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Skill Specificity on High-Skill Online Gig Platforms: Same as in Traditional Labour Markets?

Jaap van Slageren [iD][1] and Andrea M. Herrmann[2]

[1]Human Geography and Spatial Planning, Utrecht University, Utrecht, Netherlands
[2]Nijmegen School of Management, Radboud Universiteit, Nijmegen, Netherlands

Political economists and labour sociologists alike have studied how the skill specificity of workers can be explained, as it significantly affects workers' performance. However, the emergence of the gig economy may substantially change skill hiring and specificity in online labour markets because gig workers do not need formal educational credentials to offer their services. Instead, skills are "unbundled" from occupations, and platforms provide alternative ways to signal competencies, for example, via their rating and review systems. To shed light on the applicability of existing theories to explain the skill profiles of gig workers, we examine what predicts the skills hired in the online gig economy. Based on multilevel ordinal logistic regression analyses of 2336 gig worker profiles, we show that—as in traditional labour markets—gig workers with a vocational degree and longer online work experience are hired for more specific skills. However, national labour market institutions and educational systems affect the gig workers' skill specificity in the opposite direction than in traditional labour markets. Our findings thus suggest that online gig platforms allow workers to overcome restrictions imposed by national institutions as they are hired for those skills in the online gig economy that are institutionally less facilitated in their home labour markets.

Introduction

The skill profiles of workers have been of utmost interest to both economists and sociologists (Diprete et al. 2017; Streeck 2011) as they are influential for the economic performance of individuals and countries alike. High-skilled workers are systematically better paid than low-skilled workers (Bills 2003; Stephany 2021). For countries, the possession and developed skills strongly relate to favourable economic outcomes, such as economic growth, both for the Global North and South (Hanushek 2013; Hanushek and Woessmann 2012).

It is, however, not only the *level* of worker skills that influences their labour market focus but also their skill *types*, most notably the specificity of skills (Estevez-Abe et al. 2001). Developing more specific skills compared to more general skills creates both opportunities and risks for workers' economic prospects. On the one hand, more specific skills are often associated with higher wages and better labour market opportunities (Golsteyn and Stenberg 2017; Hanushek et al. 2017; Rosen 1983), because workers require less on-the-job training, making them more attractive to employers. On the other hand, acquiring specific skills makes workers more vulnerable to changes in demand (Lavrijsen and Nicaise 2017; Seifried et al. 2021), which implies that the economic benefits of more specific skill profiles are short-lived over a worker's life cycle (Forster et al. 2016; Forster and Bol 2018; Rözer and Bol 2019; Woessmann 2016).

Given the importance of skills for workers, various scholars have examined what *explains* workers' skill profiles. In other words, where does the skill set of workers in general, and the specificity of these skills in particular, stem from? Located at the intersection of political economy, labour sociology, and labour economics, this branch of literature has found that educational as well as labour market aspects, both at the individual and national level, influence the skill specificity of workers. For individual workers, longer job tenure and vocational educational training correlate with more specific skills (Diprete et al. 2017; Neal 1995). At the national level, workers tend to have more specific skills if they are from countries with higher employment protection and an education system that emphasises vocational training (Busemeyer and Iversen 2012; Di Stasio and Van de Werfhorst 2016).

These typical mechanisms leading to the acquisition of specific skills may be changing with the advent of the online gig economy, where workers provide digitally transferable services via internet-based platforms (De Stefano 2015; Koutsimpogiorgos et al. 2020). Gig platforms allow the supply and demand for service jobs to meet and transact online, whereby gig workers do not need specific educational credentials. This allows workers to present their acquired skills in new ways. Furthermore, platforms create an environment where the signalling of competencies through traditional signals, like job tenure, is less important while the platform's rating systems and written reviews are gaining importance (Herrmann et al. 2023). As a consequence, platforms offer the opportunity to deviate from standard and traditional careers, foster informal learning practices (Larke et al. 2019; Margaryan et al. 2020), and apply for jobs that are beyond reach in traditional labour markets. Finally, platforms also uncouple occupations into particular "tasks," thereby lowering the search costs for requesters to gather information about certain skills, which also implies that certain skills no longer need to co-occur in common occupational profiles (Gomez Herrera et al. 2017; Horton and Zeckhauser 2010).

The advent of online platforms raises the question of whether traditional predictors of skill specificity in general, including national education systems and labour-market institutions in particular, are still relevant in the online gig economy: *Are specific skills by workers active on online platforms correlated with the same individual and national institutional factors as in traditional offline labour markets?*

To address this question, we examine the profiles of 2336 workers in 23 countries active on one of the biggest online gig economy platforms for high-skill jobs. Based on multilevel random intercept ordinal logistic regression analyses, we investigate to what extent the skill sets of gig workers are driven by individual education and work experience and by national institutions.

This paper contributes to the sociological literature in two ways. First, it provides insights into how the established sociological literature on the relationships between skills, education, work experience, and institutions (e.g., Diprete et al. 2017; Heisig et al. 2019; Van de Werfhorst 2011) can be applied to newly emerging labour markets, such as the gig economy. Thereby, the paper highlights crucial contextual factors on which these theories are built. Second, it expands our specific understanding of these newly emerging markets and how they operate (Lehdonvirta et al. 2019; van Slageren et al. 2022). Exploring the stratification mechanisms in these "boundless" markets offers novel insights into the diversity of inequalities in the labour market.

More concretely, we find that the personal background at the individual level is highly correlated with gig skill specificity. That is, the *personal* educational trajectory of workers as well as their personal online job tenure are relevant predictors of skill specificity. Workers with a background in vocational training and a long-standing gig experience are hired for more specific skill sets. Surprisingly, however, we find that *national* education and labour-market institutions affect the skill specificity of gig workers in the opposite way than on traditional labour markets: Workers from countries with a stronger vocational education system and higher employment protection are hired for more general skills than workers from countries with lower vocational education systems and a more flexible labour market. Together with the finding that traditional job tenure also predicts workers' skill specificity in the opposite direction than expected, this suggests that the online gig economy functions as an alternative labour market, substituting those skills less frequent on traditional labour markets. Workers with less requested skill profiles on traditional labour markets are hired for precisely those skill sets in the online gig economy.

Theory
The Online Gig Economy as an Emerging International Labour Market

Although the debate about the conceptualisation of the gig economy is far from settled, there is a consensus that the boundaries of the concept are to be defined along four dimensions, namely, (1) the employment situation of the worker; (2) whether services alone, or services in combination with goods are traded; (3) whether the completed task is financially remunerated; and (4) whether the exchange is mediated by an online platform (Koutsimpogiorgos et al. 2020). When applying these four dimensions in their narrow sense, one can define the gig economy as paid, one-time service jobs mediated by platforms and carried out by freelancers (Koutsimpogiorgos et al. 2020). In our study, we follow this narrow definition, while acknowledging that this is by no means the only definition of the gig economy that holds analytical value. The reason for choosing this narrow definition is therefore not essentialist but pragmatic: any wider definition would equally include the phenomenon we investigate.

Within this narrow definition, one can classify gig work across two dimensions: whether, or not, the service requested is geographically bounded and whether the job requires high or low skills (Woodcock and Graham 2019). In the *onsite gig economy* (De Stefano 2015), geographically tethered services are transacted via online platforms, which can be low-skilled services (such as food delivery) or high-skill services (such as architectural design) (Vallas and Schor 2020). This contrasts with the *online gig economy*, where digitally transferrable labour services are matched (Graham et al. 2017). Here, low-skill gigs typically include click jobs, such as image tagging, while the high-skill services include programming and administration tasks (Vallas and Schor 2020; van Slageren et al. 2022).

Importantly, gig workers active in the high-skill, online segment of the gig economy offer their services as self-employed freelancers, rather than as dependent employees. Various studies have discussed the precarity of workers active in the gig economy (Anwar and Graham 2021; Sutherland et al. 2020). While most of this literature examines the on-site, low-skill part of the gig economy, precarious working conditions are not limited to that segment (Rözer et al. 2021). However, irrespective of whether (or not) the working conditions of online gig workers are precarious, little research has been done on the internal functioning of the high-skill, online gig economy, and its stratification process.

In this study, we examine online gig platforms transacting high-skill jobs, such as Upwork, Freelancer.com, and PeoplePerHour. On these platforms, workers can create a profile without needing an educational degree as an "entry certificate." Workers provide requesters with the relevant skill information via their profiles, indicating, e.g., their names as gig workers, profile pictures, a short introductory text about themselves, their past (offline) work experience, and their educational credentials.

