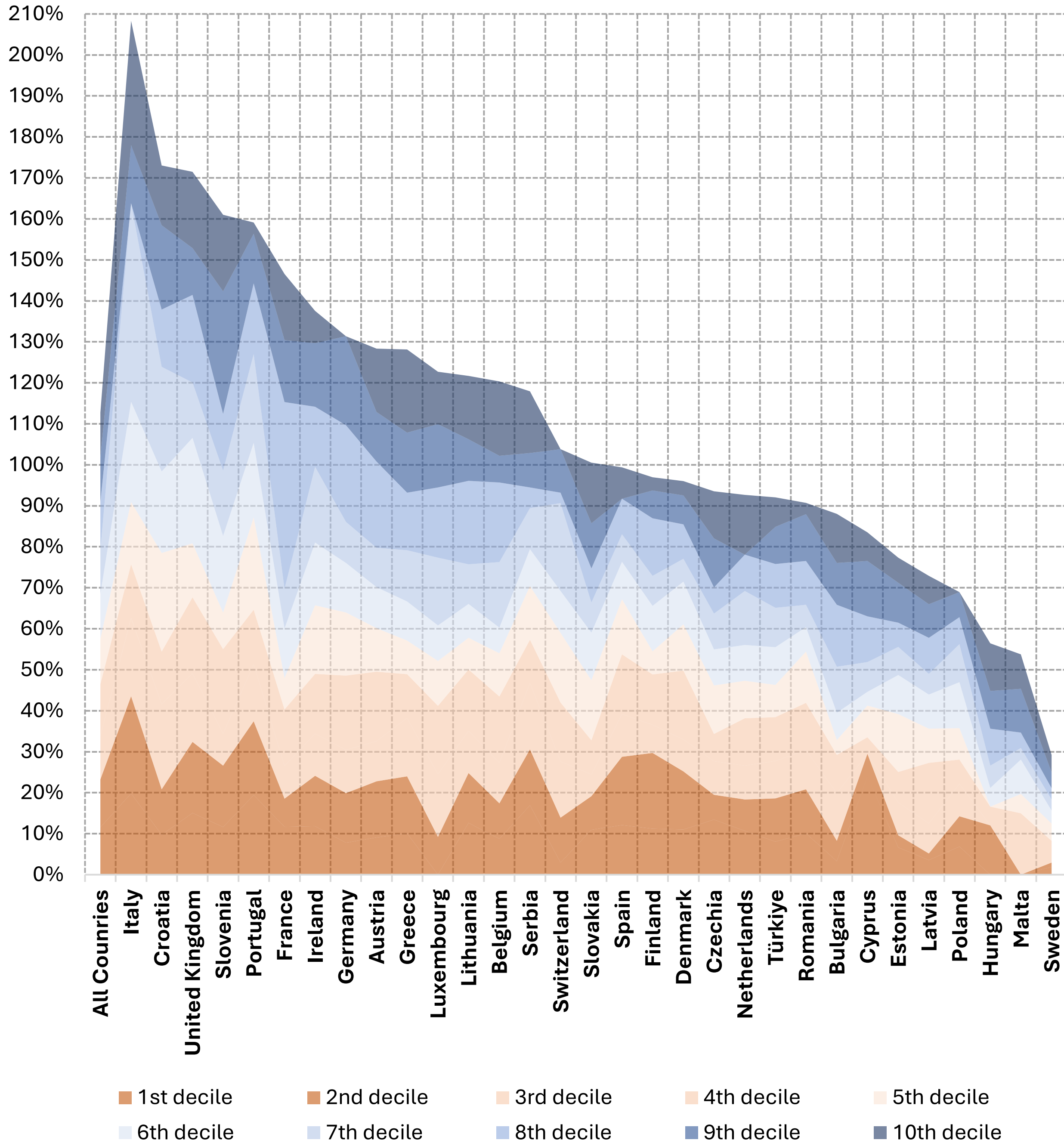


Figure 5-36: Platform work as an occasional activity by wealth and by country



5.3 Constructing the ISCO–ESCO linkage in TRAILS-I

To operationalise occupational skills in a harmonised and cross-country comparable way, the TRAILS-I survey links respondents' primary occupations to the ESCO 2022 skills taxonomy through an ISCO–ESCO mapping. The objective of this procedure is to move beyond coarse occupational groupings and quantify the skill content and skill architecture of jobs using a consistent European skills language. The detailed methodological framework underpinning this linkage is documented in Section 6 of Deliverable D5.2; the present subsection summarises the key steps and outputs as implemented for TRAILS-I and explains how the linkage supports the analysis in Sections 5 and 6.

Occupational context is essential because skills are acquired, applied, and rewarded through specific task environments. Individual competences matter, but the relevance and returns to those competences depend on what workers do at work, the technologies they interact with, and the organisational conditions under which they perform tasks. Aggregated occupational categories often obscure this variation, especially in periods of rapid technological change and in the context of green and digital transitions, where exposure to new technologies, automation pressures, and evolving task demands frequently varies within broad occupations. A granular occupational mapping therefore provides an analytically robust way to situate skill portfolios in the job contexts where they are deployed, without conflating skill measurement with labour mobility analysis (which is addressed in later work).

Mapping respondents to 4-digit ISCO occupations

TRAILS-I collects detailed occupational information through a combination of open-text and structured questions. The occupational coding approach is designed for cross-country surveys where free-text titles are often short or generic and text-only classification can generate substantial misclassification at the 4-digit level. To improve accuracy, the coding procedure applies a Heuristic Contextual Occupation Mapping approach, combining semantic information from text with contextual anchors from structured survey responses. In practice, four survey inputs are used:

- Q1: current (or most recent) main job title (open text)
- Q2: description of main tasks and duties in the main job (open text)
- Q3: selected work activity categories describing the job (multiple choice)
- Q4: industry sector of the employer/organisation (single choice)

The core methodological choice is to treat Q3 and Q4 as contextual anchors. This is critical when Q1 and Q2 are vague (e.g., "manager," "assistant," "consultant"), because tasks and sector information provide additional constraints that reduce ambiguity and improve the plausibility of 4-digit assignments.

The procedure can be summarized in the following steps as in Table 5-1:

Table 5-1: Overview of the TRAILS-I ISCO-08 4-digit coding workflow and ESCO skill mapping

Step	Title	Inputs used	Process	Output
1	Multilingual semantic matching from open-text occupational descriptions	Q1 (job title, open text) + Q2 (tasks/duties, open text)	Q1 and Q2 are concatenated into a single text string and processed using a multilingual semantic matching ensemble. Respondent text is compared to occupational reference descriptions to generate a ranked candidate pool of plausible ISCO-08 4-digit codes.	Top-ranked candidate pool of ISCO-08 4-digit codes plus a normalised semantic score capturing similarity for each candidate.
2	Task-based activity scoring using structured work activities	Q3 (work activities, multiple choice)	Candidates are scored based on consistency with the respondent's selected activity profile. Each activity option is linked to a cluster of typical ISCO-4 unit groups; candidates receive higher scores when they align with more of the selected activities.	Normalised activity-consistency score for each candidate ISCO-4 code.
3	Industry-sector alignment using sector plausibility checks	Q4 (industry sector, single choice)	Sector is used as a plausibility benchmark. Each sector category is linked to typical ISCO-4 unit groups; candidates are rewarded if they match the sector profile, with partial credit for broad but plausible alignment (e.g., same ISCO major group).	Industry-alignment plausibility score/bonus for each candidate ISCO-4 code.
4	Weighted integration and final assignment	Step 1–3 outputs	Semantic, activity, and industry scores are combined into a composite score using pre-specified weights that prioritise text evidence while using structured context to resolve ambiguity. The highest-scoring candidate is selected.	Final predicted ISCO-08 4-digit code (ISCO-4) and its composite score.
5	Diagnostic outputs for transparency and quality checks	Step 4 outputs + candidate pool diagnostics	The pipeline stores the final ISCO-4 code along with diagnostics (e.g., top candidate list, score values, ambiguity indicators, and whether contextual anchors changed the top semantic prediction).	Stored diagnostics for validation and quality assurance (e.g., top-N candidates with scores, ambiguity measures, change flags).

Once respondents' current (or most recent) main jobs have been assigned to ISCO-08 4-digit unit groups, occupational skill content is derived by mapping these ISCO codes to ESCO occupational profiles. ESCO profiles provide a structured description of the skills and competences typically associated with each occupation, allowing the occupational information collected in the survey to be translated into harmonised, quantitative indicators of job-related skill requirements. This linkage supports comparability across countries and occupations and allows the analysis to focus on underlying skill structures rather than occupational labels alone, which is particularly relevant in the context of digitalisation, the diffusion of AI, and the green transition.

Based on the ISCO–ESCO linkage, two complementary families of occupation-level indicators are constructed and assigned to each respondent through their primary occupation. First, skill intensity measures capture the relative prominence of broad skill domains within each ESCO occupational profile, expressed as shares of the total ESCO skill count for that occupation. These indicators quantify the occupational emphasis on digital, cognitive, social, physical, and green skills, alongside an automation exposure proxy defined as physical intensity minus cognitive intensity, which summarises a more manual and less cognitively intensive occupational structure. These measures characterise the structural composition of occupational skill requirements and should not be interpreted as direct measures of individuals' own skill levels.

Second, skill architecture indicators summarise how the occupational skill bundle is organised and how portable it may be across the labour market. These include skill breadth (the overall range of skills embedded in the occupation), diversification (the degree to which the skill mix is balanced across domains rather than concentrated), transferability or portability (the extent of overlap between an occupation's skills and those of other occupations, capturing structural mobility potential), and an overall skill portfolio index that aggregates these dimensions into a single measure of occupational robustness and flexibility.

In analytical terms, the ISCO–ESCO linkage provides the backbone for embedding TRAILS-I respondents within a harmonised occupational skills framework. It makes it possible to describe platform work participation not only in terms of incidence and income reliance, but also in relation to the skill environments associated with respondents' main jobs. This, in turn, supports the distributional and comparative analysis of how platform participation relates to occupational skill composition and to broader patterns of resilience and vulnerability, while reserving explicit modelling of occupational distance and labour market transitions for follow-on work where mobility is the central focus.

Where helpful for reporting clarity, the linkage outputs can be summarised as follows:

- assignment of respondents' main jobs to ISCO-08 4-digit unit groups using the multilingual, context-anchored mapping procedure based on job title, task description, work activities, and sector
- linkage of ISCO-4 codes to ESCO occupational profiles to obtain harmonised occupation-level skill requirements
- construction of skill intensity indicators (digital, cognitive, social, physical, green, automation exposure proxy) and skill architecture indicators (breadth, diversification, transferability, overall portfolio index), with stored diagnostics to support transparency and cross-country comparability

5.4 The descriptive profile of platform workers in TRAILS I

Table 5-2 summarises how platform work is distributed in the TRAILS-I sample and how platform workers differ from non-platform workers across socio-demographic characteristics, labour market status, platform work intensity, indicators of adaptability and learning, and occupation-linked skill profiles. The table also distinguishes platform workers who report platform work as their main income activity from those who report it as supplementary or occasional, highlighting important within-group heterogeneity.

Platform work is widespread but clearly patterned by age and life-course position. Platform workers are substantially younger than non-platform workers (40.45 vs 49.88 years, significant), consistent with the idea that platform work is more common among younger cohorts and those in more flexible or transitional employment arrangements. Platform workers are also less likely to be married (36.1 vs 42.9 percent, significant), which is consistent with the age gradient and the broader correlation between family status and work stability.

Gender differences are present but modest in the platform versus non-platform comparison (50.6 vs 48.7 percent men). The gap becomes much stronger when focusing on platform work as a main activity: those who rely on platforms as their main income source are disproportionately male (58.4 percent) relative to those using platforms supplementary or occasionally (49.2 percent, significant). This suggests that reliance on platform income is more gendered than participation per se.

Education patterns point to modest but meaningful stratification. Platform workers are somewhat more likely to have high education (54.3 vs 50.6 percent, significant) and less likely to have medium education (40.1 vs 43.0 percent, significant), while the low-education difference is small overall. However, among platform workers, those for whom platform work is the main activity have a noticeably higher share of low education (8.8 vs 5.0 percent, significant) and a lower share of high education (49.9 vs 55.1 percent, significant). This indicates that platform work combines both higher-skill and lower-skill entry routes, but that dependence on platform income is relatively more concentrated among lower-educated platform workers than supplementary/occasional participation.

Platform workers are more strongly attached to the labour market than non-platform workers in terms of headline employment: they are more likely to be in full-time employment (54.7 vs 47.9 percent, significant) and part-time employment (9.7 vs 7.5 percent, significant), and much less likely to be inactive (22.6 vs 35.8 percent, significant). They are also significantly more likely to be self-employed (8.9 vs 4.5 percent, significant), which aligns with the institutional positioning of many platform workers and with the interpretation of platform work as connected to non-standard work arrangements.

Within the platform workforce, reliance on platform income as a main activity is associated with a sharper reallocation across labour market statuses. Main-activity platform workers are less likely to be inactive (15.3 vs 23.9 percent, significant) and much less likely to be students (4.9 vs 9.1 percent, significant), indicating that main-activity platform work is less tied to student or transitional participation and more strongly embedded in working-age labour market attachment. They are also more likely to be self-employed (15.2 vs 7.8 percent, significant), consistent with a stronger identification with non-standard self-employment among those most reliant on platforms.

The income and wealth deciles provide a useful distributional view. Average income deciles differ little between platform and non-platform workers, but within platform workers there is a significant gap: main-activity platform workers sit lower in the income distribution (5.53 vs 5.77, significant). Wealth differences are sharper: main-activity platform workers have substantially lower wealth deciles (4.25 vs 4.84, significant). This pattern supports an interpretation in which reliance on platform work is linked less to average income differences and more to weaker asset buffers and lower wealth positions.

Differences in platform work intensity between main-activity and supplementary/occasional workers are pronounced and consistently significant. Main-activity platform workers use more platform types on average (1.83 vs 1.43) and are substantially more likely to be multi-platform workers (47.9 vs 31.2 percent). This supports the interpretation of platform work as a portfolio activity, especially for those who depend on it: reliance on platform income is associated with broader engagement across platforms and a more diversified platform activity mix.

Segment composition also differs strongly by reliance. Main-activity platform workers are much more likely to be engaged in transport/delivery and local services (33.2 vs 17.4 percent; 15.8 vs 6.2 percent, both significant), and more likely to be engaged in routine platform activities (33.2 vs 17.4 percent, significant). Supplementary/occasional platform workers are more likely to be engaged in asset-based activities (60.4 vs 42.4 percent, significant), which is consistent with occasional monetisation or income diversification strategies (e.g., selling, renting, content monetisation) rather than dependence on routine task-based gig work.

The table provides clear evidence that platform workers combine higher “behavioural” resilience with greater financial strain. Platform workers score significantly higher on adaptability, upskilling, confidence, and the labour market resilience index than non-platform workers. This pattern is even stronger among main-activity platform workers, who show significantly higher upskilling and confidence than supplementary/occasional platform workers, and substantially higher labour market resilience (4.59 vs 4.29, significant). These differences are consistent with the idea that platform workers - especially those most reliant on platforms - engage more intensively in skill maintenance and active labour market strategies.

At the same time, financial strain is higher among platform workers than non-platform workers (significant), and higher still among main-activity platform workers relative to supplementary/occasional platform workers (significant). The coping strategy counts sharpen this contrast: main-activity platform workers report fewer coping strategies in the short and medium term, and fewer in the long term as well (all significant). This reinforces the interpretation that platform workers can appear more adaptable and proactive while simultaneously facing weaker financial buffers and reduced capacity to absorb shocks - an important marker of segmentation.

By linking each respondent’s primary ISCO-08 4-digit occupation to its corresponding ESCO occupational profile, we translate job titles into a structured skills bundle and then compute skill shares as the proportion of ESCO-listed skills in each broad skill family (e.g., green, digital, knowledge, competence, self-management) relative to the total skill count for that occupation.

