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"We don't need no (higher) education" - How the gig economy challenges the education-income paradigm☆

Andrea M. Herrmann[a,*], Petra M. Zaal[b], Maryse M.H. Chappin[c], Brita Schemmann[d], Amelie Lühmann[d,e]

[a] *Department of Business Administration, Nijmegen School of Management, Radboud University, Elinor Ostrom Building, Room 3.563, Heyendaalseweg 141, 6525 AJ Nijmegen, the Netherlands*
[b] *Monitor Deloitte, Deloitte Consulting B.V., Gustav Mahlerlaan 2970, 1081 LA Amsterdam, the Netherlands*
[c] *Innovation Studies, Copernicus Institute of Sustainable Development, Faculty of Geosciences, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, Vening Meinesz building A Room 7.48, P.O. Box 80115, 3508, TC, Utrecht, the Netherlands*
[d] *School of International Business, Bremen University of Applied Sciences, Werderstrasse 73, 28199 Bremen, Germany*
[e] *Deloitte GmbH, Kurfürstendamm 23, 10719 Berlin, Germany*

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ABSTRACT

The empirical relationship between educational attainment and pay levels has been widely acknowledged in the labour-economic and labour-sociology literatures. While the causalities underlying this relationship are not conclusively established, researchers broadly agree that higher educational attainment leads to higher income levels in dependent employment, temporary hiring, and freelancing alike. The 'gig economy', where workers complete jobs mediated by online platforms, challenges this paradigm as gig workers can access jobs without any educational certificates. Building a theoretical framework based on agency-driven accounts, we investigate whether we can empirically observe a relationship between educational attainment and wage levels in the gig economy. Our OLS regression analyses of 1607 gig workers in 14 Western economies illustrate no statistically significant correlation. Instead, the platform's review system as well as the gig workers' level of previous job experience serve as the major signalling mechanisms that help to reduce information asymmetry. Qualitative insights gained from in-depth interviews explain this finding by revealing how gig workers gain the necessary qualifications for their jobs, most importantly, through self-study, learning-by-doing, and trial-and-error processes. Our findings therefore point out that advanced educational credentials are only of limited use for gig workers.

1. Introduction[1]

Empirically, the relationship between educational attainment and labour market success in the form of higher income levels is widely established in the labour-economic and labour-sociology literatures: The higher their level of formal education, the higher is the income of workers in dependent employment, temporary hiring, and freelancing alike (Miller, 1960; Becker, 1964; de Wolff and van Slijpe, 1973; Mincer, 1989; Card, 1999; Day and Newburger, 2002). While the education-income nexus is widely established, the causalities underlying this relationship are however not conclusively established and fall, broadly speaking, into three actor-centred explanations (that are particularly prominent amongst labour economists) and four institutional accounts (favoured by sociologists) (Bills, 2003).

The 'gig economy', where workers complete one-time jobs mediated by online platforms (Koutsimpogiorgos et al., 2020), has the potential to fundamentally challenge this education-income paradigm, because gig workers do not need to present any educational certificates to offer their

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* Corresponding author.
E-mail addresses: Andrea.Herrmann@ru.nl (A.M. Herrmann), pzaal@deloitte.nl (P.M. Zaal), M.M.H.Chappin@uu.nl (M.M.H. Chappin), brita.schemmann@hs-bremen.de (B. Schemmann), aluehmann@deloitte.de (A. Lühmann).
URL: https://www.andrea-herrmann.com (A.M. Herrmann).

[1] To ensure gender neutrality in the formulations without impairing precision and readability, we use the female form as a placeholder for all three genders: male, female, diverse.

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services on these online platforms. More precisely, gig workers can offer their services by opening a profile account on an online platform, for which they can – but do not need to – upload an educational certificate. Once registered on the platform, gig workers can apply for job offers, and also be contacted by gig requesters interested in hiring their profile for a specific job. The fact that no educational credentials are needed to this end is particularly noteworthy for online gig jobs that are to be completed with the help of a computer (such as translations, programming, or design tasks). Transacted by platforms, such as Fiverr, freelancer.com, PeoplePerHour, or Upwork, online gig jobs have a large high-skill segment in which gig workers around the world compete for jobs. This contrasts with on-site gig work that is to be completed at specific locations (like delivery, driving, handicraft, or cleaning tasks), transacted by platforms such as Deliveroo, Uber, TaskRabbit, or Helpling. Given that on-site gig work is sheltered from global competition and often characterized by lower skill needs, it may be less surprising that gig workers can access on-site jobs without needing to present their educational credentials. But given the fierce international competition in the online, high-skill gig economy (ILO, 2021), the absence of any requirements related to gig workers' educational credentials is puzzling. It entails the question whether the education-income relationship, which has been so widely established for traditional labour markets, also holds for the gig economy?