Furthermore, online gig platforms provide certain algorithmic information, which structures the matching process. Most importantly, platforms keep track of the number and types of gig jobs completed, as well as of the star-ratings and reviews that gig requesters award to gig workers upon job completion (Demirel et al. 2021; Rahman 2021; Wood et al. 2019a). In addition, gig workers can complete platform-provided skill tests on a certain topic (Kässi and Lehdonvirta 2022). Finally, gig platforms keep track of whether, and how often, gig workers are hired for skills that they claim to possess (K. A. Anderson 2017; Stephany 2021).

The impact of these algorithmic structures in what kind of skills workers offer and what kind of jobs they complete should not be underestimated. Wood et al. (2019a) find that algorithmic management creates an intense work pressure as there is a constant need to get new gigs and remain on top of the gig worker list displayed. Several studies show that the possibility to be selective in choosing gig jobs varies, depending on how much the worker needs this gig income (Cansoy et al. 2020; Schor et al. 2020; Sutherland et al. 2020). It is therefore plausible that some workers limit their platform work, or change the type of platform work they provide, just to remain profitable.

Skill Specificity in the Online Gig Economy

To examine skill specificity in the online gig economy, we need to define this concept. So, what is skill specificity? The concepts of skill formation and the related notion of skill specificity are central to economic-sociology and political-economy research alike (Busemeyer and Iversen 2012; Diprete et al. 2017; Estevez-Abe et al. 2001; Streeck 2011). While these literatures are similar in their focus on skill formation and skill specificity, the approaches taken towards conceptualising skill specificity differ, while a clear-cut application of skill specificity to the gig economy is missing to date.

For conceptual clarification, we depart from the prominent work of Gary Becker (1964) who points to an essential distinction between "general" and "specific" skills. Becker conceptualises *specific skills* in terms of their limited transferability. In their most extreme form, a specific skill increases the productivity of its holder only within the context of one firm, which implies that specific skills are only useful within the context of a single firm. In contrast, *general skills* are applicable across multiple firms, with the extreme form of general skills being skills applicable to all firms in the economy. Importantly, Becker explicitly describes skill acquisition as an investment into a certain kind of (human) capital that can be used in different contexts, whereby the variety of contexts determines the "generality" of the skills. Thus, the archetypical general skill increases productivity in the same amount across all firms, whereas a completely specific skill loses all applicability in any setting other than one particular firm.

Becker's rather narrow conceptualisation of specific skills is less applicable to the context of the online gig economy. In traditional labour markets, workers have an occupation, which implies that they need to hold a certain bundle of skills in order to fulfil the requirement of the respective occupation, thereby automatically having a distinct bundle of skills. Services offered in the online gig economy, by contrast, reflect the "unbundling" of skills, as gig workers are typically hired to perform distinct tasks that are not linked to traditional occupations. In other words, workers offer their services no longer under the heading of an occupation or job title, but rather indicate in their profile what individual skills they possess which, in turn, are associated with certain tasks for which they can be hired. In addition, given that gig workers offer their skills as individuals on the digital market to multiple requesters, Becker's concept of firm-specific skills cannot be directly translated to the gig economy.

Yet, building on Becker's distinction, Estevez-Abe et al. (2001) developed a more applicable concept of *industry-specific skills*. Accordingly, they propose a more fine-grained differentiation between specific skills, separating the latter into firm-specific skills (that only enhance productivity within a single firm) and industry-specific skills (which can be utilised across firms in the same industry, but not in firms of different industries). This latter concept of industry-focused skill specificity is transferable to the online gig economy as individual gig skills can be aggregated into

industries. Therefore, we here follow the definition of Estevez-Abe et al. (2001) and conceptualise specific skills as industry-specific skills rather than firm-specific skills.

The question of what skills gig workers possess is closely linked to their labour market status, because the form of hiring gig workers also influences whether, or not, they tend to build general or specific skills. This entails the complex task of conceptualising the labour market status of gig workers (see Koutsimpogiorgos et al. 2020). Are they employees, dependent (solo) self-employed workers, or independent freelancers (see Bozzon and Murgia 2022)? While *employees* are subject to the instructions of their employer, the opposite is true for *self-employed workers*. However, *dependent self-employed workers* are either economically dependent on just one client (Cieślik and van Stel 2023; Dvouletý and Nikulin 2023), or they are operationally dependent on their hiring or transacting agency (Bozzon and Murgia 2022).

Given that forms of "a-typical" work have proliferated in traditional labour markets over the past decades, a clear-cut distinction between these work forms is not always straightforward (Bozzon and Murgia 2022). This is especially true for the gig economy, where the economic and operational independence of self-employed gig workers differ—depending on the terms and conditions set by each platform, as well as by the worker's income situation outside of platform work. Yet, with some exceptions in the low-skill, on-site segment of the gig economy, where platforms employ gig workers as dependent (zero-hour) contractors (see Koutsimpogiorgos et al. 2020), gig workers in the high-skill online segment do pursue non-salaried work. Highlighting this non-salaried status, many researchers (e.g., Margaryan et al. 2020; Stephany et al. 2021; Sutherland et al. 2020) refer to gig workers as freelancers, including dependent solo self-employed workers.

So, what could explain the skill specificity of workers in the online gig economy? While the literature on self-employed freelancers remains largely silent on skill acquisition, or simply assumes that skills are exogenously given, the labour-sociology and political-economy literatures on employees and hired workers extensively examines training and skill acquisition (Busemeyer and Iversen 2012; Hanushek et al. 2017). More precisely, these literature strands point to four key aspects that influence skill specificity, namely, their *individual* (1) educational and (2) professional trajectories, as well as *the institutions* governing their country's (3) education system and (4) labour market (Busemeyer and Iversen 2012; Hanushek et al. 2017; Parsons 1972; Van de Werfhorst 2011). Importantly, educational institutions shape the skill sets of workforces independently of their type of future work. We, therefore, assume that the drivers of skill types among workers are similar to those driving skill types among gig workers.

It is important to note that the online gig economy does *per se* not constitute a random selection, nor a representative sample, of national labour markets. Consequently, one can derive competing hypotheses about the influence that national education and labour-market institutions may have on the type of skills hired in the online gig economy. On the one hand, one could expect an additionality effect, meaning that skills hired on online labour markets are, simply, of the same type as those hired on traditional labour markets, because gig workers have been exposed to the same education system and labour-market institutions as workers on traditional labour markets. On the other hand, one could expect a substitution effect, meaning that the skills hired in the online gig economy are those that are less fostered by national institutions and, hence, less available on traditional labour markets. In this setting, gig workers with a skill set that is undervalued in their traditional labour market will offer their skills through online labour markets (Wood et al. 2019b). Importantly, the substitution argument considers gig worker skills to be exogenously given, which is not the case for the additionality argument. Therefore, we here follow the additionality argument on institutional influence and, accordingly, derive our hypotheses from the same factors that were found to influence skill specificity in traditional labour markets.

Individual-Level Career Trajectories as Drivers of Skill Specificity

First, referring to the individual background of workers, various studies show that the educational trajectories of workforces shape their skill sets (Hanushek et al. 2017; Rözer and Bol 2019).

Vocational training provides workers with skills that allow them to complete tasks requested in the industry-related occupations for which they have been educated (Rözer and Bol 2019). To smoothen school-to-job transitions, vocational graduates acquire specific skills that are immediately productive and reduce on-the-job training requirements, making them more attractive for employers (Noelke et al. 2012; Van de Werfhorst 2011).

In contrast, general tertiary education focuses on a broad set of knowledge and general skills, going beyond the narrow practicability of an occupation or firm. As a result, general education graduates are trained to quickly acquire on-the-job training and be prepared for different jobs, increasing their adaptability to changes in demand (Forster et al. 2016; Krueger and Kumar 2004). Following this line of reasoning, we hypothesise

H1a: Gig workers whose highest educational credential is a vocational degree are hired for more- specific skill sets in the online gig economy than workers with other educational degrees.

H1b: Gig workers whose highest educational credential is a master or PhD degree are hired for less specific skill sets in the online gig economy than workers with other educational degrees.

Next to their educational trajectory, workers' job experience is also vital for understanding their skill profiles (Parsons 1972). Regardless of how strong the school-to-job linkage is, there will always be additional on-the-job learning for workers to function within a given firm or industry. On-the-job training and learning-by-doing generally translates into the acquisition of specific skills. As Adam Smith (1776) already argued, specialisation is beneficial for productivity and profit. Due to the repetition of similar work, workers enhance their capability of these specific skills, thereby increasing their productivity (Shaw and Lazear 2008). At a general level, this implies that—whenever markets create an efficient division of labour—these specific skills enhance productivity, thereby leading to increased wages. Rosen specifies this line of reasoning by arguing that "rationally endowed individuals are incentivised to specialise their investment in skills" (Rosen 1983).