Table 5-2: Summary statistics in TRAILS-I survey data

	Pooled sample	Platform work	No platform	Sig.	Platform work as main activity	Supplementary/ occasional platform work	Sig.
#Observations	*29,872*	*6,832*	*23,040*		*1,057*	*5,775*	
Men	49.1%	50.6%	48.7%	**	58.4%	49.2%	***
Age	47.72	40.45	49.88	***	41.03	40.34	
Married	41.4%	36.1%	42.9%	***	34.8%	36.4%	
Low education	6.2%	5.6%	6.4%		8.8%	5.0%	***
Medium education	42.4%	40.1%	43.0%	**	41.3%	39.9%	
High education	51.4%	54.3%	50.6%	**	49.9%	55.1%	**
Self-employed	5.5%	8.9%	4.5%	***	15.2%	7.8%	***
Employed full time	49.5%	54.7%	47.9%	***	56.2%	54.4%	
Employed part time	8.0%	9.7%	7.5%	***	9.3%	9.7%	
Unemployed	4.2%	4.1%	4.3%		4.0%	4.1%	
Inactive (not in labour force)	32.8%	22.6%	35.8%	***	15.3%	23.9%	***
Homemaker	3.3%	2.9%	3.4%		1.6%	3.2%	***
Student	5.5%	8.5%	4.6%	***	4.9%	9.1%	***
Net disposable income dec.	5.69	5.73	5.68		5.53	5.77	*
Wealth decile	4.74	4.74	4.73		4.25	4.84	***
Number of platforms	0.34	1.49	0.00	***	1.83	1.43	***
Multi-platform worker	7.8%	33.8%	0.0%	***	47.9%	31.2%	***
PW: transport/delivery	4.6%	19.9%	0.0%	***	33.2%	17.4%	***
PW: digital services	7.3%	31.6%	0.0%	***	42.9%	29.6%	***
PW: asset-based	13.2%	57.6%	0.0%	***	42.4%	60.4%	***
PW: local services	1.8%	7.7%	0.0%	***	15.8%	6.2%	***
PW: other activities	2.0%	8.7%	0.0%	***	12.0%	8.1%	***
PW: skill-intensive	7.3%	31.6%	0.0%	***	42.9%	29.6%	***
PW: routine activities	4.6%	19.9%	0.0%	***	33.2%	17.4%	***
Adaptability index	1.24	1.35	1.21	***	1.37	1.34	
Upskilling index	1.62	1.90	1.53	***	2.04	1.88	***
Confidence index	1.13	1.22	1.10	***	1.29	1.21	***
Labour market resilience	3.80	4.34	3.64	***	4.59	4.29	***
Financial strain index	1.02	1.11	0.99	***	1.21	1.09	**
Short-term coping strategies	1.46	1.47	1.45		1.32	1.50	***
Medium-term coping strategies	1.51	1.56	1.49	***	1.37	1.60	***
Long-term coping strategies	1.23	1.33	1.21	***	1.27	1.34	**
% green skills	2.1%	2.0%	2.2%	***	2.0%	2.1%	
% digital skills	0.1%	0.1%	0.1%		0.1%	0.1%	*
% language skills	0.0%	0.0%	0.0%		0.0%	0.0%	
% knowledge skills	21.0%	21.4%	20.9%	**	20.2%	21.6%	***
% competence skills	56.3%	56.1%	56.4%	*	57.1%	55.9%	***
% transversal skills	0.1%	0.1%	0.2%	***	0.2%	0.1%	
% thinking skills	3.8%	3.7%	3.8%		3.7%	3.8%	
% self-management skills	4.6%	4.7%	4.6%	**	5.0%	4.7%	***
% social skills	8.7%	8.6%	8.7%		8.4%	8.6%	
% life skills	3.1%	3.1%	3.1%		3.1%	3.0%	
% physical skills	0.2%	0.2%	0.2%		0.2%	0.2%	**
Occupational skill portfolio index	-0.00	-0.01	-0.00		-0.04	0.00	

Differences in occupational skill shares between platform and non-platform workers are statistically significant in several dimensions but substantively small in magnitude, which is important for interpretation. Platform workers are slightly less concentrated in green skill content and slightly more concentrated in knowledge-related skill content, while competence and transversal shares differ modestly. Within platform work, however, differences are clearer: main-activity platform workers are associated with lower knowledge-skill shares and higher competence and self-management shares than supplementary/occasional platform workers (significant), which is consistent with a more operational, routine, and self-regulated work environment among those most reliant on platform income.

The occupational skill portfolio index differs very little between platform and non-platform workers, and is lower for main-activity platform workers than for supplementary/occasional workers. This suggests that the key differences in the platform economy shown in this table lie less in broad occupation-level portfolio robustness and more in platform work intensity, task regime, learning

Overall, Table 5-2 supports three headline conclusions that guide the remainder of the analysis. First, platform work is strongly age-graded and linked to non-standard work arrangements, with particularly high reliance among self-employed workers and those outside traditional wealth buffers. Second, dependence on platform income is associated with higher platform intensity (multi-platforming and routine/transport/local services), indicating that reliance often comes with broader platform exposure rather than concentration in a single activity. Third, platform workers - especially main-activity workers - exhibit a distinctive resilience–vulnerability profile: higher adaptability, upskilling, confidence, and labour market resilience coexist with greater financial strain and fewer coping resources, suggesting that behavioural resilience does not necessarily translate into economic security.

6. Segmentation or resilience? Evidence from the TRAILS-I Survey

6.1 Who works in the gig economy in the EU and beyond?

This subsection provides an overview of the characteristics associated with participation in platform work. Understanding who engages in platform-mediated activities is important for assessing whether the gig economy primarily attracts specific groups of workers, e.g. younger individuals, those with weaker labour market attachment, or those seeking supplementary income. The analysis therefore examines the individual, labour market, and socioeconomic determinants of platform work participation across the surveyed countries. By identifying the key correlates of participation, this subsection establishes the empirical profile of workers who engage in the gig economy and provides a baseline for the more detailed analyses of platform work types and task structures presented in the following subsections.

The results from the probit models in Table 6-1 indicate that participation in platform work during the past twelve months is shaped by a combination of demographic characteristics, labour market status, and economic resources. Marginal effects are shown with standard errors in brackets. The estimated linear prediction across specifications suggests that roughly one quarter of respondents report some form of platform-mediated income generation, indicating that such activities are relatively widespread in the population. This relatively high prevalence is consistent with the broad definition of platform work used in the survey, which includes a wide range of activities such as ride-hailing, delivery services, freelance digital work, online selling, content creation, and other forms of digitally mediated labour.

Gender differences are one of the most consistent patterns in the estimates. Men are significantly more likely than women to report having engaged in platform work during the previous year. Across the different model specifications, being male increases the probability of platform work by approximately two percentage points. Given the baseline predicted probability of roughly 23–26 percent, this represents an increase of around eight to ten percent relative to the baseline participation rate. This finding suggests that platform labour markets remain somewhat gendered. A plausible explanation is that certain forms of platform work - particularly transport and delivery services - are male-dominated, while men may also be more likely to engage in freelance or entrepreneurial digital activities. In contrast, the coefficient for non-binary respondents is not statistically significant, which is likely due to the relatively small number of individuals in this category in the sample rather than indicating the absence of any systematic pattern.

Age is strongly associated with platform participation. The negative and highly significant coefficient on age indicates that the probability of engaging in platform work declines steadily with age. In most specifications, each additional year of age reduces the likelihood of platform work by close to one percentage point. Although the positive coefficient on age squared suggests some non-linearity in

Table 6-1 Who works in the gig economy in the EU and its neighbourhood?

Any platform work in past 12 months?	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.020***	0.020***	0.020***	0.019***	0.018***	0.027***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.005]	[0.006]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	0.046	0.046	0.046	0.042	0.034	0.009
	[0.046]	[0.046]	[0.046]	[0.046]	[0.050]	[0.065]
Overqualified	–	–	–	0.012	0.01	0.021
				[0.013]	[0.013]	[0.016]
Matched	–	–	–	-0.031***	-0.032***	-0.025*
				[0.011]	[0.011]	[0.014]
Underqualified	–	–	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	–	–	–	-0.011	-0.013	0.007
				[0.017]	[0.015]	[0.019]
Age	-0.009***	-0.009***	-0.009***	-0.009***	-0.008***	-0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Age squared/1,000	0.032**	0.032**	0.032**	0.034***	0.030**	-0.029
	[0.013]	[0.013]	[0.013]	[0.013]	[0.012]	[0.019]
Married	0.012	0.012	0.012	0.013	0.013	0.024**
	[0.013]	[0.013]	[0.013]	[0.013]	[0.010]	[0.011]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	0.013	0.013	0.013	0.013	0.012	0.033**
	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]	[0.015]
Unknown marital status	0.078***	0.078***	0.078***	0.079***	0.077***	0.095***
	[0.014]	[0.014]	[0.014]	[0.015]	[0.010]	[0.012]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.033	-0.033	-0.033	-0.032	-0.037*	-0.055*
	[0.020]	[0.020]	[0.020]	[0.020]	[0.022]	[0.030]
ISCED 3: Upper secondary education	-0.033*	-0.033*	-0.033*	-0.032*	-0.036*	-0.065**
	[0.019]	[0.019]	[0.019]	[0.019]	[0.020]	[0.027]
ISCED 4: Post-secondary non-tertiary	-0.033	-0.033	-0.033	-0.033	-0.032	-0.094***
	[0.026]	[0.026]	[0.026]	[0.025]	[0.024]	[0.030]
ISCED 5: Short-cycle tertiary education	-0.019	-0.019	-0.019	-0.019	-0.022	-0.055**
	[0.019]	[0.019]	[0.019]	[0.018]	[0.019]	[0.027]
ISCED 6: Bachelor's or equivalent level	-0.022	-0.022	-0.022	-0.023	-0.028	-0.063**
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.028]
ISCED 7: Master's or equivalent level	-0.015	-0.015	-0.015	-0.015	-0.02	-0.051*
	[0.020]	[0.020]	[0.020]	[0.019]	[0.021]	[0.028]
ISCED 8: Doctoral or equivalent level	0.031	0.031	0.031	0.03	0.027	0.001
	[0.022]	[0.022]	[0.022]	[0.022]	[0.023]	[0.031]
Self-employed	0.128***	0.128***	0.128***	0.133***	0.132***	0.149***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.019]
Full-time employed	0.006	0.006	0.006	0.011	0.01	0.013
	[0.016]	[0.016]	[0.016]	[0.016]	[0.015]	[0.018]

Part-time employed	0.042**	0.042**	0.042**	0.044***	0.043***	0.048***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.016]	[0.018]
Unemployed	-0.034*	-0.034*	-0.034*	-0.034*	-0.034*	-0.033*
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]	[0.020]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	-0.022	-0.022	-0.022	-0.022	-0.025	-0.023
	[0.021]	[0.021]	[0.021]	[0.021]	[0.020]	[0.022]
Other/Unknown	-0.021	-0.021	-0.021	-0.018	-0.02	-0.024
	[0.028]	[0.028]	[0.028]	[0.029]	[0.026]	[0.029]
Retired	-0.042**	-0.042**	-0.042**	-0.037**	-0.037**	–
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	
Student	-0.018	-0.018	-0.018	-0.02	-0.016	–
	[0.020]	[0.020]	[0.020]	[0.020]	[0.018]	
Income decile 10	-0.008	-0.008	-0.008	-0.004	-0.005	-0.012
	[0.013]	[0.013]	[0.013]	[0.013]	[0.010]	[0.012]
Income decile 9	-0.016**	-0.016**	-0.016**	-0.013	-0.013	-0.023*
	[0.008]	[0.008]	[0.008]	[0.008]	[0.010]	[0.012]
Income decile 8	-0.015	-0.015	-0.015	-0.013	-0.013	-0.016
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.013]
Income decile 7	-0.002	-0.002	-0.002	0.001	0.001	-0.011
	[0.009]	[0.009]	[0.009]	[0.009]	[0.010]	[0.013]
Income decile 6	0.002	0.002	0.002	0.003	0.005	0.005
	[0.013]	[0.013]	[0.013]	[0.013]	[0.011]	[0.012]
Income decile 5	-0.006	-0.006	-0.006	-0.005	-0.005	-0.01
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.015]
Income decile 4	0.01	0.01	0.01	0.011	0.012	0.006
	[0.010]	[0.010]	[0.010]	[0.010]	[0.012]	[0.015]
Income decile 3	0.007	0.007	0.007	0.008	0.01	0.014
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.013]
Income decile 2	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income decile 1	0.004	0.004	0.004	0.004	0.003	-0.013
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.013]
Income decile: DK/DA	-0.003	-0.003	-0.003	-0.002	0.001	0.002
	[0.016]	[0.016]	[0.016]	[0.016]	[0.017]	[0.023]
Wealth decile 10	0.063***	0.063***	0.063***	0.063***	0.063***	0.081***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.013]
Wealth decile 9	0.057***	0.057***	0.057***	0.058***	0.055***	0.080***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]	[0.014]
Wealth decile 8	0.069***	0.069***	0.069***	0.070***	0.069***	0.084***
	[0.015]	[0.015]	[0.015]	[0.014]	[0.011]	[0.014]
Wealth decile 7	0.066***	0.066***	0.066***	0.066***	0.067***	0.090***
	[0.014]	[0.014]	[0.014]	[0.014]	[0.013]	[0.017]
Wealth decile 6	0.060***	0.060***	0.060***	0.059***	0.062***	0.076***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.011]	[0.014]
Wealth decile 5	0.071***	0.071***	0.071***	0.070***	0.071***	0.084***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]	[0.012]
Wealth decile 4	0.065***	0.065***	0.065***	0.065***	0.066***	0.080***

	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]	[0.012]
Wealth decile 3	0.048***	0.048***	0.048***	0.048***	0.047***	0.055***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.011]
Wealth decile 2	0.044***	0.044***	0.044***	0.044***	0.043***	0.055***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.008]	[0.010]
Wealth decile 1	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth decile: DK/DA	-0.033***	-0.033***	-0.033***	-0.034***	-0.035***	-0.044***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.011]	[0.014]
Austria	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–
Belgium	0.023***	0.023***	0.023***	0.022***	–	–
	[0.004]	[0.004]	[0.004]	[0.004]		
Bulgaria	0.025***	0.025***	0.025***	0.025***	–	–
	[0.005]	[0.005]	[0.005]	[0.005]		
Croatia	0.119***	0.119***	0.119***	0.119***	–	–
	[0.008]	[0.008]	[0.008]	[0.008]		
Cyprus	-0.013*	-0.013*	-0.013*	-0.015**	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Czech Republic	-0.028***	-0.028***	-0.028***	-0.028***	–	–
	[0.005]	[0.005]	[0.005]	[0.005]		
Denmark	-0.011	-0.011	-0.011	-0.009	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Estonia	-0.067***	-0.067***	-0.067***	-0.067***	–	–
	[0.006]	[0.006]	[0.006]	[0.006]		
Finland	-0.044***	-0.044***	-0.044***	-0.043***	–	–
	[0.004]	[0.004]	[0.004]	[0.004]		
France	0.018**	0.018**	0.018**	0.018**	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Germany	0.041***	0.041***	0.041***	0.040***	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Greece	0.030***	0.030***	0.030***	0.026***	–	–
	[0.006]	[0.006]	[0.006]	[0.006]		
Hungary	0.037***	0.037***	0.037***	0.039***	–	–
	[0.005]	[0.005]	[0.005]	[0.005]		
Ireland	-0.001	-0.001	-0.001	-0.001	–	–
	[0.006]	[0.006]	[0.006]	[0.006]		
Italy	0.151***	0.151***	0.151***	0.151***	–	–
	[0.008]	[0.008]	[0.008]	[0.008]		
Latvia	-0.001	-0.001	-0.001	0.001	–	–
	[0.006]	[0.006]	[0.006]	[0.007]		
Lithuania	0.045***	0.045***	0.045***	0.045***	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Luxembourg	-0.055***	-0.055***	-0.055***	-0.053***	–	–
	[0.004]	[0.004]	[0.004]	[0.004]		
Malta	-0.111***	-0.111***	-0.111***	-0.111***	–	–
	[0.003]	[0.003]	[0.003]	[0.003]		
Netherlands	0.013***	0.013***	0.013***	0.012***	–	–
	[0.005]	[0.005]	[0.005]	[0.005]		

Poland	0.068***	0.068***	0.068***	0.070***	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Portugal	0.098***	0.098***	0.098***	0.097***	–	–
	[0.004]	[0.004]	[0.004]	[0.004]		
Romania	0.066***	0.066***	0.066***	0.067***	–	–
	[0.005]	[0.005]	[0.005]	[0.005]		
Slovakia	0.025***	0.025***	0.025***	0.025***	–	–
	[0.006]	[0.006]	[0.006]	[0.006]		
Slovenia	0.073***	0.073***	0.073***	0.071***	–	–
	[0.010]	[0.010]	[0.010]	[0.010]		
Spain	0.088***	0.088***	0.088***	0.088***	–	–
	[0.008]	[0.008]	[0.008]	[0.008]		
Sweden	0.020***	0.020***	0.020***	0.021***	–	–
	[0.003]	[0.003]	[0.003]	[0.003]		
Serbia	0.071***	0.071***	0.071***	0.072***	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
Switzerland	-0.007**	-0.007**	-0.007**	-0.006**	–	–
	[0.003]	[0.003]	[0.003]	[0.003]		
Turkey	0.112***	0.112***	0.112***	0.107***	–	–
	[0.007]	[0.007]	[0.007]	[0.007]		
United Kingdom	0.106***	0.106***	0.106***	0.106***	–	–
	[0.008]	[0.008]	[0.008]	[0.008]		
$NUTS_2$ region fixed effects	–	–	–	–	+	+
%Male effect	*8.5%*	*8.5%*	*8.5%*	*8.3%*	*7.8%*	*10.5%*
Linear Prediction	*0.2296*	*0.2296*	*0.2296*	*0.2296*	*0.2295*	*0.2608*
No. of Observations	*29,872*	*29,872*	*29,872*	*29,872*	*29,871*	*21,532*

Notes: Marginal effects from probit models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

the relationship, the overall pattern clearly points to much higher participation among younger individuals. This result is consistent with existing research highlighting that younger workers tend to adopt digital labour platforms more readily, either because they are more familiar with digital technologies or because they face more uncertain labour market conditions and therefore seek additional or flexible income sources.

Educational attainment does not show a simple linear relationship with platform participation. Relative to individuals with only primary education, those with upper secondary or post-secondary education generally display a lower probability of participating in platform work, with several of these coefficients reaching statistical significance in the more restrictive specifications. The results suggest that platform work is not concentrated exclusively among highly educated individuals, despite the presence of some forms of online freelance work that rely on advanced skills. Instead, platform participation appears to span multiple education groups but may be somewhat more common among individuals with lower or intermediate levels of formal education. At the same time, the absence of significant differences for doctoral-level education may reflect the small number of such respondents in the sample.