This question gets particularly pressing if one considers the massive growth of the gig economy since 2008, when platforms for online gig jobs started mushrooming (ILO, 2021: 47). With an average growth rate of 10 % per year before the pandemic 2020, and of about 40 % since the beginning of the pandemic in March 2020 (see also AppJobs Institute, 2020; Online Labour Index, 2020), the online gig economy is, by far, the most strongly developing labour market of the past 10 years, where – already in 2016 – about 5 % of the working population of Western European economies regularly earned (at least parts of) their living (Huws et al., 2017). Is there a new labour market developing that no longer follows one of the most widely established empirical relationships, not to say paradigms, of economic and sociological labour market studies?

To address this question and the theoretical gap whether the education-income paradigm also applies to the gig economy, we combine quantitative and qualitative evidence. In a first step, we quantitatively analyse 1607 gig workers in 14 Western economies, who are regularly active on one of the largest platforms for high-skilled online services including, in particular, programming, design, translations, and writing tasks. The results obtained from OLS regression analyses challenge – and accordingly contribute to the labour- economic and labour-sociology literatures on – the education-income paradigm: They show that the wage levels of gig workers are indeed not related to the workers' educational attainment, but rather to their previous work experience, review scores, and gender.

In a second step, we investigate and, accordingly, contribute to those research strands that shed light on the mechanisms underlying the education-income nexus, most notably human capital, signalling, and screening theories. To this end, we analyse the qualitative evidence gained from 8 semi-structured interviews with gig workers. Based on systematic case comparisons in line with Eisenhardt (1989), these interviews confirm that degrees in higher education are, indeed, hardly considered as a quality signal by gig requesters. Instead, and in line with signalling theory, gig workers explained why positive reviews and relevant work experience are essential for obtaining well-paid gig jobs. In line with human capital theory, the interviewees furthermore explained how they acquired the necessary skills both through autodidactic learning (self-study, learning-by-doing, and trial-and-error processes) as well as from prior job experience – both in traditional (employment) and prior gig jobs.

These are not only important findings to improve our understanding of platform work in general, they also challenge the established labour-economic and labour-sociology literatures on the education-income paradigm. Moreover, should the gig economy indeed grow into one of the major labour markets of the future (Friedman, 2014; De Stefano, 2016; Durward et al., 2016), our findings may also have implications for policy makers. Western education systems may, for example, benefit from being targeted more explicitly to provide those qualifications that gig workers actually need for their future jobs.

2. Theoretical framework: determinants of income levels

The nexus between educational credentials and labour market success has been widely studied by labour economists and labour sociologists alike (Mincer, 1958; Schultz, 1962; Becker, 1964; Spence, 1973; Bowles and Gintis, 1976; Meyer, 1977; Meyer and Rowan, 1977; Albrecht, 1981; Kingston and Clawson, 1985; Mincer, 1989; Boylan, 1993; Kroch and Sjoblom, 1994; Perri, 1994; Brown, 1995; Arkes, 1999; Card, 1999; Bowles and Gintis, 2002). Their agreement that higher educational credentials lead to higher labour market success (expressed in better paid work) is remarkable. While these scholars agree on the quantitative link between formal education and income levels, they offer different explanations for the causalities underlying this relationship. In his seminal article, Bills (2003) identified overall seven types of middle-range theories meant to explain the relationship: human capital, screening, signalling, control, cultural capital, institutional, and credentialist theories.

Of these, human capital theory is the most established explanation, while signalling and, respectively, screening theories are most applicable to the gig economy. ***Human capital theory*** is "remarkably simple. Schooling provides marketable skills and abilities relevant to job performance. This makes the more highly schooled applicants more valuable to employers, thus raising their incomes and their opportunities for securing [well-paid] jobs (Becker, 1964; Bowman, 1966; Mincer, 1958, 1989; Schultz, 1962)." (Bills, 2003: 444). Importantly, though, workers can register and complete jobs on gig platforms without any educational credentials. This indicates that gig workers can acquire the necessary skills outside formal schooling.