While this argument is generally applicable for work experience (irrespective of whether, or not, it is acquired within the context of the same firm), this line of reasoning is particularly applicable to job tenure, i.e., work experience acquired within one firm. Job tenure indicates the opportunity to repeat similar work and fully master the respective job, creating an additional incentive to acquire more firm-specific skills. In contrast, whenever workers switch jobs repeatedly, such on-the-job practice will be lacking. Longer job tenure also bears the opportunity to specialise within the given occupation because, to do so, a certain understanding of the basic, fundamental tasks is required. A longer job tenure thus allows workers to acquire more specific skills (Parsons 1972). On the contrary, a short job tenure implies that workers often change jobs, thereby preventing workers from acquiring specific skills but allowing them to develop general skill profiles.

Although job tenure in its traditional meaning does not exist in the online gig economy, because requesters vary and repeated gigs are rare, job experience can still provide skill specialisation. In the online gig economy, jobs are classified based on the skills needed, and the algorithms facilitate lock-in effects where gig workers are supported to be hired for the same set of skills via the algorithmic structure (Larke et al. 2019; Wood et al. 2019a). Completing only a distinct type of task provides a comparable opportunity for skill specialisation as job tenure does in the traditional labour market. Job tenure in the gig economy thus comes down to repeatedly completing the same task, thereby gaining more specific skills. Following this line of reasoning, we hypothesise that:

H2a: Workers with longer job tenure in traditional labour markets are hired for more specific skill sets in the online gig economy.

H2b: Workers with longer job tenure in the online gig economy are hired for more specific skill sets in the online gig economy.

Institutional Drivers of Skill Specificity

The economic-sociology and political-economy literatures on education point out that skill specificity of workforces is not only a result of their individual educational credentials and work experience but also of the broader institutional context governing a country's education system

and labour market flexibility. More specifically, and next to individual-level backgrounds, the skill specificity of national workforces is additionally influenced by education and labour market institutions at the national level. These institutions can reinforce, or dampen, the individual-level choice of under-going vocational and even non-vocational tertiary education by providing a more, or less, labour-market oriented trajectory.

Research into the role of education systems has a long-standing tradition in the sociological literature (Allmendinger 1989; Shavit and Muller 1998). This literature argues that education systems vary between countries on three institutional features: external differentiation, standardisation, and vocational orientation (Allmendinger 1989). External differentiation refers to the extent to which different educational programmes, with a clearly understood hierarchy, exist at the same time within an educational trajectory. The level of standardisation of an education system refers to the extent to which the quality of education meets the same standards nationwide by means of, for example, central exams and a uniform curriculum. The level of vocational orientation indicates the extent to which education provides students with vocational skills, distinguishing additionally between the specificity of these skills. It is important to note that the differences in education systems are not indicative of the quality of the education in a country. Instead, education systems have multiple societal functions, so that the positioning on all these three dimensions reflects trade-offs between these functions (Bol and Van de Werfhorst 2013a, 2013b).

For skill specificity, the relevant dimension of institutional variety is the level of vocational orientation. Continental European countries (such as Austria, Germany, and Switzerland) have highly vocational education systems. On the other hand, Anglo-Saxon countries (such as Ireland and the UK) have education systems with low levels of vocational orientation. The literature shows that workers in countries with highly vocational educational systems have more specific skills (Breen 2005; Busemeyer and Trampusch 2012). Therefore, we formulate the following hypothesis:

H3: Gig workers from countries with vocationally oriented education systems are hired for more specific skill sets in the online gig economy.

The second type of national institutions that were found to foster skill specificity is labour market flexibility. To understand the influence of labour market flexibility on skill specificity, it is important to understand that investing in specific skills has economic benefits and risks. While the benefits of having specific skills are higher wages and better occupations (Forster et al. 2016; Rözer and Bol 2019), workers with specific skills are vulnerable to changes in demand for these skills (Lavrijsen and Nicaise 2017; Seifried et al. 2021). For example, Forster et al. (2016) show that workers with specific skills have better labour prospects in the short term but have diminishing returns over their life cycle, because workers with general skills can better adapt to changes in demand. In other words, with changing jobs or industrial structures, some skill investments become obsolete.

The Varieties-of-Capitalism (VoC) literature builds on this reasoning and categorises the countries in the Global North into a dichotomy, namely, coordinated market economies (CMEs) and liberal market economies (LMEs) (Amable 2003; Estevez-Abe et al. 2001; Hall and Soskice 2001; Hancké et al. 2008). CMEs, such as Germany, are characterised by a stronger labour market regulation and, hence, lower labour market flexibility. For example, most employees can only be dismissed for specific reasons, after longer notice periods, and in consultation with a firm's works councils. The long-term perspective of working for the same firm decreases the risk that the investment into specific skills may become obsolete, thereby incentivising workers to invest in specific skills (Busemeyer and Iversen 2012). Contrary to that, LMEs, such as the United States, are characterised by low employment protection and high labour–flexible labour market. Hire-and-fire at short notice is possible without providing specific reasons and without the need to involve employee representatives or works councils. This implies that, in LMEs, specific skills have a higher risk of becoming obsolete which, in turn, incentivises workers to chiefly invest in general skills.

While the arguments of the VoC literature have originally been developed through studies of the manufacturing sector, later studies show that their logic also applies to the service sector, even though service workers overall tend to have a higher need and use of general skillsAnderson and Hassel 2008). Furthermore, Jensen (2011) shows that de-industrialisation, i.e., the transition of manufacturing workers into service sector jobs, resulted in re-skilling and a further development of national education trajectories in CMEs. This was not the case in LMEs, where the more general skill sets of manufacturing workers allowed them to transition to service sector work without specialised education and training. In addition, Anderson and Hassel (2008) argue that, in CMEs, the transition process towards a service economy was supported by the already-existing institutions, training capacity and economic logic in CMEs.

Importantly, the VoC arguments can be extended to workers beyond employees. For example, Herrmann (2008) shows that the hiring of workers in flexible (atypical) work forms is also influenced by the labour-market institutions of the country in which the hiring company is located. In addition, what type of worker becomes solo self-employed and what kind of jobs they do differs between different institutional regimes (Arslan et al. 2021; Herrmann 2019). This is because most of the VoC literature involved training and incentive structures fostering strategic behaviour, which still apply to gig workers (Hall and Soskice 2001).

While the argument of the VoC literature has become widely accepted, its dichotomisation into CMEs and LMEs has been criticised and followed by an extensive debate about *how many* varieties of capitalism should be distinguished (Amable 2003; Hancké et al. 2008; Jackson and Deeg 2006), introducing alternative categories such as dependent market economies and Mediterranean market economies (Nölke and Vliegenthart 2009). Others instead suggest a more fine-grained operationalisation of labour market institutions (Hall and Gingerich 2009; Höpner 2007). We follow this second argument to move beyond a dichotomous classification between CMEs and LMEs by considering the actual level of employment protection. After all, it is a country's labour market flexibility that influences the specificity of worker skills, not its classification as a CME, LME, or additional form of capitalist variety. Accordingly, we hypothesise that

H4: Workers from countries with stronger employment protection in the traditional labour market are hired for more specific skill sets in the online gig economy.

Method
Data Collection
To test these hypotheses, we analysed gig workers' skill profiles on one of the largest online gig platforms worldwide. The gig platform in question specialises in high-skill jobs that are digitally transferable, ranging from programming and design to writing tasks. This platform offers a thorough overview of its gig workers via their publicly available profiles, including the gig workers' skill sets, educational credentials, work history, and previous work experience.

We confined our country selection to 23 countries in the Global North because the data available for these countries make it possible to clearly identify their national education and labour-market institutions while varying sufficiently to test our hypotheses. Accordingly, we collected skill profiles from gig workers residing in one of the following countries: Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, The Netherlands, New Zealand, Norway, Poland, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and the United States.

Since gig profiles can rapidly change over time, it was essential to collect the necessary data within a short timeframe. Therefore, we collected the publicly available profiles of gig workers between December 16 and 22, 2019 using a scraping algorithm. We restricted our sample to workers who (1) have completed at least one gig job for which they obtained a review and (2) mentioned an educational degree on their profile. The aforementioned sampling approach, together with listwise deletion, led to a dataset containing 2336 gig workers.

By only collecting a limited amount of the platform's overall data, in line with our research requirements, we ensured that data collection was in line with the platform's intellectual property rights. By pseudonymising the data collected, we complied with the GDPR and privacy requirements. Our data collection process was approved following an ethics review process at our university.