The inclusion of variables capturing the match between education and job requirements provides further insights into the relationship between labour market conditions and platform work. Individuals who report that their education matches the requirements of their main job are significantly less likely to engage in platform work compared with those who are underqualified. The magnitude of this effect ranges between roughly −2.5 and −3 percentage points. In contrast, the coefficient for overqualification is positive but not statistically significant. This pattern suggests that platform work may be more common among individuals whose main job does not perfectly align with their qualifications, potentially serving as a complementary activity or alternative channel through which workers can deploy unused skills.

Labour market status emerges as one of the strongest predictors of platform participation. Self-employed individuals are substantially more likely to report platform work, with marginal effects ranging from around 13 to 15 percentage points. This is by far the largest effect observed in the table and highlights the close relationship between platform work and entrepreneurial or freelance activity. Digital platforms may provide self-employed workers with additional opportunities to find clients, market services, or sell goods online. Part-time employment is also associated with a higher likelihood of platform participation, increasing the probability by approximately four to five percentage points. This finding suggests that platform work often functions as a supplementary income source for individuals whose main job does not provide full-time hours or sufficient earnings.

Interestingly, unemployment is associated with a slightly lower probability of platform work. The marginal effect of being unemployed relative to inactivity is negative and statistically significant, at around −3 percentage points. This result contrasts with the common narrative that digital platforms primarily serve as a safety net for individuals who cannot find traditional employment. Instead, the findings suggest that platform work is more often undertaken by individuals who are already active in the labour market, particularly those combining it with other forms of employment. Retired individuals are also significantly less likely to participate in platform work, which is consistent with lower labour market attachment and possibly lower familiarity with digital technologies among older cohorts.

Household economic resources show an interesting pattern when comparing income and wealth effects. Income deciles exhibit relatively limited and inconsistent associations with platform participation. Only a small number of income categories show statistically significant differences from the reference group, and the magnitudes of these effects are relatively small. This suggests that current income levels do not play a major role in explaining who participates in platform work. In contrast, wealth deciles display a strong and highly consistent positive gradient. Individuals in higher wealth deciles are substantially more likely to engage in platform work than those in the lowest wealth group, with marginal effects ranging from approximately four to nine percentage points depending on the decile. This pattern indicates that platform work is not solely driven by financial necessity. Instead, individuals with greater financial resources may also use digital platforms as opportunities for supplementary income generation, entrepreneurial experimentation, or digital commerce.

Marital status appears to play a relatively minor role in explaining platform participation. Most marital status categories are not statistically different from single individuals in the baseline specifications. In the most restrictive model specification, however, married individuals and those who are widowed, divorced, or separated display slightly higher probabilities of platform participation. The positive and relatively large coefficient associated with unknown marital status likely reflects non-response or reporting issues rather than a substantive behavioural relationship.

Finally, the results reveal substantial cross-country differences in platform participation. Several countries exhibit significantly higher probabilities of platform work relative to the reference category, including Italy, Croatia, Turkey, the United Kingdom, Portugal, and Spain. In some of these cases, the marginal effects exceed ten percentage points, indicating markedly higher engagement with digital labour platforms. Conversely, countries such as Malta, Estonia, Luxembourg, and Finland show significantly lower participation rates. These differences likely reflect variation in labour market structures, the diffusion of digital platforms, regulatory environments, and broader economic conditions. In the later specifications, country dummies are replaced by NUTS2 regional fixed effects, suggesting that local labour market conditions and regional economic characteristics may also play an important role in shaping the prevalence of platform work.

Taken together, the results indicate that platform work participation is primarily associated with younger age, male gender, self-employment, and part-time employment, while it is less common among older individuals, retirees, and those with stable employment matching their qualifications. At the same time, the strong positive association with household wealth suggests that platform work is not simply a form of labour market marginality but may also represent an additional economic activity undertaken by individuals with sufficient resources to engage in digital entrepreneurial opportunities.

6.2 Platform work typologies, task composition, and skill transferability

This subsection examines how different forms of platform work relate to the skill content of workers' primary occupations. Rather than treating platform work as a homogeneous activity, the analysis distinguishes between several platform work types based on the nature of tasks performed. The first set of results examines how worker characteristics relate to participation across different platform work typologies, including transport and delivery, digital labour, asset-based activities, and local services. The second set of models focuses on the task composition of platform work and the extent to which skills from the primary occupation can be transferred to platform activities. Using measures derived from the ISCO–ESCO skill classification, the analysis captures both the overall skill portfolio of the worker's occupation and the relative importance of specific skill categories such as digital, social, and self-management skills. Together, these results provide insight into whether platform work tends to draw on the skills developed in workers' main jobs or instead reflects task profiles that are largely disconnected from their primary occupational skill sets. The findings also highlight the heterogeneity of platform work, showing that different platform segments are associated with distinct task structures and skill requirements.

The results in Table 6-2 present average marginal effects from probit models for five thematic types of platform work and for holding multiple platform jobs. Because these are marginal effects, each coefficient can be read as the change in the predicted probability of reporting a given platform work type associated with a one unit change in the covariate (or a shift from the reference category), holding the remaining controls constant. The typology is constructed in a way that intentionally allows overlap across types, so the outcomes are not mutually exclusive. This is important for interpretation because the estimates capture participation in each thematic segment rather than sorting into a single category. The "multiple platform jobs" outcome should therefore be understood as a marker of breadth of engagement across platform activities rather than a distinct exclusive status.

A first key message is that platform work is clearly segmented, and the correlates of participation differ sharply across types. Gender is a good example. Men are significantly more likely than women to report multiple platform jobs, transport and delivery work, digital platform work, and asset-based platform work. The marginal effects are substantively meaningful relative to baseline predicted probabilities, particularly in transport and delivery and in digital work, where the proportional differences are large. In contrast, men are significantly less likely to participate in local services platform work. This sign reversal indicates that aggregation can obscure important gendered sorting across platform segments. In practical terms, the higher male probability of platform work observed in overall participation models appears to be driven by segments such as transport, delivery, digital labour, and commerce or asset-related activities, while local services exhibit a pattern that goes in the opposite direction. The non-binary category shows some large coefficients in specific columns, but interpretation should remain cautious because these estimates are likely based on relatively small numbers and the pattern is not consistent across all outcomes.

Age is a strong and consistent predictor across most outcomes. The marginal effects for age are negative for multiple platform jobs and for each of the main platform types, indicating that younger respondents are more likely to participate across the platform economy and are also more likely to combine multiple platform activities. Some columns show a positive coefficient on the quadratic term, which suggests curvature in the age profile. However, the dominant relationship remains a declining probability of participation with age. This reinforces the idea that platform work participation is not only more common among younger cohorts in the aggregate but that the age gradient applies across several distinct segments.

The measures of job match provide additional insight into the link between platform work and labour market fit. Relative to underqualified respondents, being matched is associated with a lower probability of holding multiple platform jobs and of participating in transport and delivery and digital work in particular, while effects in local services and "other" are smaller and not robust. Overqualification is not systematically related to platform participation across the typology. Taken together, this suggests that platform engagement is more common among individuals whose main job does not fully align with their qualifications or skill profile, especially for segments that resemble conventional labour market activities, i.e., transport and delivery and digital labour. One plausible interpretation is that platform work is used to complement earnings or to find alternative channels for deploying skills when the primary job match is not strong.

Table 6-2: Who engages in multiple platform jobs and different platform work segments?

	Multiple platform jobs	Transport	Digital	Asset-based	Local	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Male	0.021***	0.017***	0.031***	-0.019***	0.005***	0.001
	[0.005]	[0.003]	[0.003]	[0.006]	[0.002]	[0.002]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	0.053**	-0.001	0.077***	0.001	–	0.011
	[0.027]	[0.040]	[0.022]	[0.043]		[0.016]
Overqualified	0.001	0.002	-0.006	0.017	0.001	0.004
	[0.009]	[0.005]	[0.006]	[0.011]	[0.004]	[0.004]
Matched	-0.015*	-0.012***	-0.020***	-0.008	-0.002	0.001
	[0.008]	[0.004]	[0.005]	[0.009]	[0.004]	[0.003]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	-0.004	-0.012**	-0.011	-0.014	-0.001	0.004
	[0.009]	[0.006]	[0.008]	[0.012]	[0.005]	[0.004]
Age	-0.005***	-0.003***	-0.003***	-0.003***	-0.001	-0.001***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
Age squared/1,000	0.034***	0.015*	0.002	-0.007	0.002	0.014***
	[0.010]	[0.008]	[0.011]	[0.011]	[0.004]	[0.005]
Married	0.001	0.005	0.001	0.013*	0.002	-0.004
	[0.006]	[0.005]	[0.007]	[0.007]	[0.002]	[0.002]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	0.002	0.010*	0.009	0.008	0.003	-0.005
	[0.008]	[0.005]	[0.009]	[0.008]	[0.004]	[0.004]
Unknown marital status	0.037***	0.025***	0.034***	0.040***	0.012***	0.005*
	[0.007]	[0.006]	[0.008]	[0.007]	[0.003]	[0.003]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.001	0.015	-0.014	-0.008	0.005	-0.004
	[0.016]	[0.010]	[0.016]	[0.025]	[0.007]	[0.006]
ISCED 3: Upper secondary education	-0.001	0.005	-0.019	0.005	-0.002	0.001
	[0.012]	[0.010]	[0.013]	[0.024]	[0.005]	[0.006]
ISCED 4: Post-secondary non-tertiary	-0.01	-0.004	-0.033**	0.02	-0.011	0.005
	[0.018]	[0.010]	[0.016]	[0.026]	[0.007]	[0.008]
ISCED 5: Short-cycle tertiary education	0.008	0.002	-0.014	0.015	-0.003	0.003
	[0.012]	[0.011]	[0.015]	[0.022]	[0.006]	[0.007]
ISCED 6: Bachelor's or equivalent level	0.005	-0.005	-0.008	0.032	-0.006	-0.003
	[0.013]	[0.011]	[0.014]	[0.024]	[0.005]	[0.006]
ISCED 7: Master's or equivalent level	0.005	-0.007	0.001	0.03	-0.009	-0.001
	[0.014]	[0.011]	[0.014]	[0.024]	[0.006]	[0.007]
ISCED 8: Doctoral or equivalent level	0.039**	0.008	0.039**	0.038	0.006	-0.001
	[0.017]	[0.015]	[0.016]	[0.027]	[0.006]	[0.008]

Self-employed	0.090***	0.032***	0.078***	0.073***	0.007	0.025***
	[0.013]	[0.008]	[0.011]	[0.014]	[0.006]	[0.007]
Full-time employed	0.048***	0.021**	0.018*	0.019	0.008	0.011
	[0.013]	[0.008]	[0.011]	[0.015]	[0.007]	[0.008]
Part-time employed	0.056***	0.019**	0.025**	0.037**	0.011	0.018**
	[0.014]	[0.008]	[0.010]	[0.016]	[0.007]	[0.009]
Unemployed	0.033**	0.005	0.002	-0.02	0.005	0.021***
	[0.013]	[0.009]	[0.011]	[0.017]	[0.007]	[0.008]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	0.015	-0.002	-0.006	-0.005	0.004	0.009
	[0.015]	[0.010]	[0.012]	[0.019]	[0.008]	[0.008]
Other/Unknown	0.011	-0.006	-0.015	0.009	-0.014	0.016
	[0.021]	[0.019]	[0.022]	[0.027]	[0.017]	[0.011]
Retired	0.022**	-0.003	-0.008	-0.011	-0.001	0.005
	[0.011]	[0.009]	[0.012]	[0.015]	[0.007]	[0.008]
Student	0.023	0.004	-0.003	0.02	0.001	0.018**
	[0.014]	[0.009]	[0.014]	[0.015]	[0.006]	[0.008]
Income decile 10	0.022***	0.009	0.002	0.008	0.001	0.005
	[0.008]	[0.007]	[0.007]	[0.010]	[0.004]	[0.003]
Income decile 9	0.008	0.003	0.001	0.001	0.003	0.002
	[0.008]	[0.008]	[0.006]	[0.010]	[0.004]	[0.004]
Income decile 8	0.01	0.006	0.001	0.002	0.004	0.003
	[0.007]	[0.007]	[0.007]	[0.009]	[0.003]	[0.004]
Income decile 7	0.01	0.006	0.003	0.01	0.001	0.001
	[0.007]	[0.006]	[0.005]	[0.009]	[0.004]	[0.004]
Income decile 6	0.014**	0.012**	0.002	0.006	0.004	0.005
	[0.007]	[0.005]	[0.005]	[0.010]	[0.004]	[0.004]
Income decile 5	0.008	0.013**	0.001	0.002	0.005*	0.001
	[0.006]	[0.006]	[0.007]	[0.009]	[0.003]	[0.004]
Income decile 4	0.018**	0.013**	0.007	0.004	0.004	0.006
	[0.007]	[0.006]	[0.006]	[0.008]	[0.003]	[0.004]
Income decile 3	0.018**	0.01	0.005	0.002	0.001	0.007*
	[0.009]	[0.007]	[0.008]	[0.009]	[0.004]	[0.004]
Income decile 2	0.009	0.009	0.006	-0.003	0.008***	0.002
	[0.006]	[0.006]	[0.005]	[0.010]	[0.003]	[0.003]
Income decile 1	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income decile: DK/DA	-0.008	0.014*	0.002	-0.008	-0.003	-0.005
	[0.012]	[0.008]	[0.013]	[0.015]	[0.006]	[0.005]
Wealth decile 10	0.028***	0.004	0.030***	0.056***	0.011***	0.005
	[0.007]	[0.006]	[0.007]	[0.010]	[0.003]	[0.004]
Wealth decile 9	0.022***	0.013**	0.022***	0.044***	0.004	0.005
	[0.008]	[0.007]	[0.007]	[0.009]	[0.004]	[0.004]
Wealth decile 8	0.029***	0.013*	0.035***	0.048***	0.015***	0.002
	[0.010]	[0.008]	[0.008]	[0.011]	[0.004]	[0.004]
Wealth decile 7	0.027***	0.020***	0.034***	0.042***	0.017***	-0.003
	[0.010]	[0.007]	[0.006]	[0.011]	[0.004]	[0.005]
Wealth decile 6	0.035***	0.017**	0.035***	0.040***	0.014***	0.004

	[0.008]	[0.007]	[0.006]	[0.011]	[0.003]	[0.003]
Wealth decile 5	0.039***	0.019***	0.044***	0.046***	0.013***	0.001
	[0.007]	[0.007]	[0.006]	[0.009]	[0.003]	[0.003]
Wealth decile 4	0.033***	0.020***	0.035***	0.041***	0.010**	0.001
	[0.006]	[0.006]	[0.005]	[0.010]	[0.004]	[0.003]
Wealth decile 3	0.034***	0.018***	0.029***	0.031***	0.008***	0.004
	[0.005]	[0.005]	[0.006]	[0.006]	[0.003]	[0.003]
Wealth decile 2	0.028***	0.018***	0.025***	0.023***	0.010***	0.004
	[0.005]	[0.004]	[0.005]	[0.008]	[0.002]	[0.003]
Wealth decile 1	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth decile: DK/DA	-0.012	-0.019***	-0.018**	-0.015	-0.006	0.002
	[0.008]	[0.007]	[0.007]	[0.010]	[0.004]	[0.003]
Austria	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Belgium	0.007***	0.008***	0.015***	-0.005**	0.035***	0.003***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.012]	[0.001]
Bulgaria	0.020***	0.046***	0.026***	-0.022***	0.041***	0.002**
	[0.003]	[0.004]	[0.003]	[0.003]	[0.013]	[0.001]
Croatia	0.058***	0.028***	0.035***	0.057***	0.036***	0.016***
	[0.005]	[0.004]	[0.005]	[0.005]	[0.012]	[0.002]
Cyprus	0.002	0.013***	-0.026***	-0.060***	0.052***	0.032***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.013]	[0.003]
Czech Republic	-0.013***	-0.003**	-0.021***	-0.034***	0.017	0.007***
	[0.002]	[0.001]	[0.002]	[0.003]	[0.013]	[0.001]
Denmark	-0.004	-0.002	-0.022***	-0.009**	0.034***	0.011***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Estonia	-0.017***	0.003	-0.024***	-0.071***	0.022*	0.003***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.013]	[0.001]
Finland	-0.024***	-0.014***	-0.027***	-0.037***	0.031**	0.002**
	[0.001]	[0.001]	[0.002]	[0.002]	[0.012]	[0.001]
France	0.012***	-0.003	-0.006*	0.024***	0.045***	0.003**
	[0.004]	[0.002]	[0.003]	[0.005]	[0.013]	[0.001]
Germany	0.018***	0.001	0.016***	0.022***	0.052***	0.004***
	[0.004]	[0.002]	[0.004]	[0.005]	[0.013]	[0.001]
Greece	-0.003	0.001	0.010***	-0.010***	0.033***	0.005***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Hungary	0.007***	0.020***	-0.003	-0.003	0.037***	0.012***
	[0.003]	[0.003]	[0.002]	[0.003]	[0.012]	[0.002]
Ireland	-0.001	0.004**	-0.005*	-0.019***	0.033***	0.008***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Italy	0.071***	0.025***	0.037***	0.143***	0.052***	0.015***
	[0.006]	[0.004]	[0.004]	[0.007]	[0.013]	[0.002]
Latvia	0.003	0.014***	-0.014***	-0.018***	0.027**	0.009***
	[0.003]	[0.003]	[0.003]	[0.004]	[0.013]	[0.002]
Lithuania	0.016***	0.011***	-0.014***	0.025***	0.026**	0.013***
	[0.004]	[0.003]	[0.004]	[0.004]	[0.013]	[0.002]
Luxembourg	-0.001	0.010***	-0.031***	-0.020***	0.015	0.001
	[0.002]	[0.003]	[0.002]	[0.003]	[0.012]	[0.001]