Still, gig requesters need to ensure that gig workers hold the required qualifications. This, in turn, suggests that ***signalling and***, respectively, ***screening theories*** are particularly applicable to understand the education-income nexus in online labour markets. "Labor market signaling complements labor market screening: Employers screen, and job seekers signal. The signaling position is most closely associated with Spence (1973, 1981), who conceptualized hiring as an investment under uncertainty (Albrecht, 1981; Kroch & Sjoblom, 1992; Perri, 1994). Employers evaluating job candidates have available to them a range of observable personal characteristics (e.g., educational credentials, job experience, race, sex)." (Bills, 2003: 446).

Ultimately, signalling theory refers to principal-agent problems in order to explain how adverse selection is prevented in labour markets (Jensen and Meckling, 1976): Employers (principals) want to hire the most productive (best skilled and best willed) workers (agents). But usually an employer cannot be sure of the skills, capabilities and intentions of a possible employee until they have been working together for an extended period of time. Without any additional information, the principal's limited knowledge of the agent's capabilities and intentions entails the risk that a less productive agent will be hired. To avoid such adverse selection, agents try to reduce information asymmetry by signalling their qualities to the principal. Principals use this information in order to decide whether, or not, to hire an employee and, if so, at what wage level. The labour economics literature (most explicitly Spence, 1973) highlights that the agent qualities signalled to the principal most importantly include the agent's (1) ***educational attainment***, (2) ***previous work experience***, (3) ***recommendations***, and even (4) ***gender*** (see also Bills, 2003: 446).

The ***educational credentials***, or ***educational attainment***, of an employee (agent) are a particularly important measure to signal the agent's qualities to a potential employer (principal). *Education* is typically understood in the labour economics literature (Becker, 1964, Mincer, 1975, see also Bills, 2003) as the way of acquiring skills and knowledge, as well as values and habits. While the *educational trajectory* describes the pathway undertaken by an individual towards obtaining skills, knowledge, values and habits, an *education programme* constitutes a part of this trajectory, e.g. a distinct set of courses at school or university, which is typically accredited by the state. At the programme's end, an *educational degree* is awarded to certify its successful completion, for example in the form of an A-level, bachelor or master degree. The highest educational degree completed by a worker, i.e. the educational credentials, defines her *educational attainment*.

Importantly, skills and knowledge can also be gained outside formal, i.e. accredited education programmes, for example through self-study or the participation in individual (online) courses, through learning by doing or watching others, or through trial-and-error processes (Cofer, 2000; Livingstone, 2001; Eaton, 2010). But given that the pursuit of an accredited educational trajectory is mandatory or, at least, supported by the state in all developed Western economies, higher levels of education, i.e. degrees obtained in higher education, are considered a strong signal of worker productivity (Spence, 1973; Mincer, 1975).

Education is typically broken down into primary, secondary and tertiary education. Primary education, or elementary school, constitutes the first stage of formal education, in which children learn to read, write, calculate, become acquainted with general knowledge and develop a sense of responsibility. Secondary education, taught during middle or high school, prepares pupils either for further studies or for a practical apprenticeship leading to a skilled trade. If a student chooses to continue studying, she obtains a degree in tertiary education from a college or university, which ultimately leads to an academic, white-collar or managerial profession. By stating the level of education achieved, i.e. her educational credentials, a potential employee thus signals that she has not only dedicated a substantial amount of time to studying a specific subject, but also had the necessary ambition, motivation, and commitment to successfully complete the respective trajectory.

Accordingly, the educational attainment of a potential employee does not only indicate a certain amount of skills and knowledge acquired but also substantially contributes to reducing the risk of adverse selection, thereby forming the basis for determining her income level (Layard and Psacharopoulos, 1974). The fact that the employee has completed the educational trajectory chosen (which, in turn, has typically been accredited by the government) ensures the employer that the potential employee has been sufficiently committed to acquire a specific level of skills and knowledge. Employees with a higher educational degree can therefore signal higher levels of skills and commitment, so that they are in a stronger position to negotiate their future salaries.