Operationalisation and Analytical Strategy

We operationalise the *skill specificity of workers* via the information provided in the profiles of gig workers who are active on the gig platform in question. In this regard, it is important to note that, although it is potentially possible that gig workers provide fake information on their profiles, this is highly unlikely and would also be irrelevant to how we measure skill specificity/generality. It is highly unlikely because gig workers have no incentive to fabricate their profiles. Gig requesters are likely to punish fake information with poor ratings and positive ratings are essential for obtaining new gigs (Herrmann et al. 2023; Lehdonvirta et al. 2019; Rahman 2021; Wood et al. 2019a). The profile information of gig workers can therefore be assumed to be of equal validity as those of traditional resumes.

But even if gig workers indicated to have different skills than those that they actually possess, this would be irrelevant for the index we use to operationalise *skill specificity* because we base our specificity/generality index on those skills for which gig workers have been hired most—which is information provided by the platform for each gig worker based on his/her work history. For every job advertised on the platform, the gig requester needs to indicate which skills are needed for successfully completing that gig job. Given that these most hired skills describe the gig worker's skill set most reliably, this indicator has been used in several investigations of the online gig economy (Anderson 2017; Stephany 2021). To indicate the most appropriate denomination for the skills needed, requesters can choose from a list of overall 1252 skills, pre-defined and described by the platform. Each of these skills is attributed by the platform to one of 12 distinct industries[1]. To determine the specificity of a worker's skill profile, we counted the number of different industries to which the five most hired skills belong. This resulted in a variable ranging from 1 (where all five most hired skills are from the same industry) to 5 (where all five most hired skills belong to different industries). Given that the variable was highly skewed, we clustered the workers where the five most hired skills belong to three or more industries together, creating a total of three categories. We reversed the order of these categories, so that workers in category one are hired for their general skill set, while workers in the third category are hired for their specific skill set[2].

The first main independent variable is the *educational attainment* of a gig worker. We operationalised a gig worker's educational degree by investigating the educational credentials on his/her profile to identify the highest educational degree obtained. Accordingly, we classified the educational credentials as a vocational degree, a bachelor's degree, a master's degree, or a PhD degree. Whenever the degree obtained could not be unambiguously determined, we removed it from our dataset. When all degrees from a worker could not be classified properly, the gig worker was removed from the analyses. Gig workers who did not indicate educational information in their profiles were removed as well[3]. Educational attainment was included in the models using dummy variables with vocational degree as the reference category.

We measured the second main independent variable at the individual level, *maximum job tenure in traditional labour markets,* by calculating the number of months a gig worker had held a position in the traditional labour market. This information was available in the online profiles of gig workers whenever they indicated their previous work experience. When multiple work experiences were indicated on the profile, the longest job tenure was taken. This resulted in a variable ranging from 0 to 647 months. Due to the indicator's skewness, we added one and log-transformed the variable.

The third main independent variable at the individual level, *job tenure in the online gig economy* was measured by using the number of completed gig jobs on the platform. This resulted in a

measurement ranging from 1 to 1593. Also, this variable is highly skewed, as 27% of the gig workers included in the sample have completed only one gig job on the platform in question. Therefore, the variable was log-transformed before including it in the respective models.

As a first independent variable at the country level, we measure the *level of vocational orientation* of a country's education system, following Bol and Van de Werfhorst (2013b). They argue that vocational orientation has two dimensions, namely, (1) the prevalence of vocational enrolment and (2) the specificity of vocational education. Since we already consider individual educational trajectories, we solely use vocational specificity as an indicator of an education system's vocational orientation. The vocational specificity is best captured by the extent to which learning occurs in a dual (school-based and work-based) form. We accordingly measure the strength of this dual system by calculating the percentage of students in upper secondary education in a dual system. We use macro-level data on the vocational specificity collected in 2014[4].

To measure the second independent variable at the institutional level, *employment protection*, we follow the institutional literature (Dilli et al. 2018; Hope and Martelli 2019; Schneider and Paunescu 2012; Witt and Jackson 2016), which frequently uses the OECD's "*indicator of regular employment protection legislation*"[5] to this end. This indicator combines information (such as the involvement of third parties in dismissal procedures and the length of notice periods to be respected) into one numeric value, ranging from 0 (no employment protection) to 6 (highly stringent employment protection). Given that the most recent moment of measurement differs between countries and given that workers have experienced their traditional labour markets at varying moments in time, we took the average value of all data measurements since 1990. We expect this indicator not to be biased by this long timeframe because institutional change is a slow, gradual process (Mahoney and Thelen 2009; Thelen 2009). The level of vocational orientation and employment protection per country are presented in Supplementary Appendix table S1.

Finally, we added a dummy as a control for all workers that did not indicate any offline work experience on their profile. Not including this control variable could bias the effect of offline job tenure because workers with no traditional job experience and gig workers who did not completely fill in their online profile are lumped together. Additionally, we control for the rating of gig workers. If workers are less highly rated, gig workers may be obliged to assume jobs that do not reflect their actual skill sets. Given the extreme skewness of the variable, we computed a dummy variable capturing whether, or not, a gig worker has an overall rating score of five stars. Finally, we control for the gender of gig workers. Given that the gender of gig workers is not automatically provided on the platform, we identified gender by using a facial recognition algorithm, combined with an algorithmic assessment of whether gig workers referred to themselves, or were referred to, as male or female in the self-description and reviews of their gig profile. We did so by combining two methodologies. First, we examined the ten last reviews of a worker to see whether the worker was addressed with female ("she" or "her") or male pronouns ("he" or "his"). If this was inconclusive, we used facial recognition software on the worker profiles to calculate the gender of the worker. Importantly, facial recognition software was only used if it could define the worker's gender with more than 75% certainty. Table 1 provides an overview of the descriptive statistics of the variables included in the analyses.

Analyses

We test our hypotheses with multilevel random-intercept ordinal logistic regression models (Liu 2015) in which individuals are nested in countries. If the multilevel structure would be ignored, the standard errors of the parameters were underestimated (Hox et al. 2010). Before estimating the regression models, we also examined possible multicollinearity problems by calculating the VIF scores of all independent variables. No multicollinearity was detected.[6] Next, we show the bivariate relationship between the institutional variables and skill specialisation and ensure that the final models do not overcontrol for the institutional effects by adding the individual variables. Model 1 only includes individual-level variables. Models 2 and 3 then add the two

Table 1. Descriptive Statistics

	Range	Mean	SD
Dependent variable			
Skill specificity: general skills	0/1	0.19	—
Skill specificity: mixed skills	0/1	0.40	—
Skill specificity: specific skills	0/1	0.40	—
Individual variables (*N* = 2.613)			
Degree: Lower than vocational	0/1	0.04	—
Degree: Vocational	0/1	0.07	—
Degree: Bachelor	0/1	0.52	—
Degree: Master	0/1	0.35	—
Degree: PhD	0/1	0.02	—
Offline job tenure (months)	0–647	65.91	72.77
Online job experience	1–1593	34.14	86.67
Five-star rating	0/1	0.45	—
Missing work experience	0/1	0.24	—
Gender	0/1	0.31	—
Country variables (*N* = 23)			
Vocational specificity	0–60	13.60	17.69
Employment protection	0–4	1.97	0.79

institutional variables separately to the analyses, whereas Model 4 shows our final model with both institutional characteristics included. Odds ratios are presented, and all hypotheses are tested two-sided.

Results

Figure 1 shows the relationship between the country-level skill specificity and institutional variables[7]. On the y-axis, the average skill specificity, measured by the three categories, is presented, and on the x-axis, the levels of vocational specificity (Panel A) and employment protection (Panel B) are shown. Both panels show no positive relationship between the institutional variables and skill specificity of gig workers. Instead, they even seem to indicate a negative relationship, opposite to what would be expected. However, these surprising results could be due to the compositional differences between countries.

Therefore, to test the hypotheses, table 2 reports the results of the regression models predicting the skill specificity of gig workers. Regarding education, the results show a clear and robust pattern across the various models (for visual presentation, see Supplementary Appendix figure S1): although not all differences are significant, education has an impact on the level of skill specificity. Workers with a vocational degree have skills with the highest level of specificity, while both workers with lower than vocational education and workers with high general education (including those with a master's and PhD degree) provide skills with a lower specificity level. Model 4, on which we test our hypotheses, shows that the difference between vocational degree (reference category) and both gig workers with a lower than vocational degree (OR = 0.576, SE = 0.147, $p < .05$) and gig workers with a master's degree is statistically significant (OR = 0.682, SE = 0.113, $p < .05$). These results show that gig workers are hired for skill types in line with their individual educational trajectories: gig workers with training that provided them with a more specific skillset are hired for more specific skills on the online gig economy and vice versa. Therefore, our results support hypotheses 1a and 1b.