Malta	-0.040***	-0.028***	-0.037***	-0.084***	–	0.003***
	[0.001]	[0.001]	[0.002]	[0.002]		[0.001]
Netherlands	0.007***	-0.004**	-0.004	0.001	0.044***	0.008***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Poland	0.021***	0.024***	0.013***	0.019***	0.041***	0.012***
	[0.004]	[0.003]	[0.005]	[0.004]	[0.013]	[0.002]
Portugal	0.024***	0.004***	0.022***	0.066***	0.042***	0.014***
	[0.002]	[0.002]	[0.002]	[0.003]	[0.013]	[0.001]
Romania	0.047***	0.040***	0.030***	0.005*	0.041***	0.019***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Slovakia	0.021***	0.028***	0.001	-0.004	0.043***	0.010***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.013]	[0.001]
Slovenia	0.037***	0.030***	0.039***	0.018***	0.033**	0.013***
	[0.005]	[0.005]	[0.006]	[0.006]	[0.013]	[0.002]
Spain	0.042***	0.007**	0.040***	0.046***	0.051***	0.014***
	[0.005]	[0.003]	[0.005]	[0.005]	[0.013]	[0.002]
Sweden	0.018***	0.006***	0.007***	-0.007***	0.046***	0.007***
	[0.002]	[0.001]	[0.002]	[0.002]	[0.012]	[0.001]
Serbia	0.057***	0.040***	0.015***	-0.023***	0.052***	0.036***
	[0.004]	[0.003]	[0.003]	[0.003]	[0.013]	[0.002]
Switzerland	0.001	0.002	-0.007***	-0.024***	0.039***	0.012***
	[0.002]	[0.001]	[0.002]	[0.002]	[0.013]	[0.001]
Turkey	0.078***	0.065***	0.083***	-0.025***	0.061***	0.024***
	[0.004]	[0.003]	[0.004]	[0.004]	[0.012]	[0.002]
United Kingdom	0.047***	0.007***	0.054***	0.090***	0.050***	0.002*
	[0.004]	[0.002]	[0.005]	[0.005]	[0.013]	[0.001]
%Male effect	*27.7%*	*38.3%*	*42.7%*	*-14.3%*	*29.9%*	*3.0%*
Linear Prediction	*0.0775*	*0.0456*	*0.0726*	*0.1321*	*0.0176*	*0.02*
No. of Observations	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*

Notes: Marginal effects from probit models are presented. The standard errors are robust and clustered at th country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

Education shows weaker and less systematic patterns than in many standard labour market participation models. Most ISCED categories do not differ significantly from the primary education reference group across the outcomes, and where differences arise they tend to be concentrated in specific segments rather than showing a uniform gradient. This implies that broad educational attainment alone does not strongly sort individuals into the thematic platform categories once other factors are controlled for. The segmented nature of platform work likely contributes to this muted education gradient. For instance, some segments can be entered with relatively low formal credentials (transport and delivery), while others can be pursued by individuals across the education spectrum through commerce, online selling, or content creation.

Labour market status is among the most powerful and substantively interpretable determinants across the table. Self-employment is strongly and positively associated with multiple platform jobs and with participation in transport and delivery, digital work, asset-based platform work, and local services, and it is also positively associated with “other.” The magnitude of these marginal effects is large, especially for multiple platform jobs and for the digital and asset-based categories. This strongly supports the view that platform work overlaps with entrepreneurial and freelance activity and often functions as an additional channel for self-directed work, client acquisition, and income diversification. Full-time and part-time employment are also positively associated with multiple platform jobs and with several platform types. This pattern is consistent with platform work being frequently undertaken as a supplementary activity rather than being limited to those outside standard employment. Part-time employment in particular shows sizable positive associations with multiple platform jobs and with transport and delivery, digital work, and asset-based participation, aligning with the notion that individuals with fewer hours in their main job may be more likely to add platform work.

The unemployment pattern is especially informative when compared with more aggregated participation models. Here, unemployed respondents are more likely than inactive respondents to hold multiple platform jobs and to report "other" platform work, and they also show a positive association with transport and delivery. At the same time, unemployment does not appear to raise participation across all segments uniformly. This indicates heterogeneity in how unemployment relates to platform engagement. Rather than serving as a general gateway into all forms of platform work, unemployment seems to be associated with particular segments that can be entered relatively quickly, i.e., transport and delivery or miscellaneous platform tasks captured by the residual category, and with broader multi-platform engagement. This is exactly the kind of nuance that becomes visible when platform work is broken down into thematic groupings rather than treated as a single binary outcome.

Income and wealth produce a contrast similar to what is often found when distinguishing short-run resources from longer-run asset positions. Income deciles display some positive marginal effects for multiple platform jobs and for transport and delivery in parts of the distribution, but the overall pattern is not monotonic and the magnitudes are relatively modest. Wealth, in contrast, shows a strong and consistent positive gradient across almost all platform types and for multiple platform jobs. Higher wealth deciles are associated with higher probabilities of transport and delivery, digital work, asset-based participation, and local services, and also with having multiple platform jobs. The association is particularly pronounced for asset-based platform work, which is substantively intuitive because activities in this category often rely on access to assets or financial buffers, i.e., the ability to sell goods at scale, to monetise property, or to engage in platform-mediated commerce that may require upfront resources. The positive wealth gradient for digital and transport and delivery suggests that platform work is not purely necessity-driven. For some individuals, it likely reflects diversification strategies, experimentation, or portfolio income behaviour. The negative coefficients for wealth non-response categories across several outcomes further suggest that those who do not report wealth differ systematically in ways that correlate with lower measured platform participation, which can reflect either true differences or reporting-related selection.

Marital status effects are generally small. Where statistically significant, they tend to be modest in magnitude and not central to the patterning of platform participation. The consistently positive coefficients for unknown marital status across outcomes likely reflect non-response patterns correlated with other unobserved characteristics rather than a substantive marital status mechanism, so these estimates are better treated as indicators of missingness rather than interpreted causally.

Country fixed effects show substantial cross-national heterogeneity, and importantly, the direction and magnitude vary across platform types. Some countries stand out for particularly high relative probabilities in asset-based participation, others in transport and delivery or digital work, and still others show lower probabilities in local services. This reinforces the idea that platform economies develop unevenly across contexts and that "more platform work" in a country does not necessarily mean expansion in the same segments everywhere. Differences in platform ecosystems, regulation, sectoral structure, and consumer adoption can plausibly shape which types become most prevalent. For a deliverable-style interpretation, the key point is that even after controlling for individual characteristics, there remains substantial country-level variation in the propensity to engage in each thematic segment, suggesting that institutional and market context matters.

Overall, the typology-based results sharpen the interpretation of platform work participation by showing that the aggregate correlates are driven by specific segments and that some determinants change sign across types. Men are more likely to participate in transport and delivery, digital work, and asset-based activities but less likely to participate in local services, indicating gendered segmentation. Younger respondents are consistently more likely to participate across types and to combine multiple platform activities. Self-employment and, to a lesser extent, part-time and full-time employment are strongly associated with participation across several segments, supporting the view of platform work as complementary to labour market attachment and entrepreneurial behaviour. Wealth is a robust predictor across nearly all segments, particularly for asset-based platforms, implying that platform work includes a substantial component linked to assets and longer-run resources rather than being driven solely by low income. Finally, unemployment is associated with some specific segments and with broader multi-platform engagement rather than with uniform participation across all types, pointing to heterogeneous pathways into platform work depending on labour market position.

While the previous table shows that participation in platform work varies significantly across different platform segments, it does not reveal how these activities relate to the skills workers possess in their primary occupations. The typology highlights that platform work encompasses a wide range of activities with potentially very different task structures, e.g. transport and delivery, digital labour, or asset-based commerce. This raises an important question about the extent to which platform work draws on the skills developed in workers' main jobs or instead relies on task profiles that are largely independent of their primary occupational expertise. The next table addresses this issue by examining the relationship between the skill content of workers' primary occupations and the type of platform work they perform. Using skill measures derived from the ISCO–ESCO classification, the analysis links occupational skill portfolios and specific skill categories to different platform work task profiles, distinguishing between skill-intensive, intermediation, and routine platform activities. This allows us to assess whether platform work primarily represents an extension of existing occupational skills or whether it reflects tasks that require a different set of capabilities.

Table 6-3 examines how the skill content of a respondent's primary occupation relates to the type of platform work they perform. The models estimate marginal effects from probit regressions in which platform work activities are grouped according to their task profile into skill-intensive, intermediation, and routine activities. Two alternative approaches are used to measure skill transferability from the main job. Columns (1), (3), and (5) rely on an occupational skill portfolio index derived from the ISCO–ESCO mapping of occupational skill content, while columns (2), (4), and (6) decompose the skill profile of the primary occupation into sectoral, transferable, and basic skill shares. The coefficients therefore capture how the skill composition of a respondent's main occupation is associated with the probability of performing different types of platform work.

The first set of results shows that occupational skill intensity is strongly related to the type of platform work performed. The occupational skill portfolio index is positively associated with skill-intensive platform work and negatively associated with routine platform work. The marginal effect for skill-intensive activities indicates that individuals whose primary occupation involves a richer and more diverse skill portfolio are more likely to engage in platform work characterised by more complex or knowledge-intensive tasks. In contrast, the negative coefficient in the routine platform work model suggests that workers with more complex skill portfolios are less likely to perform platform tasks that rely primarily on routine or repetitive activities. The coefficient for intermediation work is small and not statistically significant, implying that the skill complexity of the primary occupation does not strongly differentiate participation in this segment. Taken together, these results suggest that some platform activities may allow workers to transfer higher level skills from their main occupation, whereas others may involve task profiles that are largely detached from the skill intensity of the worker's primary job.

The specification that decomposes the skill structure of the primary occupation provides additional insight into which types of skills are associated with participation in different platform segments. Sectoral skill shares show several positive associations with skill-intensive platform work. A higher share of physical, life, and green sectoral skills in the worker's primary occupation increases the probability of performing skill-intensive platform work. This indicates that the knowledge domains embedded in occupational skill structures may translate into specific types of platform tasks. In the case of intermediation work, physical skill shares also show a positive and statistically significant association, suggesting that workers with a stronger physical skill component in their occupational profile may be somewhat more likely to perform platform activities that involve coordination, brokerage, or task matching functions. For routine platform work, however, the sectoral skill composition of the primary occupation does not appear to play a significant role.

Transferable skill shares also display meaningful relationships with platform work participation. A higher share of self-management skills in the primary occupation significantly increases the probability of performing skill-intensive platform work. Social and competence skills show similar positive associations. These patterns suggest that workers whose main jobs involve a higher share of transferable behavioural and organisational skills are more likely to engage in platform activities that require autonomy, coordination, or interaction with clients. The estimates for intermediation work show a weaker pattern, with only social skills displaying a marginally significant positive effect. For routine platform work, transferable skills are not significantly associated with participation. This again points to a segmentation of platform tasks, where activities that rely on higher levels of autonomy and interaction are more strongly linked to transferable skills developed in the primary job.

Table 6-3: Do skills from the primary job transfer to different types of platform work?

	Skill-intensive		Intermediation		Routine	
	(1)	(2)	(3)	(4)	(5)	(6)
Occupational skill portfolio index	0.004***	–	-0.002	–	-0.005***	–
	[0.001]		[0.002]		[0.001]	
Sectoral skill share: Physical	–	0.013*	–	0.017***	–	0.001
		[0.008]		[0.006]		[0.004]
Sectoral skill share: Life	–	0.010**	–	0.005	–	-0.002
		[0.005]		[0.005]		[0.003]
Sectoral skill share: Green	–	0.010**	–	0.007	–	-0.002
		[0.005]		[0.005]		[0.003]
Transferrable skill share: Self	–	0.013***	–	0.007	–	0.001
		[0.005]		[0.005]		[0.003]
Transferrable skill share: Social	–	0.010**	–	0.008*	–	-0.001
		[0.005]		[0.005]		[0.003]
Transferrable skill share: Transversal	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Transferrable skill share: Competence	–	0.010**	–	0.008	–	-0.001
		[0.005]		[0.005]		[0.003]
Basic skill share: Digital	–	0.016**	–	0.001	–	0.005
		[0.007]		[0.010]		[0.005]
Basic skill share: Knowledge	–	0.011**	–	0.008	–	-0.002
		[0.005]		[0.005]		[0.003]
Basic skill share: Thinking	–	0.011**	–	0.008*	–	-0.004
		[0.005]		[0.005]		[0.003]
Male	0.031***	0.030***	-0.012**	-0.012**	0.018***	0.017***
	[0.003]	[0.003]	[0.006]	[0.006]	[0.003]	[0.003]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	0.076***	0.075***	0.007	0.006	-0.001	0.001
	[0.022]	[0.022]	[0.044]	[0.043]	[0.030]	[0.031]
Overqualified	-0.005	-0.005	0.02	0.02	0.002	0.002
	[0.006]	[0.006]	[0.014]	[0.014]	[0.006]	[0.005]
Matched	-0.020***	-0.021***	-0.011	-0.011	-0.011**	-0.011**
	[0.005]	[0.005]	[0.012]	[0.012]	[0.005]	[0.005]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	-0.007	-0.015*	-0.015	-0.013	-0.017***	-0.022***
	[0.009]	[0.008]	[0.016]	[0.015]	[0.006]	[0.006]
Age	-0.003***	-0.003***	-0.006***	-0.006***	-0.003***	-0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Age squared/1,000	0.002	0.003	0.024**	0.024**	0.015**	0.014**
	[0.011]	[0.011]	[0.012]	[0.012]	[0.006]	[0.006]
Married	0.002	0.002	0.011	0.011	0.005	0.004
	[0.007]	[0.007]	[0.007]	[0.007]	[0.005]	[0.005]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	0.009	0.01	0.001	0.001	0.01	0.009

	[0.009]	[0.009]	[0.010]	[0.010]	[0.006]	[0.006]
Unknown marital status	0.034***	0.034***	0.054***	0.054***	0.025***	0.025***
	[0.008]	[0.008]	[0.009]	[0.009]	[0.005]	[0.005]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.014	-0.014	-0.007	-0.006	0.015	0.012
	[0.016]	[0.016]	[0.019]	[0.019]	[0.012]	[0.011]
ISCED 3: Upper secondary education	-0.02	-0.02	0.003	0.002	0.006	0.005
	[0.013]	[0.013]	[0.019]	[0.019]	[0.011]	[0.011]
ISCED 4: Post-secondary non-tertiary	-0.034**	-0.034**	0.017	0.017	-0.004	-0.004
	[0.016]	[0.016]	[0.023]	[0.023]	[0.014]	[0.013]
ISCED 5: Short-cycle tertiary education	-0.015	-0.016	0.019	0.017	0.003	0.004
	[0.015]	[0.015]	[0.019]	[0.019]	[0.011]	[0.011]
ISCED 6: Bachelor's or equivalent level	-0.01	-0.012	0.024	0.023	-0.003	-0.001
	[0.014]	[0.013]	[0.020]	[0.020]	[0.011]	[0.011]
ISCED 7: Master's or equivalent level	-0.001	-0.003	0.022	0.021	-0.005	-0.002
	[0.014]	[0.014]	[0.019]	[0.019]	[0.011]	[0.011]
ISCED 8: Doctoral or equivalent level	0.035**	0.034**	0.043**	0.043**	0.011	0.011
	[0.016]	[0.016]	[0.021]	[0.021]	[0.013]	[0.014]
Self-employed	0.077***	0.077***	0.094***	0.093***	0.031***	0.034***
	[0.011]	[0.010]	[0.016]	[0.016]	[0.010]	[0.010]
Full-time employed	0.017	0.018*	0.028	0.028	0.021**	0.024**
	[0.011]	[0.011]	[0.018]	[0.018]	[0.010]	[0.010]
Part-time employed	0.025**	0.026**	0.055***	0.055***	0.018*	0.020*
	[0.010]	[0.010]	[0.020]	[0.020]	[0.011]	[0.011]
Unemployed	0.002	0.002	-0.002	-0.002	0.006	0.007
	[0.011]	[0.011]	[0.017]	[0.016]	[0.012]	[0.011]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	-0.006	-0.006	0.005	0.005	-0.003	-0.002
	[0.012]	[0.013]	[0.019]	[0.019]	[0.013]	[0.012]
Other/Unknown	-0.016	-0.016	0.021	0.02	-0.005	-0.003
	[0.022]	[0.022]	[0.025]	[0.025]	[0.017]	[0.017]
Retired	-0.008	-0.007	-0.01	-0.01	-0.003	0.001
	[0.012]	[0.012]	[0.016]	[0.016]	[0.012]	[0.011]
Student	-0.004	-0.005	0.025	0.026	0.004	0.005
	[0.014]	[0.014]	[0.018]	[0.018]	[0.011]	[0.011]
Income fixed effects	+	+	+	+	+	+
Wealth fixed effects	+	+	+	+	+	+
Country fixed effects	+	+	+	+	+	+
%Male effect	*42.2%*	*40.7%*	*-7.6%*	*-7.6%*	*39.6%*	*37.0%*
Linear Prediction	*0.0727*	*0.0728*	*0.1614*	*0.1614*	*0.0456*	*0.0454*
No. of Observations	*29,776*	*29,776*	*29,776*	*29,776*	*29,776*	*29,776*

Notes: Marginal effects from probit models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

Basic skill shares produce similar patterns. Digital, knowledge, and thinking skills are positively associated with skill-intensive platform work. These results are consistent with the idea that workers whose occupations rely more heavily on digital and cognitive abilities may be better positioned to undertake more complex online or knowledge-based platform activities. In contrast, these basic skill shares are not significantly related to routine platform work, suggesting that routine platform activities do not rely heavily on the digital or cognitive skill structure of the main occupation.