Accordingly, the labour economics literature (Miller, 1960, Mincer, 1975, 1989, Day and Newburger, 2002) agrees that educational attainment constitutes an important predictor of income levels. Labour economic research into the relation between education and income levels already gained momentum in the 1960s and 1970s. These early contributions demonstrate that more education – both in terms of an employee's total years of formal education (de Wolff and van Slijpe, 1973; Lazear, 1976) and in terms of the total years spent on college education (Miller, 1960) – leads to a higher income in later life. Given that labour markets have become ever more flexible since the 1960s, more recent studies assessed whether the positive relationship between education and income still applies (Day and Newburger, 2002) and, if so, whether it also applies to temporary and a-typical forms of work. Importantly, also these more recent studies unanimously confirm that workers with higher educational degrees earn more – irrespective of whether they are hired on the basis of a permanent employment contract, a temporary contract, or a freelancing contract (Wandesjö & Andersson 2004, Payoneer, 2018; see also Gill, 1988). Given that online gig work has also been referred to as micro-entrepreneurship, it is furthermore important to note that the positive relationship between schooling and performance also applies to entrepreneurship and self-employment. Based on meta-analyses, the review article of Van der Sluis et al. (2008) highlights the broad agreement amongst entrepreneurship scholars that higher education translates into better entrepreneurial performance: "[M]ore precisely, the higher the schooling level or the more years of education have been pursued, the higher are the chances that [entrepreneurial] performance is good: earnings are higher, growth is more likely, survival chances are better." (Van der Sluis et al., 2008: 817). Translating these insights to the gig economy, we expect to find that, all else being equal,

H1 *the higher the level of educational attainment signalled by gig workers, the higher their income.*

(2) While educational degrees constitute an important 'entry ticket' to the labour market, their signalling strength decreases as time goes by. The more time has passed since graduation, the less the degree obtained says something about the agent's present skills, motivation and commitment. Instead, the agent's ***work experience*** gains in importance and signalling power, thereby constituting a means to reduce information asymmetry and prevent adverse selection. Skills and knowledge are not only acquired through the pursuit of formal education programmes or individual learning initiatives, they are also learned on the job Lazear (1976); Mincer (1989). The longer an agent holds a position, the more skills and knowledge she gains in relation to her job and the tasks assigned to her. This, in turn, signals the type of work she is capable and willing to do, which decreases the adverse selection risk to hire the 'wrong' person. Akin to a worker's educational attainment, also her work experience helps to evaluate her capabilities and willingness and, thus, to place the right person into the right job (Spence, 1973).

Accordingly, research shows that work experience constitutes an important basis for income negotiations. Like with research into educational attainment, the labour-economic research into the role of work experience as a driver of income levels took off in the early 1970s. Thereby, experience is usually defined as the number of years a person works in the same or a related field. Accordingly, Lazear (1976) as well as Mincer (1975) find that previous work experience is significantly correlated with income levels. More recent studies into the causal links between work experience and income levels confirm this relationship (Booth and Frank, 1996; Altonji and Williams, 2005). Accordingly, Krueger and Rouse (1998) illustrate that the correlation can partly be explained by on-the-job training which has a positive influence on income levels as it increases worker skills and job bids.

Given that different forms of flexible work – including part-time (Visser, 2002) and temporary employment as well as solo self-employment – have been steadily increasing since the turn of the millennium (Friedman, 2014), more recent studies re-assess the relationship between work experience and income levels. Accordingly, Jahn and Pozzoli (2013) find that the pay gap between temp agency workers and employees closes the longer the former work in the same industry. This indicates that the income levels of temporary workforces increase as time goes by, which is often attributed to the on-the job training of temporary workers (see also Booth et al., 2002). Translating these insights to the gig economy, we expect to find that, all else being equal,

H2 *the higher the relevant work experience signalled by gig workers, the higher their income.*

(3) Another important mechanism to lower the risk of adverse selection on the one hand, and to determine income levels on the other, are ***references*** provided by a previous work requester (Mill, 2011; Pallais, 2014; Gandini et al., 2016). Given that references report not only about the specific tasks a worker performed during employment and the quality with which they were completed, but also about the personal characteristics of that worker, references serve as a strong mechanism to signal quality. As a third party, the referee typically shares how she experienced the performance of the worker, thereby providing useful insights into how the latter completed the tasks assigned to her. Such insights serve as an important indicator of a worker's skills, ambition, and commitment and, thus, as a source to reduce asymmetric information and to prevent adverse selection.