When looking at the association between maximum job tenure and skill specificity, the results are insightful as they are less clear-cut than expected. When examining the maximum
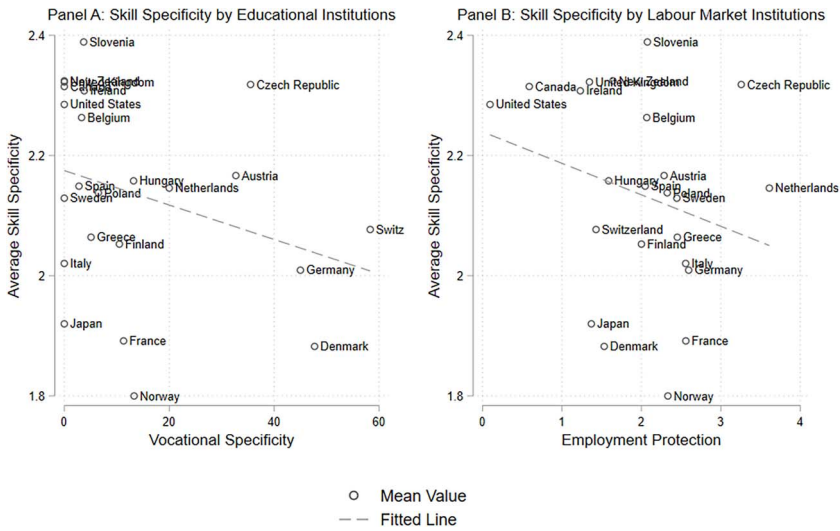
Figure 1. Country's average skill specificity, by educational and labour market institutions.

Table 2. Multilevel Ordinal Logistic Regression Models Predicting the Skill Specificity of Gig Workers

	Model 1		Model 2		Model 3		Model 4	
	OR	SE	OR	SE	OR	SE	OR	SE
Education (vocational = ref):								
Lower than vocational	0.567**	(0.146)	0.578**	(0.148)	0.564**	(0.145)	0.576**	(0.147)
Bachelor	0.784	(0.137)	0.795	(0.129)	0.777	(0.126)	0.791	(0.128)
Master	0.682**	(0.113)	0.689**	(0.114)	0.673**	(0.112)	0.682**	(0.113)
PhD	0.635	(0.187)	0.640	(0.188)	0.622	(0.183)	0.631	(0.185)
Offline job tenure (Ln)	0.805**	(0.075)	0.802**	(0.074)	0.806**	(0.075)	0.802**	(0.073)
Online job experience (Ln)	1.128**	(0.058)	1.131**	(0.058)	1.129**	(0.058)	1.131**	(0.058)
Vocational specificity	—	—	—	—	0.897*	(0.052)	0.934	(0.049)
Employment protection	—	—	0.797***	(0.053)	—	—	0.827***	(0.055)
Gender	1.179*	(0.102)	1.170*	(0.101)	1.176*	(0.102)	1.168*	(0.101)
Average five-star rating (0/1)	0.879	(0.085)	0.884	(0.085)	0.880	(0.085)	0.884	(0.085)
Missing work experience (0/1)	0.596**	(0.127)	0.590**	(0.125)	0.601**	(0.128)	0.594**	(0.126)
R^2 (McKelvey & Zavoina)	.015		.032		.019		.032	
N (countries)	23		23		23		23	
N (individuals)	2336		2336		2336		2336	

$^*p < .10$ $^{**}p < .05$ $^{***}p < .01$

job tenure in the offline labour market, we find a negative effect on skill specificity where a positive effect was hypothesised (OR = 0.3802, SE = 0.073, $p < .05$). Gig workers with a longer maximum offline job tenure are hired for more general, rather than more specific, skills in

the online gig economy. It seems that specialisation via job tenure in the offline labour market does not immediately translate into specialisation in specific skills in the online gig economy as well. Therefore, Hypothesis 2a is rejected. Interestingly, though, the opposite relationship can be observed for online maximum job tenure. The results indicate a strong positive relationship between the number of reviewed transactions a gig worker has completed and his/her skill specificity (OR = 1.131, SE = 0.058, $p < .05$). In other words, the more tasks a worker completes, the more specific his/her skillset becomes. We thus find specialisation via job tenure in the online gig economy when examining online job tenure. This supports hypothesis 2b.

Finally, the results regarding national institutions show surprising results[8]. Contrary to our expectations, we find that the level of employment protection has a negative association with the specificity of gig workers' skills in the online gig economy. This association remains statistically significant in the final model (OR = 0.827, SE = 0.055, $p < .01$). Gig workers from countries with more employment protection are hired for more general rather than more specific skills in the online gig economy.

A similarly surprising finding emerges for the association between the level of a country's vocational specificity and the skill specificity of gig workers from that country: Model 3 shows a negative effect of the level of vocational specificity of a country and the skill specificity of gig workers from that country, significant at an alpha of .10 (OR = 0.897, SE = 0.052, $p < .10$), whereby this association loses any significance when controlled for the level of employment protection in a country (OR = 0.934, SE = 0.049, $p = .20$). In sum, both results suggest the reverse relationship between skill specificity and national institutions to what was expected based on the literature for traditional offline labour markets. We thus do not find support for hypotheses 3 and 4.

Discussion

Long-established literature strands in economic sociology and labour economics examine the factors that explain the level and specificity of workers' skills in the labour market (Diprete et al. 2017; Streeck 2011). They have shown that individual career characteristics, such as educational training and job tenure, as well as national socio-economic institutions, influence the specificity of worker skills. This study examines whether the online gig economy challenges these existing theories of skill specificity: in particular, whether the online gig economy is a novel kind of market with its own set of rules, or whether skill specificity in the online gig economy reflects well-known mechanisms from traditional labour markets. By using multilevel ordinal logistic regression models on 2336 worker profiles from one of the largest online gig platforms worldwide, we investigate whether individual-level education, traditional and online job tenure, as well as national education and labour-market institutions, determine skill specificity in the digital economy. The findings demonstrate that gig workers with a vocational educational degree and more work experience on the online platform are hired for more specific skills. However, neither job tenure in the traditional labour market nor national socio-economic institutions affect gig workers' skill specificity in the direction that was expected from the *institutional* literature.

In line with the established literature (Cedefop 2020; Hanushek et al. 2017; Lehdonvirta et al. 2019; Noelke et al. 2012; Rözer and Bol 2019), our study finds that *individual* education trajectories influence the specificity of the skills of gig workers in the same way as it does in the traditional labour market. The education of gig workers influences the type of skills they are hired for on gig platforms, creating an indirect influence of education on the digital labour market structure. In addition, we find that individual work experience facilitates specialisation effects in the online setting. In line with a growing part of the gig economy literature, our study thus shows that online gig platforms create a context of informal learning (Margaryan 2019). Our findings thus speak to earlier studies which show that high-skill online gig workers frequently developed new skills during their platform work often closely related to their area of expertise (Larke et al. 2019; Margaryan et al. 2020). Our study adds the insight that learning via platform work does not only

allow workers to develop more skills but also more specific skills that allow them to specialise in certain gig tasks.

Moreover, and contrary to the established political economy literature (Parsons 1972; Shaw and Lazear 2008), our study does not find a positive relationship between job tenure in the traditional labour market and the specificity of skills workers are hired for on the platform. Instead, we find that workers with longer offline job tenure are hired for more general skills. One explanation could be that the specific skills acquired in the traditional job market are not transferable to the context of the online gig economy (Cedefop 2020). Through job tenure in traditional labour markets, workers repeatedly do the same type of job, thereby specialising in a bundle of tasks specific to one firm or industry. These bundled specialisations do not relate to the task structure in the online gig economy, where workers are hired for a particular task, algorithmically structured by the type of skills within a task, and frequently by varying requesters. In addition, the signalling value of offline job tenure might be weak compared to the skill signals provided or verified by the platform (Lehdonvirta et al. 2019).

While individual level explanators of skill specificity are mostly in line with the expectations of the literature, *institutional* explanators of skill specificity have the opposite effects to the expected ones. Contrary to the institutional literature on worker skills (Busemeyer and Trampusch 2012; Van de Werfhorst 2011), we find that gig workers from countries where the institutions foster specific skill accumulation—by having a more vocationally oriented education system and a more regulated labour market—are not hired for more specific skills on online gig platforms. Instead, indications of the opposite relationship were found—albeit not significant across all models. This finding supports the argument provided by various scholars (e.g., Frenken and Fuenfschilling 2020; van Slageren 2023; Wood et al. 2019a) that online gig platforms create new institutional environments. This new institutional environment can create demand for those worker' skills that are less valued in their traditional labour market. Thereby, online labour markets enable workers to offer and develop skill profiles independent of the value in their traditional labour markets.