Turning to the demographic controls, the gender pattern is consistent across the models. Men are significantly more likely than women to perform skill-intensive and routine platform work, while they are less likely to perform intermediation work. The magnitude of these marginal effects is substantial relative to the baseline probabilities reported in the table. This suggests that the gender differences observed in earlier participation models persist across specific platform task profiles, although the direction differs across segments.

Age is negatively associated with participation in all three types of platform work. The marginal effects indicate that younger workers are more likely to engage in skill-intensive, intermediation, and routine platform activities. The positive coefficient on age squared in the intermediation and routine models suggests some curvature in this relationship, although the overall pattern remains one of declining participation with age.

Labour market status again emerges as an important determinant. Self-employment is strongly and positively associated with participation in all three types of platform work. The marginal effects are particularly large for intermediation activities, indicating that individuals already operating in self-directed or entrepreneurial labour market positions are significantly more likely to engage in platform tasks across the skill spectrum. Part-time employment is also positively associated with participation in each platform category, while full-time employment is positively associated with routine platform work. These results reinforce the interpretation that platform work often complements existing labour market activity rather than replacing it.

The measures of job match also provide relevant insights. Individuals whose education matches the requirements of their main job are significantly less likely to perform skill-intensive and routine platform work compared with those who are underqualified. This suggests that platform work may be used by individuals experiencing some degree of mismatch in their main employment to access additional labour market opportunities or to utilise skills not fully rewarded in their primary occupation.

Education shows relatively limited systematic effects across most platform types. However, individuals with doctoral education are significantly more likely to perform both skill-intensive and intermediation platform work, which may reflect a higher likelihood of engaging in specialised freelance or knowledge-based tasks through digital platforms. Other education levels do not show consistent patterns once the full set of controls is included.

Overall, the results indicate that the relationship between platform work and occupational skills is not uniform across platform segments. Skill-intensive platform activities appear to be more closely connected to the skill content of workers' primary occupations, particularly in terms of transferable behavioural skills and cognitive abilities. Routine platform work, by contrast, shows weaker links with the occupational skill structure and appears less dependent on the skills embedded in the worker's main job. Intermediation activities occupy an intermediate position, displaying some association with specific sectoral or social skill components but generally weaker links with overall skill intensity. These findings suggest that platform work can serve both as an extension of existing occupational skill sets and as an alternative activity that does not necessarily rely on the skills developed in the primary job, depending on the type of platform tasks performed.

6.3 Segmentation or Competition? The Role of Platform Work in Workers' Income Portfolios

This subsection examines whether platform work primarily functions as a substitute for traditional labour market income or as a complementary activity within broader income portfolios. The previous analyses established who participates in platform work and how different types of platform activities relate to workers' skills and occupational profiles. However, these results do not directly address how platform work fits into individuals' overall labour market strategies. A key question in the literature is whether the gig economy reflects competitive substitution, in which platform work replaces standard employment, or segmentation, in which it operates alongside other sources of income as a supplementary or occasional activity. To explore this issue, the analysis distinguishes between three forms of platform engagement: platform work as a main income source, as a supplementary source of income, or as an occasional activity. These categories are compared to individuals who report no platform work. Table 4-3 presents marginal effects from a multinomial probit model that estimates the probability of belonging to each category while controlling for demographic characteristics, labour market status, income, wealth, and country-level factors.

The results indicate that platform work is most commonly observed as a supplementary or occasional income activity rather than as a primary source of earnings. The linear predictions suggest that the probability of reporting platform work as the main income source is relatively small compared with the probabilities of supplementary or occasional engagement. The probability of having no platform work remains substantially higher than any of the other categories. This pattern is broadly consistent with the interpretation that platform work frequently functions as a complementary labour market activity rather than a direct substitute for traditional employment.

Gender differences provide one of the clearest indicators of this segmentation logic. Men are significantly more likely than women to report platform work both as a main and as a supplementary income source, while they are less likely to report occasional engagement or no platform work. This suggests that men are more strongly represented among individuals who integrate platform activities into their income portfolios in a systematic way. The gender gap is particularly visible in supplementary platform work, which is consistent with the idea that platform labour is frequently used as a secondary income channel rather than a primary occupation.

Table 6-4: Does platform work complement or substitute traditional employment?

	Main income source (1)	Supplementary source (2)	Occasional activity (3)	No plarform work (4)
Male	0.012***	0.017***	-0.011***	-0.018***
	[0.002]	[0.003]	[0.004]	[0.005]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	-0.002	0.023	0.043	-0.063
	[0.021]	[0.030]	[0.034]	[0.047]
Overqualified	0.004	0.016**	-0.006	-0.013
	[0.006]	[0.007]	[0.008]	[0.011]
Matched	0.006	-0.006	-0.028***	0.028***
	[0.005]	[0.007]	[0.008]	[0.010]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	0.001	-0.009	-0.036***	0.043***
	[0.006]	[0.008]	[0.010]	[0.013]
Age	-0.002***	-0.003***	-0.003***	0.008***
	[0.001]	[0.001]	[0.001]	[0.001]
Age squared/1,000	0.011*	0.011	0.005	-0.027**
	[0.006]	[0.008]	[0.010]	[0.013]
Married	0.003	0.004	0.003	-0.01
	[0.003]	[0.004]	[0.005]	[0.007]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	0.005	-0.001	0.009	-0.013
	[0.005]	[0.008]	[0.008]	[0.011]
Unknown marital status	0.018***	0.040***	0.016***	-0.074***
	[0.004]	[0.005]	[0.006]	[0.008]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.014	0.012	0.01	-0.008
	[0.010]	[0.017]	[0.020]	[0.024]
ISCED 3: Upper secondary education	-0.028***	0.02	0.028	-0.019
	[0.009]	[0.016]	[0.018]	[0.022]
ISCED 4: Post-secondary non-tertiary	-0.023**	0.003	0.037*	-0.017
	[0.011]	[0.018]	[0.021]	[0.026]
ISCED 5: Short-cycle tertiary education	-0.026***	0.021	0.034*	-0.029
	[0.009]	[0.016]	[0.019]	[0.023]
ISCED 6: Bachelor's or equivalent level	-0.033***	0.022	0.040**	-0.029
	[0.009]	[0.016]	[0.018]	[0.023]
ISCED 7: Master's or equivalent level	-0.033***	0.017	0.057***	-0.041*
	[0.009]	[0.016]	[0.018]	[0.023]
ISCED 8: Doctoral or equivalent level	-0.021*	0.034*	0.072***	-0.086***
	[0.011]	[0.018]	[0.021]	[0.027]
Self-employed	0.049***	0.081***	0.022	-0.151***
	[0.009]	[0.013]	[0.015]	[0.019]

Full-time employed	0.011	0.024*	0.007	-0.042**
	[0.009]	[0.013]	[0.013]	[0.018]
Part-time employed	0.011	0.047***	0.019	-0.078***
	[0.009]	[0.013]	[0.014]	[0.019]
Unemployed	0.001	0.019	-0.009	-0.01
	[0.010]	[0.014]	[0.016]	[0.020]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	-0.016	0.022	0.01	-0.016
	[0.011]	[0.015]	[0.016]	[0.021]
Other/Unknown	0.002	0.016	0.004	-0.022
	[0.015]	[0.021]	[0.022]	[0.029]
Retired	-0.012	0.016	-0.011	0.008
	[0.010]	[0.014]	[0.015]	[0.019]
Student	-0.013	0.023*	0.024	-0.033*
	[0.010]	[0.014]	[0.015]	[0.020]
Income decile 10	-0.010**	0.015**	0.004	-0.009
	[0.004]	[0.006]	[0.008]	[0.010]
Income decile 9	-0.004	0.017***	-0.01	-0.003
	[0.005]	[0.006]	[0.008]	[0.010]
Income decile 8	-0.007	0.015**	0.001	-0.008
	[0.005]	[0.007]	[0.008]	[0.010]
Income decile 7	-0.003	0.01	0.005	-0.013
	[0.005]	[0.007]	[0.008]	[0.010]
Income decile 6	-0.005	0.011	0.015*	-0.020*
	[0.005]	[0.007]	[0.008]	[0.010]
Income decile 5	-0.005	0.009	0.004	-0.008
	[0.005]	[0.007]	[0.008]	[0.011]
Income decile 4	0.004	0.017**	0.004	-0.025**
	[0.005]	[0.007]	[0.008]	[0.011]
Income decile 3	-0.003	0.012*	0.009	-0.018*
	[0.005]	[0.007]	[0.008]	[0.011]
Income decile 2	0.007	0.004	0.003	-0.013
	[0.005]	[0.007]	[0.008]	[0.010]
Income decile 1	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income decile: DK/DA	-0.006	-0.01	0.004	0.012
	[0.008]	[0.010]	[0.011]	[0.015]
Wealth decile 10	-0.002	0.042***	0.032***	-0.073***
	[0.006]	[0.007]	[0.008]	[0.011]
Wealth decile 9	0.011*	0.025***	0.031***	-0.067***
	[0.006]	[0.008]	[0.010]	[0.012]
Wealth decile 8	0.006	0.036***	0.039***	-0.081***
	[0.006]	[0.007]	[0.009]	[0.012]
Wealth decile 7	0.014**	0.038***	0.025***	-0.076***
	[0.005]	[0.007]	[0.009]	[0.011]
Wealth decile 6	0.016***	0.040***	0.018**	-0.074***
	[0.005]	[0.007]	[0.009]	[0.011]
Wealth decile 5	0.020***	0.038***	0.018**	-0.076***

	[0.005]	[0.007]	[0.008]	[0.010]
Wealth decile 4	0.020***	0.032***	0.026***	-0.077***
	[0.004]	[0.006]	[0.007]	[0.009]
Wealth decile 3	0.019***	0.030***	0.007	-0.057***
	[0.004]	[0.006]	[0.007]	[0.009]
Wealth decile 2	0.019***	0.020***	0.013**	-0.052***
	[0.004]	[0.006]	[0.007]	[0.008]
Wealth decile 1	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth decile: DK/DA	-0.015***	-0.006	-0.004	0.025**
	[0.005]	[0.007]	[0.008]	[0.010]
Austria	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Belgium	0.008	0.031***	-0.008	-0.031*
	[0.007]	[0.010]	[0.013]	[0.016]
Bulgaria	0.006	0.044***	-0.032***	-0.017
	[0.006]	[0.010]	[0.013]	[0.016]
Croatia	0.012	0.060***	0.053***	-0.126***
	[0.008]	[0.012]	[0.016]	[0.019]
Cyprus	-0.005	0.013	-0.042***	0.034*
	[0.008]	[0.013]	[0.016]	[0.020]
Czech Republic	0.001	-0.009	-0.018	0.025
	[0.006]	[0.008]	[0.013]	[0.016]
Denmark	-0.006	0.001	0.006	-0.001
	[0.006]	[0.009]	[0.014]	[0.016]
Estonia	-0.005	-0.002	-0.054***	0.062***
	[0.006]	[0.009]	[0.012]	[0.015]
Finland	-0.010*	-0.001	-0.023*	0.034**
	[0.005]	[0.008]	[0.013]	[0.015]
France	0.018**	0.014	0.002	-0.034**
	[0.008]	[0.009]	[0.014]	[0.017]
Germany	0.021**	0.019*	0.005	-0.045***
	[0.008]	[0.010]	[0.014]	[0.017]
Greece	0.013*	0.022**	0.001	-0.036**
	[0.007]	[0.009]	[0.014]	[0.017]
Hungary	0.023***	0.043***	-0.023*	-0.044**
	[0.009]	[0.011]	[0.013]	[0.017]
Ireland	0.011*	0.006	-0.005	-0.012
	[0.006]	[0.008]	[0.013]	[0.016]
Italy	0.022***	0.030***	0.112***	-0.164***
	[0.008]	[0.011]	[0.017]	[0.019]
Latvia	0.002	0.030***	-0.036***	0.004
	[0.007]	[0.010]	[0.013]	[0.017]
Lithuania	0.002	0.030***	0.003	-0.035**
	[0.007]	[0.010]	[0.014]	[0.017]
Luxembourg	0.003	-0.030***	-0.015	0.042**
	[0.008]	[0.007]	[0.016]	[0.019]
Malta	-0.006	-0.023***	-0.065***	0.093***
	[0.007]	[0.008]	[0.013]	[0.017]

Netherlands	0.009	0.035***	-0.027**	-0.017
	[0.007]	[0.010]	[0.013]	[0.016]
Poland	0.020***	0.098***	-0.046***	-0.071***
	[0.008]	[0.012]	[0.012]	[0.017]
Portugal	0.019**	0.038***	0.049***	-0.106***
	[0.008]	[0.010]	[0.015]	[0.017]
Romania	0.029***	0.057***	-0.017	-0.069***
	[0.008]	[0.011]	[0.013]	[0.017]
Slovakia	0.020**	0.014	-0.008	-0.026
	[0.008]	[0.009]	[0.014]	[0.017]
Slovenia	0.007	0.034***	0.038**	-0.079***
	[0.007]	[0.011]	[0.015]	[0.018]
Spain	0.037***	0.042***	0.023	-0.102***
	[0.009]	[0.011]	[0.015]	[0.018]
Sweden	0.038***	0.065***	-0.083***	-0.02
	[0.008]	[0.011]	[0.011]	[0.016]
Serbia	0.002	0.053***	0.013	-0.068***
	[0.007]	[0.011]	[0.015]	[0.018]
Switzerland	0.002	-0.004	0.003	-0.001
	[0.006]	[0.007]	[0.014]	[0.016]
Turkey	0.057***	0.087***	-0.033***	-0.111***
	[0.010]	[0.011]	[0.013]	[0.017]
United Kingdom	0.020**	0.065***	0.038***	-0.123***
	[0.008]	[0.011]	[0.015]	[0.018]
%Male effect	*34.1%*	*25.2%*	*-10.2%*	*-2.3%*
Linear Prediction	*0.0357*	*0.0679*	*0.1068*	*0.7896*
No. of Observations	*29,872*	*29,872*	*29,872*	*29,872*

Notes: Marginal effects from multinomial probit models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

Age also plays a significant role. The negative marginal effects for age across the three platform work categories indicate that younger individuals are more likely to engage in platform work in any form, while older individuals are more likely to report no platform activity. This age gradient suggests that platform work is more strongly integrated into the labour market strategies of younger cohorts, potentially reflecting greater familiarity with digital technologies, lower barriers to entry, or greater willingness to combine multiple sources of income.

Labour market status further reinforces the interpretation of platform work as a complementary activity. Self-employed individuals show strong positive associations with both main and supplementary platform work. This pattern indicates that individuals already engaged in entrepreneurial or freelance activities are more likely to incorporate platform-mediated work into their broader business strategies. Full-time and part-time employees are also more likely to report supplementary platform work than inactive individuals, although the magnitude of the effect is smaller. This suggests that many workers combine traditional employment with platform activities rather than replacing one with the other. At the same time, the absence of strong effects for unemployment indicates that platform work does not primarily function as a substitute for job loss, which again supports the segmentation interpretation.

Education patterns provide additional insight into how platform work fits within the broader labour market structure. Higher levels of education are associated with a lower probability of relying on platform work as the main income source but a higher probability of performing it occasionally. For example, individuals with bachelor's, master's, or doctoral degrees are significantly more likely to report occasional platform activity than those with primary education. This suggests that highly educated individuals may participate in platform work on a limited or opportunistic basis, e.g. through digital freelancing, content creation, or asset-based activities, rather than as a primary source of income.

Income and wealth measures reveal further evidence of segmentation. Higher income deciles are generally associated with a greater likelihood of supplementary platform work rather than main platform income. Similarly, wealth deciles show a strong positive association with supplementary and occasional platform work and a negative association with having no platform activity. Individuals with higher levels of wealth appear more likely to participate in platform markets, particularly in ways that complement other sources of income. This may reflect greater access to assets that can be monetised through platforms, e.g. property, vehicles, or capital used for online commerce.

Finally, the country-level coefficients indicate substantial cross-national variation in how platform work is integrated into income portfolios. Several countries display particularly strong positive associations with supplementary platform work, while others show higher probabilities of occasional engagement. These differences likely reflect variation in labour market institutions, digital platform penetration, and the availability of specific platform sectors across countries.

Overall, the results provide strong evidence that platform work is primarily embedded within segmented labour market strategies rather than representing a direct substitute for traditional employment. Most participation occurs either as supplementary income generation or as occasional activity, while relatively few individuals rely on platforms as their main source of earnings. The patterns across employment status, income, and wealth suggest that platform work is frequently used to diversify income sources or complement existing labour market positions rather than to replace them. This supports the view that the gig economy operates as a flexible layer within the labour market, allowing workers to combine multiple forms of work rather than competing directly with standard employment.

The multinomial probit results in the previous table indicate that platform work is not a single, uniform labour market state but is instead embedded in different income strategies, ranging from platform work as a main income source to supplementary and occasional engagement. That framing motivates a natural next step for assessing segmentation versus competition: if platform work is segmented into distinct participation modes, we should also observe systematic differences in the capabilities that workers bring to these modes, particularly in forms of practical knowledge that matter for navigating markets, institutions, and digital environments. The literacy profiles Table 6-5 extends the segmentation logic by shifting attention from "how platform work fits into income portfolios" to "what kinds of human capital profiles are associated with those portfolio positions." In other words, it asks whether the groups identified previously (main-income platform workers, supplementary platform workers, and occasional platform workers) differ in the kinds of literacies that support economic resilience and effective participation in digitally mediated work.