One of the first studies on the importance of references as signalling tools revealed that many positions are not only filled on the basis of workers' resumes but, for an important part, also on the basis of referrals from other employers (Christopherson et al. 1999, as quoted in Gill, 2002). With the advent of the digital era, research attention shifted towards the importance of online reviews as a means of quality assurance and, thus, a predictor of price and income levels. Marketing scholars were the first to analyse the effects of online reviews on the sales of products and services. For the tourism industry, Vermeulen and Seegers (2009) illustrated that consumers are more likely to consider booking a hotel if they have previously been exposed to its online reviews, whereby positive reviews improved their attitudes towards the respective hotels. Interestingly, further studies on online purchases showed that (the amount of) negative consumer reviews have a stronger negative effect on sales than positive consumer reviews on the propensity to buy a good (Chevalier and Mayzlin, 2006; Ren et al., 2018).

A similar effect was identified for the impact of reviews on job offers and income levels of gig workers: the more positive the reviews, the more jobs are offered to a gig worker, the higher the worker's income (Pallais, 2014; Moreno and Terwiesch, 2014; Gandini et al., 2016). The (positive) effect of (positive) reviews is so strong that it even mitigates less favourable negotiating conditions, such as being from a developing country (Mill, 2011). The reason for this, simply, is that positive reviews are considered a proof of quality (Zhang et al., 2010; Cui et al., 2012; Schemmann et al., 2016). References can therefore be important to reduce information asymmetry and provide a basis to ask for higher income levels. Translating these insights to the gig economy, we expect to find that, all else being equal,

H3 *the higher the review scores of gig workers, the higher their income.*

(4) Also ***gender*** has been mentioned as a signal of worker productivity and as a major determinant of income levels (Bills, 2003: 446). Given that women participated – if at all – at best on a part-time basis in traditional labour markets in the 1960s, early (labour economic) studies did not investigate pay differences between men and women (for example: Miller, 1960; de Wolff and van Slijpe, 1973). This only began to change over the 1970s and 1980s, when women started to enter and participate in the labour market in similar ways as men. Ever since, research across the social sciences found that, for doing the same work, women earn systematically and persistently less than men (for example Baroudi and Igbaria, 1994; Booth et al., 2002; Gill, 2002; Bobbitt-Zeher, 2007). This pay gap also exists for male and female workers with the same qualifications. Accordingly, Bobbitt-Zeher (2007) shows that women in their mid-20s with a similar, or even higher, education as their male counterparts earn on average $7000 less per year. The systematic pay gap between men and women also applies to multiple industries. For example for the media industry, Gill (2002) found that women are offered significantly fewer contracts and have substantially lower salaries than their male colleagues. One of the major reasons for this systematic income gap seems to be that men make significantly higher salary requests, and do so more frequently, than women (Barron, 2003). Men, simply, seem to ask for, and thus obtain, higher salaries (Barron, 2003). While we know for online labour markets that work requesters have an overall preference for hiring women over men (Chan and Wang, 2018), research into possible pay differences between female and male gig workers remain understudied. In line with the literature on traditional labour markets, we therefore expect that, all else being equal,

H4 *male gig workers have a higher income than female gig workers.*

Fig. 1 provides an overview of the theoretical framework developed above and illustrates how the income level of gig workers is expected to be influenced by their level of educational attainment, years of relevant work experience, review scores, and gender.

3. Methodology

To shed light on the above hypotheses and their underlying mechanisms, we proceed in two steps, developing an explanatory sequential mixed method design approach (Creswell, 2003). In a first step, we test

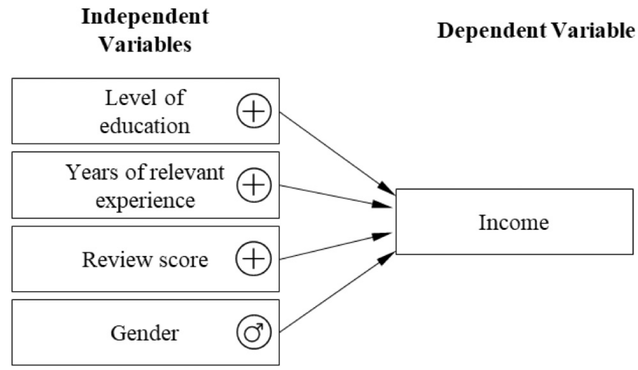

Fig. 1. Theoretical framework: determinants of income levels.

the hypotheses with the help of quantitative OLS regression analyses based on a large-N dataset. In a second step, we then reveal the underlying causalities with the help of the qualitative insights gained from semi-structured interviews with overall 8 gig workers.