Yet, our findings have their limitations. First, it is important to note that our study gives insights into the functioning of the high-skill online gig economy, which cannot be generalised nor translated one-to-one to the low-skill gig economy or to the onsite gig economy. The low-skill online gig economy is very supply driven, with little change or benefit for skill specialisation (Vallas and Schor 2020). While this is different for the on-site gig economy, the latter is geographically bounded, which limits the opportunities to circumvent national institutions.

Furthermore, it should be noted that we do not measure whether the skills, for which gig workers are hired, are indeed the skills they most strongly possess, or those skills for which they started doing gig work. It could be possible that gig workers hold skills, or have started to offer gig work for skills, different than the ones for which they are mostly hired. Importantly, though, it is the latter that we use as an indicator to establish the skill specificity of gig workers. Our results thus show that gig workers of one country are mostly hired for those—general or, respectively, specific—skill sets that national education and labour-market institutions provide least within their traditional labour market.

Furthermore, we limit our sample to countries in the Global North, which is both a strength and limitation to this study. We did so since there are few reliable systematic indicators of national education and labour market institutions available that can be used to compare countries in the Global North and South. To not let our results be biased by alternative confounding attributes, we chose for a narrower scope of institutionally well-examined countries. Therefore, our results provide conservative estimates of the impact of national institutions on the skill profiles of gig workers since the Global North has a more limited variety of labour market and educational institutions. We encourage further research to assess how generalisable our results are beyond Western, educated, industrial, rich, and democratic (WEIRD) countries.

In addition, the online gig economy does not include a representative sample of workers in national labour markets. Various push and pull factors can influence whether, or not, workers

will seek jobs on online gig platforms. To counter-steer potential selection effects, we have here not investigated what kind of skills gig workers actually possess but, rather, for what skill types they are hired. Even if working in the gig economy would imply that workers are better off if they developed and, hence, possessed more specific (or general) skill sets, this does not necessarily correspond to the specific/general skill sets for which they are actually hired.

Finally, we did not assess the dynamic career paths and gig workers' opportunities and situations outside of the platform. Various scholars point out that a substantial part of gig workers do not depend on the gig economy as their main source of income and that multiple jobholding is a not uncommon phenomena (Campion et al. 2020; Schor 2020; Schor et al. 2020). It is therefore plausible that offline life events influence acquired skills, even if these events do not appear on the gig workers' profiles. Future research should connect online data to survey questionnaires in which the offline lives of workers could be explicitly asked about and measured, thereby linking offline structures to online platforms even better.

Overall, our study shows that the online gig economy fosters specialisation in specific skills, since being longer active on online gig platforms positively correlates with specialisation in specific skills. This specialisation is one of the selling points of online gig platforms: specialisation in specific skills allows for further division of labour and, therefore, for better leverage of the competitive advantage of gig workers, who can leverage their scarce skillset (Wood et al. 2019b). However, by allowing for online specialisation, online gig platforms also create a paradox. On the one hand, they offer workers flexibility in tasks and the freedom to choose preferred jobs even when these are different from their traditional work experience. On the other hand, both the platforms' algorithmic management as well as the workers' specialisation patterns create path dependency and a lack of diversification options (O'Mahony and Bechky 2006). It also makes the position of the online gig worker more vulnerable to the volatility of demand, which is especially prevalent in the online gig economy (Seifried et al. 2021). Specialising in specific skills is therefore a two-edged sword creating economic benefits in the short term, but extra vulnerability for the already precarious position of workers in the longer run.

Endnotes

1. These industries are: "Business, Accounting, Human Resources & Legal," "Data Entry & Admin," "Design, Media & Architecture," "Engineering & Science," "Freight, Shipping & Transportation," "Local Jobs & Services," "Mobile Phones & Computing," "Product Sourcing & Manufacturing," "Sales & Marketing," "Translation & Languages," "Websites, IT & Software," and "Writing & Content."
2. Given that the skill hirings are dependent on supply and demand, we used it as an alternative measurement for skill specificity of self-reported skills presented on the profile. We again classified these skills based on 12 categories, creating a skill specificity index ranging from 1 to 9. Accordingly, we here use multilevel linear regression models. Using this alternative dependent variable, our results proved to be robust (see Supplementary Appendix table S2).
3. As a robustness check, we redid the analyses by including those gig workers who did not report their educational credentials. We classified these workers into an additional educational category, named "no valid educational trajectory reported." This did not change the substantive interpretation of any of our results. The analyses are available on request.
4. The dataset used to classify education systems can be downloaded from the following webpage: http://thijsbol.com/data/
5. https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm
6. The VIF scores are presented in Supplementary Appendix table S3.
7. Given that the vocational specificity index shows a rather skewed distribution, we tested the reliability of the results obtained via the following robustness check: Rather than introducing the variable as a scale indicator, we classified the different countries in quantiles and then

included this quantile categorisation as an ordinal variable in our respective models. As shown in Supplementary table S4 of the Supplementary Appendix, this did not change the direction of the respective coefficients.

8. To assess the possibility of one country skewing our results, we have employed a jack-knife re-estimation. By sequentially removing one country at the time, we could examine its influence on the results. These additional jack-knife analyses showed our results to be robust. Results are available on request.

About the Authors

Jaap van Slageren is an assistant professor at the Human Geography and Spatial Planning, Utrecht University. His research interests combine perspectives from political sociology, stratification sociology, and political economy. His current research projects study geographical and educational inequalities in democratic values and institutional critiques. Jaap's work has been published in journals such as *Socio-Economic Review, Electoral Studies,* and *Policy & Internet.*

Andrea M. Herrmann is a professor of Innovation and Entrepreneurship at Radboud University (Nijmegen). She holds a PhD from the European University Institute (Florence) and has obtained several renowned research funds, including an ERC Consolidator Grant. Her research investigates how incumbent firms and entrepreneurs innovate and how they are helped (or hindered) by their institutional environment. Her research interests comprise the areas of political economy, institutional theory, innovation management, entrepreneurship, and online labour markets.

Supplementary Material

Supplementary material is available at *Social Forces* online.

Data availability

References

Allmendinger, J. 1989. "Educational Systems and Labor Market Outcomes." *European Sociological Review* **5**(3):231–50. https://doi.org/10.1093/oxfordjournals.esr.a036524.

Amable, B. 2003. *The Diversity of Modern Capitalism*. Oxford: Oxford University Press.

Anderson, K.A. 2017. "Skill Networks and Measures of Complex Human Capital." *Proceedings of the National Academy of Sciences* **114**(48):12720–4. https://doi.org/10.1073/pnas.1706597114.

Anderson, K.M. and A. Hassel 2013. "Pathways of Change in CMEs Training Regimes in Germany and the Netherlands". In *The Political Economy of the Service Transition*, edited by Wren, A. New York: Oxford University Press. 171–195.

Anwar, M.A. and M. Graham 2021. "Between a Rock and a Hard Place: Freedom, Flexibility, Precarity and Vulnerability in the Gig Economy in Africa." *Competition & Change* **25**(2):237–58. https://doi.org/10.1177/1024529420914473.

Arslan, A., A. Ruman, P. Hurmelinna-Laukkanen and T. Ali 2021. "Varieties of capitalism and the base of pyramid population segment in affluent economies: Discussion on entrepreneurship financing and skills development". In *Base of the Pyramid Markets in Affluent Countries: Innovation and Challenges to Sustainability*, edited by Gold, S., Arnold, M.G., Munthuri, J.N., Rueda, X. Oxon: Routledge.

Becker, G. 1964. *Human Capital*. Chicago: The University of Chicago Press.

Bills, D.B. 2003. "Credentials, Signals, and Screens: Explaining the Relationship between Schooling and Job Assignment." *Review of Educational Research* **73**(4):441–69. https://doi.org/10.3102/00346543073004441.

Bol, T. and H.G. Van de Werfhorst 2013a. "Educational Systems and the Trade-off between Labor Market Allocation and Equality of Educational Opportunity." *Comparative Education Review* **57**(2): 285–308. https://doi.org/10.1086/669122.

Bol, T. and H.G. Van de Werfhorst 2013b. "The Measurement of Tracking, Vocational Orientation, and Standardization of Educational Systems: A Comparative Approach". *AIAS*, GINI Discussion Paper 81.

Bozzon, R. and A. Murgia 2022. "Independent or Dependent? European Labour Statistics and Their (In)ability to Identify Forms of Dependency in Self-employment." *Social Indicators Research* **160**(1): 199–226. https://doi.org/10.1007/s11205-021-02798-1.