Conceptually, this matters because segmentation implies more than differences in how much people rely on platform work. It implies that platform work may be stratified into tiers with different resources, constraints, and opportunities. Literacy measures provide one way to observe this stratification. If platform work primarily reflects competitive substitution, i.e., workers moving into platform work because they cannot secure standard employment, we might expect lower literacy profiles among those relying on platform work as their main income source, reflecting weaker general resources and potentially greater vulnerability. If platform work primarily reflects complementary diversification, i.e., workers adding platform work on top of other income sources, we might instead expect neutral or even higher literacy profiles among supplementary or occasional participants, consistent with a group that uses platforms opportunistically and can navigate financial, digital, and informational demands. The literacy table operationalises this test by comparing each platform engagement category with the reference group of those without platform work, holding constant a wide set of socio-demographic and labour market controls.

In the results from OLS estimates in Table 6-5. the pattern in the literacy profiles provides a clear bridge to the segmentation interpretation. Respondents for whom platform work is the main income source display substantially lower scores across a wide range of literacies, including financial, retirement, health, digital finance, media, AI, environmental, and sustainable finance literacies. These negative and statistically significant associations are large in magnitude and broad in scope, suggesting that main-income platform workers, on average, are less equipped in multiple domains that are likely to matter for longer-term economic security and informed decision-making. This profile is consistent with a more disadvantaged segment for whom platform work may be less a strategic choice and more a constraint-driven outcome, aligning with a competition or substitution narrative for this subgroup. At the same time, the coefficients show that this group is positively associated with data literacy, implying that lower literacy is not universal across all domains and that some platform-reliant workers may develop or select into specific competencies linked to data handling or data-related tasks even while lagging in other forms of literacy.

The supplementary income group also shows negative associations for several literacies, but the pattern is weaker and more selective than for main-income platform workers. Significant negative coefficients remain for financial, retirement, health, media, AI, environmental, and sustainable finance literacy, but the magnitudes are smaller, and there is no statistically significant disadvantage in digital finance literacy. This suggests that supplementary platform workers occupy an intermediate position: they resemble a segmented group that is more resourced than main-income platform workers but still differs from non-platform workers in ways that may indicate constraints or uneven access to certain forms of knowledge. The positive association with data literacy is again present and sizeable, reinforcing the idea that some platform engagement is linked to specific competencies even when broader literacy profiles are lower.

In contrast, occasional platform workers exhibit a distinctly different profile. They show positive and statistically significant associations across many literacies, including financial literacy, digital finance literacy, media literacy, AI literacy, data literacy, political literacy, environmental literacy, sustainable finance literacy, human literacy, and cultural agility. This consistent pattern of positive coefficients suggests that occasional platform work is associated with a comparatively advantaged

Table 6-5: How do literacy profiles vary across modes of platform work participation?

	Financial literacy (1)	Retirement literacy (2)	Health literacy (3)	Digital finance literacy (4)	Media literacy (5)	AI literacy (6)	Data literacy (7)	Political literacy (8)	Environ-mental literacy (9)	Sustainab-le finance literacy (10)	Human literacy (11)	Cultural agility (12)
PW: Main	-0.364***	-0.227***	-0.396***	-0.266***	-0.374***	-0.853***	0.330***	0.014	-0.251***	-0.658***	-0.047	-0.067**
income source	[0.046]	[0.050]	[0.042]	[0.040]	[0.035]	[0.088]	[0.033]	[0.042]	[0.030]	[0.039]	[0.039]	[0.031]
PW: Supplement.	-0.131***	-0.087***	-0.142***	0.021	-0.087***	-0.318***	0.273***	0.097**	-0.089***	-0.255***	0.046	0.033
income	[0.026]	[0.024]	[0.032]	[0.024]	[0.023]	[0.064]	[0.033]	[0.037]	[0.019]	[0.025]	[0.027]	[0.027]
PW: Occasional	0.041**	0.02	0.023	0.117***	0.075***	0.177***	0.122***	0.123***	0.048***	0.054***	0.046***	0.036**
activity	[0.015]	[0.012]	[0.019]	[0.017]	[0.018]	[0.044]	[0.018]	[0.025]	[0.013]	[0.015]	[0.016]	[0.014]
No platform work	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Male	0.313***	0.090***	-0.151***	0.026**	0.071***	0.217***	0.256***	0.297***	0.131***	0.008	-0.119***	-0.070***
	[0.016]	[0.013]	[0.013]	[0.011]	[0.015]	[0.029]	[0.023]	[0.017]	[0.011]	[0.014]	[0.012]	[0.012]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	0.02	0.001	-0.052	-0.169	0.277**	0.554**	-0.118	0.188	0.253***	0.169*	0.136	0.06
	[0.132]	[0.098]	[0.131]	[0.116]	[0.121]	[0.220]	[0.122]	[0.154]	[0.065]	[0.097]	[0.138]	[0.098]
Overqualified	0.123***	0.052	0.092***	0.111***	0.104***	0.257***	0.166***	0.139***	0.071***	0.155***	0.109***	0.069**
	[0.035]	[0.032]	[0.024]	[0.026]	[0.033]	[0.073]	[0.025]	[0.035]	[0.023]	[0.026]	[0.029]	[0.027]
Matched	0.097***	0.065**	0.104***	0.126***	0.096***	0.146**	0.131***	0.132***	0.077***	0.145***	0.186***	0.083***
	[0.026]	[0.029]	[0.026]	[0.021]	[0.027]	[0.071]	[0.023]	[0.032]	[0.023]	[0.029]	[0.023]	[0.025]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	-0.161***	-0.076**	-0.106***	-0.145***	-0.114***	-0.383***	0.02	-0.125***	-0.065**	-0.137***	-0.073**	-0.069***
	[0.032]	[0.033]	[0.030]	[0.023]	[0.031]	[0.072]	[0.032]	[0.030]	[0.026]	[0.031]	[0.032]	[0.024]
Age	-0.003	0.020***	0.009***	-0.013***	-0.006	0.001	-0.016***	0.001	0.002	0.014***	-0.008**	0.002
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.008]	[0.005]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]
Age	0.058*	-0.208***	-0.057*	0.097**	0.013	-0.091	0.039	0.094***	-0.014	-0.086***	0.084**	0.004
squared/1,000	[0.032]	[0.035]	[0.031]	[0.038]	[0.039]	[0.075]	[0.045]	[0.029]	[0.029]	[0.028]	[0.032]	[0.024]
Married	0.024	0.006	0.065***	-0.013	-0.059***	-0.183***	0.056**	-0.033*	-0.014	-0.02	0.050***	0.004
	[0.019]	[0.018]	[0.017]	[0.014]	[0.020]	[0.039]	[0.025]	[0.019]	[0.012]	[0.019]	[0.018]	[0.013]

Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Div./	-0.003	0.008	0.016	-0.009	-0.066*	-0.129**	0.036	-0.123***	-0.018	-0.002	0.045*	-0.007
Separated	[0.028]	[0.024]	[0.025]	[0.027]	[0.033]	[0.055]	[0.031]	[0.030]	[0.019]	[0.029]	[0.024]	[0.022]
Unknown	-0.049	-0.063**	-0.049	0.011	-0.092***	-0.292***	0.065***	-0.083**	-0.083***	-0.076**	0.04	-0.01
marital status	[0.030]	[0.030]	[0.032]	[0.019]	[0.030]	[0.069]	[0.023]	[0.033]	[0.017]	[0.031]	[0.027]	[0.025]
Primary educatior	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Lower secondary	0.007	-0.016	0.012	0.089	-0.036	0.049	-0.088	0.035	0.031	0.081	0.005	0.044
education	[0.063]	[0.048]	[0.047]	[0.053]	[0.061]	[0.104]	[0.084]	[0.061]	[0.043]	[0.052]	[0.055]	[0.052]
Upper secondary	0.226***	0.130***	0.150***	0.209***	0.157**	0.605***	0.129	0.247***	0.139***	0.276***	0.084	0.158***
education	[0.055]	[0.043]	[0.044]	[0.052]	[0.064]	[0.090]	[0.077]	[0.052]	[0.047]	[0.060]	[0.054]	[0.055]
Post-sec. non-	0.239***	0.185***	0.187***	0.246***	0.183**	0.787***	0.227**	0.296***	0.176***	0.375***	0.134*	0.232***
Tertiary educ.	[0.065]	[0.045]	[0.058]	[0.068]	[0.072]	[0.124]	[0.108]	[0.074]	[0.063]	[0.072]	[0.076]	[0.060]
Short-cycle	0.318***	0.182***	0.248***	0.252***	0.262***	0.841***	0.269***	0.320***	0.202***	0.345***	0.128**	0.234***
tertiary educ.	[0.059]	[0.047]	[0.040]	[0.050]	[0.060]	[0.087]	[0.085]	[0.051]	[0.050]	[0.060]	[0.054]	[0.058]
Bachelor's or eq.	0.449***	0.284***	0.280***	0.289***	0.375***	1.083***	0.408***	0.454***	0.254***	0.467***	0.219***	0.321***
	[0.055]	[0.049]	[0.040]	[0.054]	[0.061]	[0.092]	[0.079]	[0.055]	[0.048]	[0.059]	[0.054]	[0.055]
Master's or eq.	0.557***	0.361***	0.363***	0.319***	0.455***	1.358***	0.523***	0.568***	0.304***	0.519***	0.273***	0.359***
	[0.061]	[0.047]	[0.044]	[0.054]	[0.069]	[0.106]	[0.080]	[0.060]	[0.049]	[0.065]	[0.062]	[0.059]
Doctoral or eq.	0.485***	0.296***	0.331***	0.224***	0.403***	1.247***	0.588***	0.487***	0.287***	0.440***	0.277***	0.295***
	[0.053]	[0.052]	[0.049]	[0.059]	[0.077]	[0.127]	[0.083]	[0.102]	[0.067]	[0.084]	[0.071]	[0.067]
Self-employed	0.199***	0.130***	0.046	-0.087*	-0.003	0.027	0.122**	-0.012	-0.022	0.02	-0.047	-0.045
	[0.043]	[0.038]	[0.043]	[0.045]	[0.047]	[0.088]	[0.048]	[0.043]	[0.029]	[0.041]	[0.042]	[0.031]
Full-time	0.111***	0.041	0.011	-0.132***	-0.172***	-0.263***	0.184***	-0.067	-0.033	-0.052	-0.106***	-0.072**
employed	[0.039]	[0.036]	[0.041]	[0.038]	[0.043]	[0.082]	[0.046]	[0.042]	[0.030]	[0.040]	[0.033]	[0.031]
Part-time	0.095**	0.051	0.025	-0.094**	-0.128***	-0.171**	0.090*	0.005	-0.04	-0.051	-0.042	-0.049
employed	[0.036]	[0.033]	[0.037]	[0.040]	[0.045]	[0.082]	[0.045]	[0.042]	[0.035]	[0.036]	[0.039]	[0.032]
Unemployed	0.134***	0.078*	0.027	0.026	-0.006	0.036	0.194***	0.003	0	0.079*	0.012	-0.057
	[0.047]	[0.039]	[0.045]	[0.043]	[0.044]	[0.093]	[0.051]	[0.043]	[0.033]	[0.042]	[0.049]	[0.037]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	0.051	-0.01	0.042	-0.095**	-0.125***	-0.044	0.093	-0.096*	-0.047	-0.091	-0.069	-0.098**

	[0.048]	[0.042]	[0.039]	[0.040]	[0.039]	[0.082]	[0.056]	[0.048]	[0.039]	[0.058]	[0.044]	[0.040]
Other/Unknown	0.130*	0.085*	0.015	-0.022	-0.009	0.056	0.139*	0.018	0.046	0.094	0.018	-0.142***
	[0.076]	[0.049]	[0.046]	[0.068]	[0.063]	[0.123]	[0.073]	[0.071]	[0.061]	[0.075]	[0.069]	[0.050]
Retired	0.151***	0.049	0.067	-0.094**	-0.068	-0.07	0.065	0.035	0.025	0.054	-0.016	-0.046
	[0.040]	[0.033]	[0.043]	[0.040]	[0.040]	[0.092]	[0.053]	[0.046]	[0.034]	[0.041]	[0.035]	[0.029]
Student	0.444***	0.170***	0.301***	0.161***	0.195***	0.586***	0.396***	0.322***	0.200***	0.318***	0.173***	0.102**
	[0.042]	[0.046]	[0.046]	[0.047]	[0.035]	[0.093]	[0.051]	[0.060]	[0.039]	[0.043]	[0.042]	[0.046]
Income F.E.	+	+	+	+	+	+	+	+	+	+	+	+
Wealth F.E.	+	+	+	+	+	+	+	+	+	+	+	+
Country F.E.	+	+	+	+	+	+	+	+	+	+	+	+
%Male effect	*14.9%*	*9.5%*	*-6.9%*	*1.4%*	*5.1%*	*6.1%*	*9.2%*	*17.9%*	*7.4%*	*0.4%*	*-11.1%*	*-6.7%*
Linear Prediction	*2.1052*	*0.9519*	*2.2043*	*1.925*	*1.3902*	*3.5655*	*2.779*	*1.6592*	*1.771*	*2.2842*	*1.0719*	*1.0355*
# Observations	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*	*29,872*

Notes: Coefficients from linear regression models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

literacy profile. Conceptually, this aligns closely with the segmentation argument developed from the multinomial results: occasional engagement appears more characteristic of workers who can use platforms opportunistically as a flexible complement to other activities, supported by higher levels of informational and digital capability. In segmentation terms, occasional platform work looks less like a fallback and more like a choice enabled by resources and adaptability.

Taken together, the literacy table deepens the segmentation story by showing that the three platform engagement modes map onto systematically different capability profiles. Main-income platform workers appear concentrated in a segment with broad literacy disadvantages, supplementary platform workers occupy an intermediate position, and occasional platform workers show consistently higher literacy levels across multiple domains. This layered pattern is difficult to reconcile with a simple one-dimensional story in which platform work is either uniformly empowering or uniformly precarious. Instead, it supports an interpretation in which platform work contains qualitatively different strata, and where the degree of reliance on platform income is associated with differences in the resources that workers bring to platform markets and their ability to navigate the institutional and informational demands that accompany digitally mediated work.

6.4 Resilience and vulnerability in the platform economy

The previous subsection examined whether platform work participation reflects patterns of segmentation in terms of income reliance and skill endowments. The results suggested that platform work is not a homogeneous labour market phenomenon but instead encompasses distinct groups of workers with different levels of attachment to digital labour markets and different profiles of knowledge and literacies. While literacy indicators provide insight into the cognitive resources workers possess, they do not necessarily capture how individuals perceive their capacity to cope with labour market risks or adapt to changing economic conditions. To further assess whether platform work participation is associated with structural vulnerability or adaptive labour market behaviour, this subsection turns to indicators of labour market resilience. In particular, the analysis examines whether workers who rely on platform work as a main, supplementary, or occasional income source differ in their reported levels of labour market resilience, adaptability, engagement in upskilling, and confidence in navigating employment transitions. These indicators provide an additional perspective on the segmentation of platform work by examining whether greater reliance on platform income is associated with weaker labour market resources or, alternatively, with stronger adaptive capacities.

The estimates reported in Table 6-6 indicate that individuals engaged in platform work display significantly higher levels of labour market resilience across several dimensions compared with those who do not participate in platform activities. The strongest effects are observed for individuals who rely on platform work as their main source of income. These workers report substantially higher levels of overall labour market resilience, with a marginal effect of 0.575, alongside significantly higher levels of adaptability, engagement in upskilling activities, and confidence in navigating labour market transitions. Workers who rely on platform work as a supplementary income source exhibit a very similar pattern.

Table 6-6: Do platform workers exhibit labour market resilience?