3.1. *Empirics: sampling approach and datasets*

To test these hypotheses and shed light on the underlying mechanisms, we analysed gig workers who are active on one of the largest international platforms transacting high-skilled online gig jobs, including in particular programming, design, translations, and writing tasks. We carefully selected this platform on the basis of the following three considerations:

First, the tasks transacted on this platform are exclusively *high-skilled jobs*, for which educational attainment is particularly relevant. The focus on high-skill tasks is necessary because it is important that educational trajectories, providing the skills needed for the respective jobs, exist and are pursued by most dependent employees working in this area. Given that, on traditional labour markets, low-skilled jobs, such as simple cleaning or delivery jobs, do usually not require specific educational qualifications, it only makes sense to look at high-skill platforms transacting jobs for which educational credentials are required on traditional labour markets, which may then also translate into higher income levels in traditional (dependent or temporary) employment.

Second, it was also necessary to select a platform that allows gig workers to *individually determine their own income levels*. The explanatory power of income levels would, simply, be meaningless if they were determined by the platform rather than the gig worker. On the platform selected, gig workers are free to choose their income levels as the platform does not impose a minimum rate nor other pay restrictions.

It was finally necessary to select a platform that gives gig workers the *option to report their educational degree*. Platforms that do not offer gig workers the possibility to signal their educational attainment can, by definition, not provide insights into the importance of educational attainment for income levels.

3.1.1. *Large-N dataset for quantitative analyses*

On the selected platform, we then identified those gig workers that had at least three reviews and were active in one of the following 14 Western economies: Canada, France, Germany, Greece, Hungary, Italy, the Netherlands, Poland, Portugal, Romania, Spain, Sweden, the United Kingdom, and the United States of America.

We decided to base our analyses on *gig workers with at least three reviews* to avoid reliability problems. Importantly, a substantial part of gig workers registered on platforms complete not more than one - maximal two - jobs (de Groen et al., 2016). They do not pursue gig work on a regular basis. Such occasional gig workers typically have only a tentative idea of the income levels they can ask for. This also tends to be the case for gig workers who newly entered a platform. Next to fairly random income levels, also the average review score of gig workers with less than three reviews are still less proven. Taken together, this implies that the results obtained from analyses of gig workers with less than three reviews are hardly reliable. Focusing on repeated gig workers thus ensures that their income levels requested as well as their average review scores reflect the workers' actual market value.

Our *country selection* was driven by the two following considerations: First, educational degrees can only have a comparable impact on income levels if they have been obtained in comparable education systems. Given that the design and rigour of education systems tend to differ between - in particular, Western and developing - countries, we decided to focus our analyses on Western economies with comparable education systems, namely the current EU member states as well as the US and Canada. Ever since the Maastricht Treaty of 1992, the EU member states made substantial efforts to harmonize national education systems, which culminated in the Bologna declaration of 1999, signed by the education ministers of 29 European countries. This entailed numerous reforms of national education systems with the aim of ensuring the comparability of educational degrees. More specifically, all European member states started to model their higher-education systems along the lines of the Anglo-Saxon economies by introducing the distinction between bachelor, master, and PhD degrees – next to vocational training trajectories. While differences between national education systems continue to persist, this harmonization process has led to the comparability of higher-education degrees amongst the Anglo-Saxon economies and EU member states, which is at the basis of our country selection.

Second, our country selection was furthermore driven by data availability. It could be the case that, even though online gig tasks can be accessed and completed by gig workers around the globe, income levels are - at least partly - country-specific. The reason might, for example, be that gig workers in countries with lower cost of living ask for lower remuneration in order to attract gig requests (Mill, 2011; Gomez-Herrera et al., 2017). To control for possible country-specific income differences (McGrattan and Schmitz, 1999; Caselli, 2005), a minimum number of 40 gig workers – with at least 3 reviews and information on their educational background – was included per country. This, in turn, implied that smaller EU countries with <40 applicable gig workers had to be excluded from the sample.[2] This approach limited the sample to the 14 aforementioned Western economies.

For these countries, which we could isolate thanks to the algorithmic search tool of the platform, we did not consider all profiles but focused on all gig workers on the platform in question who had received at least 3 reviews and who provided information regarding their educational attainment. This, in turn, led to a sample of overall 2327 gig workers.[3] For this sample, we collected the necessary data from the gig workers' profile pages with the help of a scraping algorithm. By collecting only a very 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 necessary legal requirements. Our data collection process was approved by the ethics review board (ERB) of our university. In line with our ERB application, we revealed the platform's name to the paper's reviewers but shall not make it public to additionally honour data anonymity.