Breen, R. 2005. "Explaining Cross-National Variation in Youth Unemployment: Market and Instutional Factors." *European Sociological Review* **21**(2):125–34. https://doi.org/10.1093/esr/jci008.

Busemeyer, M.R. and T. Iversen 2012. "Collective Skill Systems, Wage Bargaining, and Labor Market Stratification". In *The Political Economy of Collective Skill Formation*, edited by Busemeyer, M.R. and Trampush, C. pp. 205–33. Oxford: Oxford University Press.

Busemeyer, M.R. and C. Trampusch 2012. *The Political Economy of Collective Skill Formation*. Oxford: Oxford University Press.

Campion, E.D., B.B. Caza and S.E. Moss 2020. "Multiple Jobholding: An Integrative Systematic Review and Future Research Agenda." *Journal of Management* **46**(1):165–91. https://doi.org/10.1177/0149206319882756.

Cansoy, M., S. Eddy, I. Ladegaard and J. Schor 2020. "Homines Diversi: Heterogeneous Earner Behaviors in the Platform Economy." *Sociologica* **14**(3):143–65.

Cedefop. 2020. *Developing and Matching Skills in the Online Platform Economy*. Findings on New Forms of Digital Work and Learning from Cedefop's CrowdLearn Study. Luxembourg: Publications Office. Cedefop reference series; No 116.

Cieślik, J. and A. van Stel 2023. "Solo self-employment—Key policy challenges." *Journal of Economic Surveys*. . https://doi.org/10.1111/joes.12559.

De Stefano, V. 2015. "The Rise of the Just-in-Time Workforce: On-Demand Work, Crowdwork, and Labor Protection in the Gig-Economy." *Comparative Labor Law & Policy Journal* **37**:471–505. https://doi.org/10.2139/ssrn.2682602.

Demirel, P., E. Nemkova and R. Taylor 2021. "Reproducing Global Inequalities in the Online Labour Market: Valuing Capital in the Design Field." *Work, Employment & Society* **35**(5):914–30. https://doi.org/10.1177/0950017020942447.

Di Stasio, V. and H.G. Van de Werfhorst 2016. "Why Does Education matter to Employers in Different Institutional Contexts? A Vignette Study in England and the Netherlands." *Social Forces* **95**(1): 77–106. https://doi.org/10.1093/sf/sow027.

Dilli, S., N. Elert and A.M. Herrmann 2018. "Varieties of Entrepreneurship: Exploring the Institutional Foundations of Different Entrepreneurship Types through "Varieties-of-Capitalism" Arguments." *Small Business Economics* **51**(2):293–320. https://doi.org/10.1007/s11187-018-0002-z.

Diprete, T.A., C.C. Eller, T. Bol and H.G. van de Werfhorst 2017. "School-To-Work Linkages in the United States, Germany, and France." *American Journal of Sociology* **122**(6):1869–938. https://doi.org/10.1086/691327.

Dvouletý, O. and D. Nikulin 2023. "Dependent self-employed individuals: Are they different from paid employees?" *Employee Relations: The International Journal* **45**(3):704–20. https://doi.org/10.1108/ER-11-2022-0502.

Estevez-Abe, M., T. Iversen and D. Soskice 2001. "Social Protection and the Formation of Skills: A Reinterpretation of the Welfare State". In *Varieties of Capitalism: The Institutional Foundation of Comparative Advantage*, edited by Hall, P.A., Soskice, D., pp. 145–183: Oxford: Oxford University Press.

Forster, A.G. and T. Bol 2018. "Vocational Education and Employment over the Life Course using a New Measure of Occupational Specificity." *Social Science Research* **70**:176–97. https://doi.org/10.1016/j.ssresearch.2017.11.004.

Forster, A.G., T. Bol and H.G. Van de Werfhorst 2016. "Vocational Education and Employment over the Life Cycle." *Sociological Science* **3**:473–94. https://doi.org/10.15195/v3.a21.

Frenken, K. and L. Fuenfschilling 2020. "The Rise of Online Platforms and the Triumph of the Corporation." *Sociologica* **14**(3):101–13.

Golsteyn, B. and A. Stenberg 2017. "Earnings over the Life Course: General versus Vocational Education." *Journal of Human Capital* **11**(2):167–212. https://doi.org/10.1086/691798.

Gomez Herrera, E., B. Martens and F. Mueller-Langer 2017. "Trade, Competition and Welfare in Global Online Labour Markets: A "Gig Economy" Case Study". *JRC Digital Economy Working Paper no. 2017-05*, European Commission, Joint Research Centre (JRC), Seville.

Graham, M., I. Hjorth and V. Lehdonvirta 2017. "Digital Labour and Development: Impacts of Global Digital Labour Platforms and the Gig Economy on Worker Livelihoods." *Transfer* **23**(2):135–62. https://doi.org/10.1177/1024258916687250.

Hall, P.A. and D.W. Gingerich 2009. "Varieties of Capitalism and Institutional Complementarities in the Political Economy: An Empirical Analysis." *British Journal of Political Science* **39**(3):449–82. https://doi.org/10.1017/S0007123409000672.

Hall, P.A. and D. Soskice 2001. "An Introduction to Varieties of Capitalism". In *Varieties of Capitalism: The Institutional Foundation of Comparative Advantage*, edited by Hall, P.A., Soskice, D., pp. 1–68: Oxford: Oxford University Press.

Hancké, B., M. Rhodes and M. Thatcher 2008. *Beyond Varieties of Capitalism: Conflict, Contradictions, and Complementarities in the European Economy*. Oxford: Oxford University Press.

Hanushek, E.A. 2013. "Economic Growth in Developing Countries: The Role of Human Capital." *Economics of Education Review* **37**:204–12. https://doi.org/10.1016/j.econedurev.2013.04.005.

Hanushek, E.A., G. Schwerdt, L. Woessmann and L. Zhang 2017. "General Education, Vocational Education, and Labor-Market Outcomes over the Lifecycle." *Journal of Human Resources* **52**(1):48–87. https://doi.org/10.3368/jhr.52.1.0415-7074R.

Hanushek, E.A. and L. Woessmann 2012. "Do Better Schools lead to more Growth? Cognitive Skills, Economic Outcomes, and Causation." *Journal of Economic Growth* **17**(4):267–321. https://doi.org/10.1007/s10887-012-9081-x.

Heisig, J.P., M. Gesthuizen and H. Solga 2019. "Lack of Skills or Formal Qualifications? New Evidence on Cross-Country Differences in the Labor Market Disadvantage of Less-Educated Adults." *Social Science Research* **83**:102314. https://doi.org/10.1016/j.ssresearch.2019.06.005.

Herrmann, A.M. 2008. "Rethinking the Link between Labour Market Flexibility and Corperate Competitiveness: A Critique of the Institutionalist Literature." *Socio-Economic Review* **6**(4):637–69. https://doi.org/10.1093/ser/mwn013.

Herrmann, A.M. 2019. "A Plea for Varieties of Entrepreneurship." *Small Business Economics* **52**(2):331–43. https://doi.org/10.1007/s11187-018-0093-6.

Herrmann, A.M., P.M. Zaal, M.M.H. Chappin, B. Schemmann and A. Lühmann 2023. ""We don't need no (Higher) Education"—How the Gig Economy Challenges the Education-Income Paradigm." *Technological Forecasting and Social Change* **186**:122136. https://doi.org/10.1016/j.techfore.2022.122136.

Hope, D. and A. Martelli 2019. "The Transition to the Knowledge Economy, Labor Market Institutions, and Income Inequality in Advanced Democracies." *World Politics* **71**(2):236–88. https://doi.org/10.1017/S0043887118000333.

Höpner, M. 2007. "Coordination and Organization: The Two Dimensions of Nonliberal Capitalism." *MPIfG Discussion Paper* **7**(12):1–32.

Horton, J.J. and R.J. Zeckhauser 2010. "Algorithmic Wage Negotiations: Applications to Paid Crowdsourcing." *Proceedings of CrowdConf* **4**:2–5.

Hox, J., M. Moerbeek and R. Van de Schoot 2010. *Multilevel Analysis: Techniques and Applications*. New York: Routledge.

Jackson, G., and R. Deeg. 2006. "How Many Varieties of Capitalism." MPIfG Discussion Paper No. 06/2. pp 1–49. https://www.mpifg.de/discussion-papers.

Jensen, C. 2011. "Capitalist Systems, Deindustrialization, and the Politics of Public Education." *Comparative Political Studies* **44**(4):412–35. https://doi.org/10.1177/0010414010393475.

Kässi, O. and V. Lehdonvirta 2022. "Do Microcredentials Help New Workers Enter the Market? Evidence from an Online Labor Platform." *Journal of Human Resources* 0519–10226R3. https://doi.org/10.3368/jhr.0519-10226R3.