	Labour market resilience index (1)	Adaptability (2)	Upskilling (3)	Confidence (4)
Platform work is main income source	0.575***	0.075***	0.368***	0.097***
	[0.063]	[0.019]	[0.028]	[0.026]
Platform work is supplementary income	0.526***	0.083***	0.335***	0.062***
	[0.049]	[0.019]	[0.023]	[0.021]
Platform work is occasional activity	0.242***	0.028**	0.145***	0.025*
	[0.034]	[0.010]	[0.019]	[0.014]
No platform work	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Male	0.073**	0.070***	-0.030*	0.036***
	[0.027]	[0.009]	[0.016]	[0.011]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	0.238	-0.022	0.398**	-0.019
	[0.228]	[0.092]	[0.146]	[0.109]
Overqualified	0.460***	0.154***	0.109***	0.216***
	[0.060]	[0.021]	[0.034]	[0.028]
Matched	0.654***	0.154***	0.188***	0.326***
	[0.042]	[0.019]	[0.028]	[0.023]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	-0.103*	0.025	-0.023	0.091***
	[0.059]	[0.026]	[0.032]	[0.030]
Age	-0.015***	-0.012***	-0.009***	-0.007***
	[0.005]	[0.002]	[0.003]	[0.002]
Age squared/1,000	-0.043	0.060***	0.035	-0.006
	[0.053]	[0.018]	[0.030]	[0.024]
Married	0.124***	0.029*	0.024	0.064***
	[0.041]	[0.014]	[0.025]	[0.015]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	0.200***	0.051**	0.077**	0.056**
	[0.057]	[0.024]	[0.032]	[0.024]
Unknown marital status	0.218***	0.047***	0.100***	0.074***
	[0.054]	[0.016]	[0.027]	[0.020]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.047	-0.019	-0.089	0.01
	[0.126]	[0.051]	[0.062]	[0.056]
ISCED 3: Upper secondary education	0.313***	0.058	0.107*	0.059
	[0.108]	[0.050]	[0.053]	[0.041]
ISCED 4: Post-secondary non-tertiary education	0.560***	0.109*	0.225***	0.143***
	[0.141]	[0.057]	[0.063]	[0.051]

ISCED 5: Short-cycle tertiary education	0.541***	0.087*	0.303***	0.07
	[0.107]	[0.050]	[0.053]	[0.042]
ISCED 6: Bachelor's or equivalent level	0.615***	0.100*	0.347***	0.059
	[0.111]	[0.051]	[0.050]	[0.041]
ISCED 7: Master's or equivalent level	0.809***	0.137**	0.474***	0.086*
	[0.120]	[0.050]	[0.054]	[0.046]
ISCED 8: Doctoral or equivalent level	0.855***	0.164***	0.510***	0.064
	[0.121]	[0.055]	[0.065]	[0.044]
Self-employed	0.873***	0.125***	0.360***	0.371***
	[0.080]	[0.033]	[0.046]	[0.042]
Full-time employed	0.877***	0.113***	0.367***	0.360***
	[0.076]	[0.030]	[0.044]	[0.035]
Part-time employed	0.708***	0.047	0.304***	0.306***
	[0.083]	[0.032]	[0.044]	[0.044]
Unemployed	0.516***	0.114***	0.310***	0.018
	[0.090]	[0.033]	[0.050]	[0.046]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	0.047	0.022	-0.071	0.084
	[0.103]	[0.035]	[0.058]	[0.052]
Other/Unknown	0.425***	0.087**	0.185**	0.189***
	[0.102]	[0.037]	[0.071]	[0.065]
Retired	0.312***	0.062**	0.063	0.252***
	[0.081]	[0.029]	[0.050]	[0.040]
Student	1.068***	0.168***	0.495***	0.315***
	[0.090]	[0.035]	[0.051]	[0.053]
Income fixed effects	+	+	+	+
Wealth fixed effects	+	+	+	+
Country fixed effects	+	+	+	+
%Male effect	*1.9%*	*5.6%*	*22.2%*	*3.2%*
Linear Prediction	*3.7998*	*1.2443*	*1.6191*	*1.1261*
No. of Observations	*29,872*	*29,872*	*29,872*	*29,872*
	.	.	.	.
Notes: Coefficients from linear regression models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01				

The magnitude of the effects is slightly smaller but remains strongly positive and statistically significant across all resilience indicators. Individuals who engage in platform work only occasionally also display higher levels of labour market resilience, although the estimated effects are more moderate compared with workers who rely more heavily on platform income.

These results suggest that platform workers, particularly those who depend on platform work for a significant share of their income, tend to report stronger perceptions of their ability to adapt to changing labour market conditions and to acquire new skills when needed. One interpretation is that engagement in platform work itself may foster adaptive behaviour, as digital labour markets often require workers to manage fluctuating demand, continuously search for tasks, and maintain a flexible approach to income generation. Alternatively, workers with stronger adaptive orientations may be more likely to enter and remain active in platform-mediated labour markets in the first place.

The findings also reveal clear differences across labour market statuses and educational attainment. Individuals whose qualifications match or exceed the requirements of their current occupation report substantially higher levels of labour market resilience, adaptability, and confidence compared with underqualified workers. Higher levels of formal education are also strongly associated with higher resilience indicators, particularly with respect to engagement in upskilling activities. Employment status plays a similar role, with self-employed individuals, full-time employees, and students displaying higher resilience scores across most indicators relative to inactive individuals. These patterns are consistent with the broader literature emphasising the role of human capital and labour market attachment in shaping workers' capacity to respond to structural change.

Taken together, the results complicate a purely vulnerability-based interpretation of platform work. Although previous tables indicated that some groups of platform workers exhibit lower literacy levels in several domains, the resilience indicators presented here suggest that many platform workers simultaneously report stronger adaptive capacities and a greater willingness to engage in skill development. This combination points to a more nuanced form of segmentation within the platform economy, where workers may simultaneously face structural constraints in terms of income stability or skill profiles while also displaying high levels of behavioural adaptability. The following analysis extends this perspective by examining whether similar patterns emerge with respect to financial resilience, which provides an additional indicator of workers' ability to cope with economic shocks and income volatility.

The previous analysis examined labour market resilience among platform workers, focusing on indicators such as adaptability, upskilling behaviour, and confidence in navigating employment transitions. While these indicators provide insight into workers' perceived capacity to respond to labour market changes, they do not necessarily reflect the degree of financial security associated with different forms of platform work. Resilience in terms of adaptability and skill acquisition may coexist with significant economic vulnerability if workers face unstable income streams or limited financial buffers. To further assess the implications of platform work for economic security, the next table examines financial resilience and financial strain across different forms of platform work participation. In addition to an overall indicator of financial resilience, the analysis distinguishes between short-term, medium-term, and long-term financial coping strategies, thereby providing a more nuanced view of how workers manage financial risks and income volatility.

The results presented in Table 6-7 indicate that platform work is associated with lower levels of financial resilience and higher levels of financial strain, particularly among individuals who rely on platform work as their main source of income. Workers for whom platform work constitutes their primary income source report significantly lower levels of financial resilience compared with individuals who do not engage in platform work, alongside a higher probability of experiencing financial strain. These workers are also less likely to report having short-term or medium-term financial coping mechanisms available. The results therefore suggest that heavy reliance on platform income is associated with weaker financial buffers and greater exposure to economic insecurity.

Table 6-7: Financial resilience and financial coping strategies among platform workers

	Financial resilience (1)	Financial strain (2)	Short-term means (3)	Medium-term means (4)	Long-term means (5)
PW is main income source	-0.262***	0.144***	-0.162***	-0.186***	-0.031
	[0.045]	[0.042]	[0.021]	[0.028]	[0.025]
PW is supplementary income	-0.149***	0.068**	-0.048***	-0.062**	0.034
	[0.037]	[0.033]	[0.017]	[0.025]	[0.023]
PW is occasional activity	-0.095***	0.054**	0.074***	0.137***	0.090***
	[0.026]	[0.025]	[0.016]	[0.017]	[0.020]
No platform work	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Male	0.022	-0.065***	0.011	0.038**	0.060***
	[0.017]	[0.014]	[0.010]	[0.016]	[0.012]
Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Non binary	-0.164	0.112	0.123	0.27	0.085
	[0.248]	[0.212]	[0.173]	[0.168]	[0.145]
Overqualified	0.153***	-0.148***	0.059**	0.062*	0.042*
	[0.040]	[0.039]	[0.025]	[0.033]	[0.023]
Matched	0.336***	-0.308***	0.023	0.011	-0.014
	[0.025]	[0.026]	[0.021]	[0.027]	[0.016]
Underqualified	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Never worked	0.210***	-0.149***	-0.187***	-0.247***	-0.241***
	[0.038]	[0.036]	[0.030]	[0.032]	[0.022]
Age	-0.026***	0.030***	-0.004	0.011***	0.004
	[0.004]	[0.004]	[0.003]	[0.004]	[0.003]
Age squared/1,000	0.337***	-0.371***	0.009	-0.181***	-0.102***
	[0.043]	[0.037]	[0.035]	[0.040]	[0.028]
Married	0.037	-0.032	0.003	0.02	0.01
	[0.023]	[0.023]	[0.015]	[0.023]	[0.022]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Widowed/Divorced/Separated	-0.106**	0.108***	0.001	0.042	0.022
	[0.039]	[0.033]	[0.026]	[0.030]	[0.033]
Unknown marital status	-0.084	0.071*	-0.009	-0.012	0.02
	[0.051]	[0.041]	[0.020]	[0.022]	[0.027]
ISCED 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary	-0.113	0.067	0.049	0.048	0.091*
	[0.081]	[0.072]	[0.052]	[0.042]	[0.051]
ISCED 3: Upper secondary	-0.075	0.037	0.172***	0.155***	0.140**
	[0.074]	[0.069]	[0.049]	[0.042]	[0.052]
ISCED 4: Post-secondary non-	0.044	-0.071	0.217***	0.207***	0.167***
	[0.087]	[0.083]	[0.057]	[0.043]	[0.051]
ISCED 5: Short-cycle tertiary	0.01	-0.075	0.217***	0.214***	0.209***
	[0.076]	[0.070]	[0.051]	[0.043]	[0.057]

ISCED 6: Bachelor's or	0.058	-0.127*	0.281***	0.279***	0.243***
	[0.076]	[0.070]	[0.052]	[0.040]	[0.053]
ISCED 7: Master's or	0.119	-0.193**	0.321***	0.362***	0.286***
	[0.079]	[0.071]	[0.052]	[0.041]	[0.053]
ISCED 8: Doctoral or	0.077	-0.149**	0.269***	0.230***	0.231***
	[0.074]	[0.073]	[0.071]	[0.054]	[0.057]
Self-employed	0.440***	-0.320***	0.075*	0.07	0.05
	[0.058]	[0.048]	[0.038]	[0.043]	[0.044]
Full-time employed	0.458***	-0.353***	0.038	0.075*	0.06
	[0.050]	[0.044]	[0.036]	[0.038]	[0.038]
Part-time employed	0.334***	-0.222***	0.056	0.111**	0.04
	[0.043]	[0.040]	[0.034]	[0.044]	[0.044]
Unemployed	-0.015	0.063	0.041	0.148***	0.106**
	[0.064]	[0.060]	[0.039]	[0.043]	[0.047]
Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Homemaker	0.204***	-0.139**	0.081**	0.018	0.055
	[0.064]	[0.054]	[0.032]	[0.039]	[0.039]
Other/Unknown	0.315***	-0.198***	0.056	0.077	0.035
	[0.083]	[0.071]	[0.051]	[0.068]	[0.061]
Retired	0.316***	-0.247***	0.067**	-0.024	-0.017
	[0.051]	[0.041]	[0.027]	[0.036]	[0.041]
Student	0.378***	-0.287***	0.243***	0.269***	0.192***
	[0.064]	[0.056]	[0.046]	[0.051]	[0.048]
Income fixed effects	+	+	+	+	+
Wealth fixed effects	+	+	+	+	+
Country fixed effects	+	+	+	+	+
%Male effect	*0.9%*	*-6.4%*	*0.8%*	*2.5%*	*4.9%*
Linear Prediction	*2.403*	*1.0197*	*1.4551*	*1.5071*	*1.2337*
No. of Observations	*28,905*	*28,905*	*29,872*	*29,872*	*29,872*

Notes: Coefficients from linear regression models are presented. The standard errors are robust and clustered at the country level. The asterisks denote the following levels of significance: * p<0.10, ** p<0.05, *** p<0.01

A similar but somewhat weaker pattern is observed among individuals who use platform work as a supplementary income source. Although the magnitude of the estimated effects is smaller, supplementary platform workers also display lower levels of financial resilience and higher levels of financial strain compared with non-platform workers. In addition, these workers report fewer short-term and medium-term financial coping strategies. These findings suggest that platform work used as a secondary income stream may not necessarily improve financial security and may instead reflect attempts to compensate for insufficient income from primary employment.

In contrast, individuals who engage in platform work only occasionally exhibit a different pattern. While occasional platform workers still report slightly lower overall financial resilience and somewhat higher financial strain, they are significantly more likely to report access to short-term, medium-term, and long-term financial coping mechanisms. This pattern suggests that occasional engagement in platform work may function as a supplementary income diversification strategy rather than as a primary response to financial vulnerability.

Taken together, the results highlight an important contrast between labour market and financial resilience among platform workers. While previous results indicated that platform workers often display relatively high levels of adaptability and engagement in upskilling, the findings presented here suggest that these adaptive capacities do not necessarily translate into stronger financial security. Instead, workers who depend most heavily on platform income appear to face greater financial vulnerability despite reporting higher levels of labour market adaptability. This combination of adaptive behaviour and economic insecurity is consistent with the broader interpretation of the platform economy as a segmented labour market, where some workers actively leverage digital labour markets as a flexible income source while others rely on them in response to structural economic constraints.

The results presented in this subsection highlight an important tension in the economic position of platform workers. On the one hand, individuals engaged in platform work tend to report higher levels of labour market resilience, including stronger adaptability, greater engagement in upskilling activities, and higher confidence in navigating employment transitions. These patterns suggest that platform workers often display behavioural characteristics associated with flexible and adaptive labour market strategies. On the other hand, the financial resilience indicators point in the opposite direction, showing that individuals who rely most heavily on platform work as their main income source face lower levels of financial security and higher levels of financial strain. This combination of relatively strong adaptive capacity alongside weaker financial buffers suggests that participation in the platform economy may involve a trade-off between flexibility and economic stability. In this sense, the findings reinforce the broader interpretation of the platform economy as a segmented labour market, in which some workers use platform work as a flexible supplementary activity while others rely on it more heavily despite facing greater financial vulnerability.

7. Policy implications

The expansion of platform-mediated work represents one of the most visible transformations of labour markets in Europe over the past decade. Digital platforms increasingly mediate economic activity across a wide range of sectors, from local services and delivery to knowledge-intensive freelance work. This expansion has been facilitated by advances in digital technologies, evolving business models, and changing worker preferences regarding flexibility and autonomy. At the same time, it has introduced new forms of labour market organisation that challenge established institutions, including occupational classifications, employment regulation, and systems for skills development.

A key feature of platform work is its heterogeneity. Platform-mediated labour encompasses a broad spectrum of activities that differ significantly in terms of skill requirements, autonomy, income stability, and long-term career prospects. Some forms of platform work involve complex and knowledge-intensive tasks requiring specialised skills and continuous learning. Others consist of routine or task-based activities characterised by lower skill requirements and greater income volatility. These differences imply that platform workers cannot be treated as a homogeneous category within labour market policy.

Another important dimension concerns the relationship between flexibility and economic security. Participation in platform work often reflects a combination of intrinsic motivations, such as preferences for autonomy or flexible working arrangements, and extrinsic motivations, including the need to supplement income or compensate for limited employment opportunities elsewhere. While many platform workers demonstrate strong adaptability and engagement in skill acquisition, individuals who depend heavily on platform income may face greater financial vulnerability and weaker access to traditional forms of social protection. These dynamics highlight the potential for both opportunity and risk within the platform economy.

From a policy perspective, these developments raise a number of important questions regarding how platform work should be classified, how workers' incentives to invest in skills can be strengthened, and how labour market institutions can adapt to ensure that platform-mediated employment contributes to sustainable and inclusive economic development. Addressing these challenges requires a careful balance between supporting innovation and flexibility on the one hand, and ensuring adequate worker protection and opportunities for skill development on the other.

The following subsections discuss several key areas where policy responses may be particularly relevant, including the classification of platform work within existing labour market frameworks, the design of incentives for skill development, and the broader implications for labour market competitiveness and segmentation.

7.1 Rethinking the classification of platform work

A persistent obstacle for effective policy in the platform economy is that many existing classification systems were designed for a labour market dominated by stable jobs, relatively fixed task bundles, and clear employer–employee relationships. In that setting, it is reasonable to assign workers to an occupation based on a job title and a typical set of duties. Platform-mediated work, by contrast, often combines multiple roles, task types, and income sources, sometimes within the same week or even the same day. This makes classification more than a technical matter: it shapes what is visible in labour market statistics, who is captured by regulatory and social protection frameworks, and how skills needs are diagnosed.

A first issue is that job-title based approaches can be systematically misleading when workers describe themselves using broad or platform-specific labels (for example, "freelancer," "consultant," "content creator," or "online worker"). Such labels may conceal substantial differences in task content, required skills, autonomy, and exposure to platform governance. The same label can correspond to high-skill project work in one case and routine microtasking in another. When classification systems rely on these titles, they can over-aggregate fundamentally different work regimes and understate inequality in working conditions and prospects.

A second issue is that platform work frequently reflects a task-based organisation rather than an occupation-based organisation. Workers may carry out a portfolio of tasks that span administrative work, creative production, data-related tasks, customer interaction, and logistics. In these settings, it is often more informative to describe work as a combination of tasks and competencies rather than as membership in a single occupation. This matters for skills policy because training needs emerge from task requirements and transitions between tasks, not only from occupational labels. A classification system that cannot represent mixed task bundles may struggle to identify which skills are missing, which are being developed, and which are transferable into other labour market opportunities.

A third issue is that conventional classification tends to assume one "main job," whereas platform work often co-exists with standard employment, education, caregiving, or other forms of self-employment. Many workers use platforms as a supplementary or occasional activity, while others depend on them more heavily. If statistical systems only capture the main job, they risk missing the scale and structure of platform participation, as well as the degree to which platform work contributes to income diversification or compensates for shortfalls in other earnings. This can lead to policy blind spots: underestimating labour supply in platform markets, misreading vulnerability, or overlooking groups whose platform work is economically significant even if it is not their principal employment.

A fourth issue concerns how classification interacts with regulation and rights. In policy debates, employment status often becomes the central axis of classification. Yet a status-only approach can fail to reflect the organisational reality of platform work, where control can be exercised through task design, rating systems, performance monitoring, and algorithmic allocation. Two workers with the same nominal status may experience very different levels of autonomy and constraint depending on the type of platform activity and the governance mechanisms used. This suggests that classification for policy purposes should be multidimensional, capturing not only legal status but also indicators of task routinisation, discretion, dependence, and exposure to platform control.

A practical implication is the need to complement occupation-based systems with skills- and task-based descriptors that can accommodate hybrid work and portfolio careers. A useful direction is a layered approach that keeps a link to standard occupational categories for comparability, but enriches that link with structured information on task bundles and competencies. Such an approach can improve labour market intelligence while preserving continuity with existing statistical standards. It can also strengthen the recognition of skills acquired in non-standard work by making them legible to education systems, employment services, and employers.

Finally, improved classification requires improved measurement infrastructure. Survey instruments and administrative data systems should be adapted so they can identify platform work participation (including multiple platform types), the role of platform income in overall income portfolios, and the nature of tasks performed. Where appropriate, there is also scope to explore frameworks for responsible data sharing or reporting from platforms themselves, subject to privacy safeguards, proportionality, and clear governance rules. Better measurement is a precondition for designing targeted interventions and for monitoring how labour market outcomes evolve as regulation changes.

Policy considerations emerging from this discussion include the following:

- Develop classification approaches that combine occupational anchors with task- and skill-based descriptors, allowing hybrid roles and mixed task bundles to be represented.
- Expand labour market measurement to capture multi-activity work patterns, including supplementary and occasional platform work, rather than focusing exclusively on a single main job.
- Use multidimensional descriptors for policy-relevant classification, distinguishing legal status from organisational features such as autonomy constraints, routinisation, and exposure to platform control.
- Improve the visibility and recognition of transferable skills developed in platform settings to support transitions into other forms of employment and training pathways.
- Strengthen harmonisation of concepts and measures across countries to support comparability, monitoring, and coordinated policy development at European level.

7.2 Incentives for upskilling platform workers

Skills development is central to how platform-mediated labour markets operate, because access to tasks, earnings potential, and longer-term opportunities depend heavily on workers' ability to acquire, update, and combine competencies. Yet the incentives and constraints surrounding upskilling differ sharply across segments of platform work and across modes of participation. Evidence from platform-worker microdata highlights a clear contrast between a higher-autonomy, project-based segment and a more routine, task-fragmented segment. Evidence from population survey patterns further shows that platform work is often part of broader income and job portfolios, and that the groups most reliant on platform income can face the strongest financial constraints. Taken together, these insights imply that upskilling incentives must be designed in a differentiated way, aligned with segment-specific work organisation, motivations, and feasible learning pathways.

A first implication concerns heterogeneity in learning environments. In higher-autonomy, project-based forms of platform work, workers are more likely to engage in deliberate learning activities and to report skill development that is closely aligned with professional advancement, such as technical or specialty skills and communication-intensive competencies. These patterns are consistent with a work environment where tasks are varied, feedback is richer, and learning can be directly applied to win more complex projects. In more routine and task-fragmented forms of platform work, learning is more constrained by standardised tasks, limited discretion, and weaker progression ladders. Skill gains in this segment tend to be more general or foundational, including learning-to-learn, analytical routines, computer literacy, and language exposure. This does not imply that routine segments are "learning free," but rather that learning may be less structured, less rewarded within the platform environment, and less likely to translate automatically into upward mobility without external support.

A second implication relates to motivation and the perceived returns to training. Workers in higher-autonomy segments are more likely to view platform work as an arena for autonomy, task choice, and professional development, which strengthens intrinsic incentives to invest in skills. In routine segments, participation is more often shaped by secondary motives such as time-filling, enjoyment, or low-commitment income supplementation. In such cases, training interventions that assume strong career orientation may underperform. Effective incentives need to meet workers where they are: short, accessible learning offers that create immediate value and provide clear links to better tasks, higher pay, or recognised credentials.

A third implication is that training policy must be designed around real constraints revealed by population evidence. Platform workers frequently combine platform activity with standard employment, study, or caregiving responsibilities. This makes time a binding constraint and favours modular training formats. More importantly, a consistent pattern is that workers who depend most heavily on platform income can exhibit higher financial strain and weaker financial buffers, even when they report strong adaptability and engagement with upskilling. This combination suggests a policy paradox: the need for training may be high precisely where the ability to finance training or take time off is low. Even supplementary platform work can reflect attempts to compensate for insufficient income elsewhere rather than a route to greater security. By contrast, occasional engagement aligns more with income diversification and broader coping capacity. Incentive design therefore has to account for income volatility and liquidity constraints, not just willingness to learn.

A fourth implication concerns the structure of incentives and who bears the costs. In standard employment, firms often co-invest in training because they internalise part of the productivity return. In platform work, responsibility for training is frequently shifted onto individuals, which risks reinforcing segmentation: workers with higher earnings and stability can invest more, while financially constrained workers underinvest and remain in low-return tasks. Policies that rely solely on individual financing are therefore likely to widen gaps. A more balanced approach combines portable individual entitlements with shared financing arrangements that reflect the collective interest in maintaining human capital and preventing low-skill traps. This can include learning accounts, vouchers, training allowances, or contributory training funds that are compatible with non-standard work and multiple job holding.

A fifth implication is that platforms can be leveraged as learning intermediaries, not only as marketplaces. Platforms often have granular information on task requirements, worker performance, and progression pathways. With appropriate safeguards, this information can support targeted skill diagnostics and personalised training recommendations. Platforms can also support credible signalling by providing structured records of tasks completed and competencies demonstrated, enabling workers to present platform-acquired skills to other employers and training providers. However, policy must also manage risks: if training access is tied to opaque ratings or algorithmic management, it may reproduce bias or lock workers into platform-specific pathways. Any platform role in training should therefore be linked to minimum expectations on transparency, fairness, and worker control over data.

A sixth implication is that upskilling incentives should be integrated with wider labour market institutions rather than treated as a standalone platform issue. Public employment services, vocational education and training systems, and adult learning providers can play a stronger role in supporting platform workers by recognising platform experience, offering bridging modules into in-demand occupations, and validating informal learning. Because platform work often sits at the intersection of employment and self-employment, eligibility rules and outreach strategies may need adjustment to ensure that platform workers can effectively access training opportunities. Where financial vulnerability is a barrier, training support may need to be bundled with income stabilisers or practical supports (for example, childcare support, transport subsidies, or compensated learning time).

Policy considerations emerging from this discussion include the following:

- Design modular, stackable learning offers that fit multi-activity and intermittent platform work patterns, enabling gradual accumulation of recognised skills.
- Differentiate training strategies by segment: support specialised and productivity-enhancing upskilling in higher-autonomy project work, and focus on mobility-oriented transferable skill bundles and progression pathways in routine task-based work.
- Reduce financial and time barriers for workers with high platform-income reliance through portable learning entitlements, vouchers, and training allowances that account for income volatility.
- Promote shared financing models for training that do not place the burden solely on individuals, in order to limit the reinforcement of segmentation and low-skill traps.
- Encourage platforms to support learning and credible skill signalling (task/competency records, training partnerships, diagnostics), tied to safeguards on transparency, fairness, and worker control over personal data.
- Strengthen links between platform work and mainstream training and employment services, including validation of informal learning and bridging pathways into more stable or higher value-added work.

7.3 Implications for competitiveness and segmentation

Platform-mediated labour markets are often presented as inherently competitive environments: large pools of workers and clients interact through digital marketplaces, tasks are allocated through open listings or matching systems, and the ability to secure work depends on skills, reputation signals, responsiveness, and price. This narrative highlights potential efficiency gains, including lower search costs, greater geographic reach, and new income opportunities for workers who can access demand beyond local labour markets. At the same time, evidence points to strong internal differentiation within the platform economy. Differences in task regimes, autonomy, skill portfolios, learning opportunities, and vulnerability suggest that platforms can function not as a single integrated market, but as a set of partially segmented labour market tracks with uneven opportunity structures.

A first implication concerns how competitiveness is shaped by task regime and worker sorting. Higher-autonomy, project-based segments typically involve a wider range of tasks and stronger rewards for specialised capabilities and transferable skill bundles. In these environments, skill diversification can increase competitiveness by enabling workers to bid for varied projects, adapt to changing demand, and move into higher value-added work. Learning investments are more likely to translate into better task access and higher earnings because project work provides scope for skill application, feedback, and portfolio building. By contrast, routine and task-fragmented segments are more likely to be organised around standardised microtasks or tightly specified activities. Here, competition may be stronger on price and speed, learning returns are less predictable, and progression pathways are weaker. The result is that "competitiveness" can mean very different things across segments: in one case it reflects skill-based advancement, in the other it may reflect intensified competition under limited autonomy.

A second implication concerns the risk of a two-tier platform economy. Segmentation can emerge when different groups of workers are channelled into different types of platform work and face systematically different returns to skill investment. Workers entering routine segments may do so because of lower entry barriers, weaker outside options, or constraints that limit access to standard employment. If these workers also face task regimes with limited discretion and few pathways toward higher-complexity work, then the platform economy can reproduce or amplify labour market inequalities. Meanwhile, workers in higher-skill segments may use platforms to extend professional careers, access global clients, and convert learning into mobility and higher income. Over time, these dynamics can create persistent stratification between an "advancement track" and a "containment track," even though both operate under the broad label of platform work.

A third implication is that segmentation is not only about income dependence, and vulnerability is not only about whether platform work is a main job. Population patterns indicate that heavy reliance on platform income is associated with weaker financial buffers and higher financial strain, even when workers report strong adaptability and learning engagement. This implies that some workers may be simultaneously active and adaptive while remaining economically vulnerable. At the same time, routine task regimes can generate worker-like conditions through constrained discretion and standardised tasks even when platform work is supplementary rather than dominant in income. This distinction matters for policy: interventions that focus exclusively on income dependence risk missing organisational vulnerabilities that arise from task design and governance, and interventions that focus only on employment status may overlook the ways platform work is embedded in wider income portfolios.

A fourth implication concerns the role of skills policy as a competitiveness policy. If platform markets reward certain skill bundles and penalise others, skills development becomes central to whether the platform economy contributes to productivity growth or to a low-skill, low-wage equilibrium. Strengthening transferable skills, digital competencies, and pathways into more complex tasks can raise the "quality of competition" by shifting competition away from purely price-based rivalry toward capability-based differentiation. At the same time, skills policy on its own is unlikely to overcome segmentation if task regimes are structurally designed to limit discretion and learning. This suggests that policies to support competitiveness and inclusion need to combine skill development with measures that influence platform work organisation, for example through transparency requirements, fair access to tasks, and mechanisms that reduce lock-in effects.

A fifth implication is that institutions matter for whether platform work integrates with or segments away from the wider labour market. When platform-acquired skills are recognised, portable, and visible to employers, platform work can function as a stepping stone into better opportunities. When skills are not legible, experience is not formally recognised, and progression ladders are absent, platform work is more likely to become a parallel labour market with weaker mobility. This implies a strong role for public employment services, qualification systems, and labour market information tools in making platform work more "connected" to standard labour market pathways.

A final implication is that policy should aim to support sustainable and productive platform work while avoiding incentives that inadvertently reinforce segmentation. This includes recognising that some platform work can be genuinely developmental and productivity-enhancing, while other forms can concentrate insecurity and low-return competition. Differentiated policy design is therefore essential: measures that improve conditions and mobility in routine segments should not inadvertently undermine the flexibility and innovation that characterise high-skill project work, and measures that support high-skill competitiveness should not leave vulnerable workers in routine segments without progression routes.

Policy considerations emerging from this discussion include the following:

- Treat platform labour markets as internally differentiated, and design interventions that reflect differences in task regimes, autonomy, and the returns to skill investment across segments.
- Prevent a two-tier platform economy by strengthening progression pathways from routine task-based work into higher value-added activities, including skill-based ladders and recognition mechanisms.
- Address vulnerability using a multidimensional approach that considers organisational features of work (autonomy, routinisation, governance) alongside income reliance and employment status.
- Use skills policy to improve the quality of competition by supporting transferable and digital skill bundles that enable mobility and capability-based differentiation, not only price-based competition.

- Strengthen the connectivity between platform work and the wider labour market through recognition of platform-acquired skills, portable credentials, and active involvement of employment services and training institutions.
- Combine skill development measures with requirements or incentives that improve fairness and transparency in task allocation and reduce lock-in, so that learning can translate into real mobility and improved outcomes.

8. Conclusions

This report examined skill diversification and new types of work in the platform economy, focusing on how platform workers combine skills into portfolios, how these portfolios differ across platform segments, and how motivations and labour market outcomes vary before and after the pandemic. Using complementary evidence from detailed platform-worker data and population survey data, the analysis documented substantial heterogeneity within platform work and highlighted how differences in task regimes, skill composition, and worker motivations shape learning behaviour, upgrading outcomes, and vulnerability.

First, platform work is internally diverse and cannot be treated as a single labour market segment. A central distinction emerges between higher-autonomy, project-based forms of platform work and more routine, task-fragmented forms. These segments differ not only in the type of tasks performed but also in the skills workers bring from their broader occupational backgrounds, the degree to which tasks allow discretion and creativity, and the extent to which platform work functions as a developmental environment.

Second, platform workers rely on skill portfolios that combine technical or task-specific competencies with basic and transferable skills. The portfolio perspective is essential for understanding platform work because many workers operate across hybrid roles and perform tasks that cut across conventional occupational boundaries. The analysis also indicates that occupational skill portfolios differ systematically across platform segments, with implications for how workers access tasks and how they convert platform participation into skill upgrading.

Third, motivations for engaging in platform work are segment-specific and align with differences in task regimes. Higher-autonomy segments are more closely associated with motivations related to autonomy, task choice, and professional orientation, while routine segments are more strongly associated with secondary or consumption-oriented motives such as time-filling and enjoyment. These motivational profiles matter because they shape workers' willingness and capacity to invest in skill development and to pursue progression pathways.

Fourth, learning investments and reported upgrading outcomes differ across segments in ways consistent with the structure of platform work. In higher-autonomy segments, workers engage more in deliberate learning behaviours and are more likely to report upgrading in specialised and communication-intensive skills. In routine segments, reported improvements are more often concentrated in general or foundational competencies, reflecting greater task turnover but weaker structured pathways for professional advancement. These patterns suggest that the platform economy can generate both skill accumulation and skills stagnation, depending on the segment and task environment.

Fifth, population evidence highlights a tension between labour market adaptability and economic security. Platform workers often display relatively strong adaptability and engagement in upskilling activities, yet those who rely most heavily on platform income tend to face weaker financial buffers and higher financial strain. This combination implies that vulnerability in platform work is not solely a matter of low skill: it can also reflect income volatility, limited protection, and constrained capacity to absorb the costs of training and career transitions. The evidence also suggests that supplementary platform work does not necessarily translate into improved financial security and may, in some cases, reflect efforts to compensate for insufficient income from other employment, while occasional platform work is more consistent with income diversification strategies.

The report contributes to understanding new types of work by showing why a skills portfolio approach is necessary in platform-mediated labour markets. Rather than treating skills as tied to single occupations or job titles, the portfolio perspective captures how workers combine competencies across tasks, platforms, and income sources. This is particularly relevant in non-standard employment settings, where workers often self-direct their learning and where the boundaries between occupational roles are increasingly blurred.

A further contribution lies in demonstrating that motivation is not a secondary feature of platform work but a central mechanism shaping worker behaviour and outcomes. Motivations interact with task regimes and governance structures to influence whether platform work supports deliberate learning, transferable skill development, and upward mobility, or instead functions as an intermittent, low-progression activity. By linking motivations and learning behaviour to task environments and skill portfolio structures, the analysis provides a stronger foundation for designing policies that support upskilling while mitigating segmentation.

Finally, the combination of detailed platform-worker evidence with population-representative survey insights strengthens the interpretation of platform work as simultaneously a space of adaptability and a potential source of vulnerability. This duality is crucial for policy, as it suggests that interventions must address both skill development and the institutional conditions that determine whether skills translate into stable and improving labour market outcomes.

The conclusions should be interpreted in light of two scope and measurement considerations. First, a substantial part of the evidence is cross-sectional and is therefore best suited to documenting patterns and differences across platform work segments rather than identifying causal effects of platform work on skills, motivations, or outcomes. Second, the ESCO-based skill portfolio measures are derived from occupation-level profiles linked to ISCO-08 unit groups; they reflect typical skill requirements of occupations rather than individuals' precise competencies. Accordingly, the ESCO linkage provides a harmonised and policy-relevant way to characterise job-related skill structures, but it should be read as capturing occupational skill architectures rather than direct individual-level skill endowments.

The findings provide a direct foundation for the next stage of analysis in Task 5.4, which focuses on effective skills portfolios and labour market mobility across European regions. Task 5.4 extends the portfolio approach beyond platform work by examining the skills portfolios of European workers more broadly and by identifying which bundles of skills are most conducive to mobility toward the jobs of the future, particularly in the green and digital economies.

Building on the primary evidence from the TRAILS European survey and an innovative approach to combining secondary data from the European Labour Force Survey with the ESCO 2022 classification, Task 5.4 will move from documenting segmentation within platform work to analysing occupational distance and transitions across the wider labour market. It will propose new mechanisms for identifying skill bundles that support mobility, including pathways into green and digital jobs, and it will generate new evidence on the skill combinations that facilitate resilient transitions, higher productivity, and more efficient search and matching.

In this way, the analysis of platform work in Task 5.3 serves as a focused case study of how new task environments reshape skill formation, transferability, and vulnerability. Task 5.4 will generalise and extend these insights by examining how skill portfolios operate across regions and occupations, how workers move between jobs in times of change, and which policy levers can strengthen curriculum development, upskilling incentives, and skills matching for emerging forms of work. This progression ensures continuity from understanding skill diversification in new types of work to identifying the skill portfolios that enable labour mobility and support Europe's transition toward a more resilient, productive, and future-oriented labour market.

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