Koutsimpogiorgos, N., J. Van Slageren, A.M. Herrmann and K. Frenken 2020. "Conceptualizing the Gig Economy and Its Regulatory Problems." *Policy and Internet* **12**(4):525–45. https://doi.org/10.1002/poi3.237.

Krueger, D. and K.B. Kumar 2004. "Skill-Specific rather than General Education: A Reason for US–Europe Growth Differences?" *Journal of Economic Growth* **9**(2):167–207. https://doi.org/10.1023/B:JOEG.0000031426.09886.bd.

Larke, L., S. Brooke, H. Davies, A. Margaryan and V. Lehdonvirta 2019. "Skill Formation and Skills Matching in Online Platform Work". In *Proceedings of the British Sociological Association Annual Conference 2019*. Durham: BSA Publications Ltd.

Lavrijsen, J. and I. Nicaise 2017. "Returns on Vocational Education over the Life Cycle: Between Immediate Labour Market Preparation and Lifelong Employability." *International Review of Education* **63**(2):257–80. https://doi.org/10.1007/s11159-017-9630-9.

Lehdonvirta, V., O. Kässi, I. Hjorth, H. Barnard and M. Graham 2019. "The Global Platform Economy: A New Offshoring Institution Enabling Emerging-Economy Microproviders." *Journal of Management* **45**(2):567–99. https://doi.org/10.1177/0149206318786781.

Liu, X. 2015. *Applied Ordinal Logistic Regression using Stata: From Single-Level to Multilevel Modeling*. Thousand Oaks, CA: Sage Publications.

Mahoney, J. and K. Thelen 2009. *Explaining Institutional Change: Ambiguity, Agency, and Power*. Cambridge: Cambridge University Press.

Margaryan, A. 2019. "Comparing Crowdworkers' and Conventional Knowledge Workers' Self-Regulated Learning Strategies in the Workplace." *Human Computation* **6**:83–97. https://doi.org/10.15346/hc.v6i1.5.

Margaryan, A., T. Charlton-Czaplicki, and U. Gadiraju. 2020. *Learning and Skill Development in Online Platform Work. Comparing Microworkers' and Online Freelancers' Practices (CrowdLearnPlus)*. Fredriksberg: Copenhagen Business School (CBS).

Neal, D. 1995. "Industry-Specific Human Capital: Evidence from Displaced Workers." *Journal of Labour Economics* **13**(4):653–77. https://doi.org/10.1086/298388.

Noelke, C., M. Gebel and I. Kogan 2012. "Uniform Inequalities: Institutional Differentiation and the Transition from Higher Education to Work in Post-Socialist Central and Eastern Europe." *European Sociological Review* **28**(6):704–16. https://doi.org/10.1093/esr/jcs008.

Nölke, A. and A. Vliegenthart 2009. "Enlarging the Varieties of Capitalism: The Emergence of Dependent Market Economies in East Central Europe." *World Politics* **61**(4):670–702. https://doi.org/10.1017/S0043887109990098.

O'Mahony, S. and B.A. Bechky 2006. "Stretchwork: Managing the Career Progression Paradox in External Labor Markets." *Academy of Management Journal* **49**(5):918–41. https://doi.org/10.5465/amj.2006.22798174.

Parsons, D.O. 1972. "Specific Human Capital: An Application to Quit Rates and Layoff Rates." *Journal of Political Economy* **80**(6):1120–43. https://doi.org/10.1086/259961.

Rahman, H.A. 2021. "The Invisible Cage: Workers' Reactivity to Opaque Algorithmic Evaluations." *Administrative Science Quarterly* **66**(4):945–88. https://doi.org/10.1177/00018392211010118.

Rosen, S. 1983. "Specialization and Human Capital." *Journal of Labor Economics* **1**(1):43–9. https://doi.org/10.1086/298003.

Rözer, J.J. and T. Bol 2019. "Labour Market Effects of General and Vocational Education over the Life-Cycle and across Time: Accounting for Age, Period, and Cohort Effects." *European Sociological Review* **35**(5):701–17. https://doi.org/10.1093/esr/jcz031.

Rözer, J.J., A. Van der Torre, and A. Roeters. 2021. *Platformisering en de Kwaliteit van Werk*. Sociaal en Cultureel Planbureau (SCP), Den Haag.

Schneider, M.R. and M. Paunescu 2012. "Changing Varieties of Capitalism and Revealed Comparative Advantages from 1990 to 2005: A Test of the Hall and Soskice Claims." *Socio-Economic Review* **10**(4): 731–53. https://doi.org/10.1093/ser/mwr038.

Schor, J.B. 2020. *After the Gig: How the Sharing Economy Got Hijacked and How to Win It Back*. Oakland, CA: University of California Press.

Schor, J.B., W. Attwood-Charles, M. Cansoy, I. Ladegaard and R. Wengronowitz 2020. "Dependence and Precarity in the Platform Economy." *Theory and Society* **49**(5):833–61. https://doi.org/10.1007/s11186-020-09408-y.

Seifried, M., R. Jurowetzki and T. Kretschmer 2021. "Career Paths in Online Labor Markets: Same, Same but Different?" *ZEW - Centre for European Economic Research Discussion Paper No. 20-090*. Mannheim. https://doi.org/10.2139/ssrn.3774773.

Shavit, Y. and W. Muller 1998. *From School to Work. A Comparative Study of Educational Qualifications and Occupational Destinations*. Oxford: Oxford University Press.

Shaw, K. and E.P. Lazear 2008. "Tenure and Output." *Labour Economics* **15**(4):704–23. https://doi.org/10.1016/j.labeco.2007.08.004.

Smith, A. 1776. *An Inquiry into the Wealth of Nations*. London: Strahan and Cadell.

Stephany, F. 2021. "When does it Pay Off to Learn a New Skill? Revealing the Complementary Benefit of Cross-Skilling." arXiv preprint arXiv:2010.11841.

Stephany, F., O. Kässi, U. Rani and V. Lehdonvirta 2021. "Online Labour Index 2020: New ways to measure the world's remote freelancing market." *Big Data & Society* **8**(2):205395172110432. https://doi.org/10.1177/20539517211043240.

Streeck, W. 2011. "Skills and Politics: General and Specific." MPIfG Discussion Paper No. 11/1. pp 1–32. https://www.mpifg.de/discussion-papers.

Sutherland, W., M.H. Jarrahi, M. Dunn and S.B. Nelson 2020. "Work Precarity and Gig Literacies in Online Freelancing." *Work, Employment & Society* **34**(3):457–75. https://doi.org/10.1177/0950017019886511.

Thelen, K. 2009. "Institutional Change in Advanced Political Economies." *British Journal of Industrial Relations* **47**(3):471–98. https://doi.org/10.1111/j.1467-8543.2009.00746.x.

Vallas, S. and J. Schor 2020. "What do Platforms do? Understanding the Gig Economy." *Annual Review of Sociology* **46**(16):273–94. https://doi.org/10.1146/annurev-soc-121919-054857.

Van de Werfhorst, H.G. 2011. "Skill and Education Effects on Earnings in 18 Countries: The Role of National Educational Institutions." *Social Science Research* **40**(4):1078–90. https://doi.org/10.1016/j.ssresearch.2011.03.004.

Van Slageren, J. 2023. *Beyond National Reach? An Institutional Analysis of the High-Skill Online Gig Economy in the Global North*. Utrecht University Dissertation. Alblasserdam: RidderPrint.

Van Slageren, J., A.M. Herrmann and K. Frenken 2022. "Is the Online Gig Economy Beyond National Reach? A European Analysis." *Socio-Economic Review.* **21**:1795–821. https://doi.org/10.1093/ser/mwac038.

Witt, M.A. and G. Jackson 2016. "Varieties of Capitalism and Institutional Comparative Advantage: A Test and Reinterpretation." *Journal of International Business Studies* **47**(7):778–806. https://doi.org/10.1057/s41267-016-0001-8.

Woessmann 2016. "The economic case for education." *Education Economics* **24**(1):3–32. https://doi.org/10.1080/09645292.2015.1059801.

Wood, A.J., M. Graham, V. Lehdonvirta and I. Hjorth 2019a. "Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy." *Work, Employment and Society* **33**(1):56–75. https://doi.org/10.1177/0950017018785616.

Wood, A.J., M. Graham, V. Lehdonvirta and I. Hjorth 2019b. "Networked but Commodified: The (Dis)Embeddedness of Digital Labour in the Gig Economy." *Sociology* **53**(5):931–50. https://doi.org/10.1177/0038038519828906.

Woodcock, J. and M. Graham 2019. *The Gig Economy. A Critical Introduction*. Cambridge: Polity.