3.1.2. Small-N dataset for qualitative analyses

To explore the causalities underlying the quantitative analyses of step one (in line with Creswell (2008)), we conducted eight in-depth interviews with gig workers to gain a deeper understanding of how educational credentials are important for obtaining well-paid gig jobs. To this end, we followed an explanatory sequential form of a mixed-method study, whereby we used our prior quantitative data as a basis for the qualitative inquiry (see also Cameron, 2009). We selected the sample in line with Eisenhardt's (1989) seminal guidelines on comparative case studies and the logic of comparison underlying Mill's method of difference (Hancké, 2009: chapter 3). Accordingly, we selected one gig worker who was particularly representative of the following three characteristics: a ***country***'s education system, the qualifications required within a specific ***industry***, and the gig worker's ***educational background***.

While some ***countries*** (in particular Germany) have a highly coordinated and publicly funded education system, others (in particular the US) are characterized by a large diversity of education providers, which do not systematically contribute to nationally coordinated educational trajectories and are typically funded by high private tuition fees. This may imply that educational credentials have a stronger signalling effect for US than for German gig workers. Similarly, some ***industries*** (such as IT-programming) require more technical skills than others (in particular writing), which may mean that educational credentials are more important for gig-programmers than for gig-writers to acquire well-paid jobs. Finally, the ***educational background*** that gig workers display on their profiles differs quite notably: While some highlight their formal educational credentials, others stress the individual self-study efforts they made to acquire the necessary gig skills, e.g. via online courses. This may imply that gig workers highlighting their formal educational credentials deem these more important than gig workers highlighting their individually gained qualifications for obtaining well-paid jobs.

By composing a "most-different" case sample (Hancké, 2009: chapter 3) according to these three dimensions, we were able to control for their impact, while focusing on the role of formal education to this end. Fig. 2 summarizes the 2x2x2 approach taken to compose the qualitative sample of our study.

Gig workers with the applicable characteristics were identified, first, by using the platform's search tool to select workers in Germany and the US, offering writing and IT skills. Then, the profiles of gig workers were studied (in the order in which they were listed on the platform's webpage) to discern those that reported the most complete information about their formal educational credentials and, respectively, their self-study efforts. Applicable gig workers were then contacted (again, in the order in which they appeared on the platform) with the request to participate in an interview of maximum 30 min duration. Gig workers were offered the hourly pay rate, indicated on their profile, for participating in the interview. The first eight gig workers with an applicable profile, who agreed to participate, were interviewed.

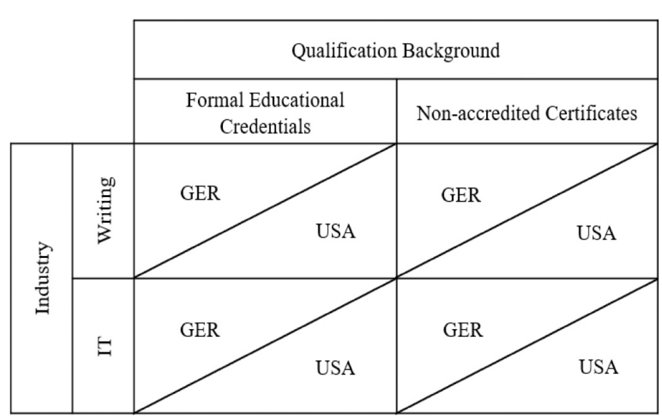

Fig. 2. Case composition for Small-N analyses.

[2] These countries include Austria, Belgium, Bulgaria, Denmark, Estonia, Finland, Ireland, Croatia, Latvia, Lithuania, Luxemburg, Malta, Slovakia, Slovenia, the Czech Republic, and Cyprus.

[3] From this sample, we deleted 2 outlier cases in which gig workers asked for more than $300 per hour, because these income requests seemed to include one digit by mistake.

3.2. Operationalisations

3.2.1. Quantitative measurements

To assess how gig income is correlated with its various predictors, we manually cross-checked and cleaned the following information collected for each of the 2327 gig worker of the large-N dataset: the worker's hourly gig income, highest educational degree obtained, years of relevant work experience, the average review score, as well as the worker's gender. Given that educational degrees, years of work experience and gender are self-reported, it was not possible to verify whether this information was provided truthfully. Importantly, though, gig workers who are found to provide untruthful information risk losing their credibility and, hence, employability. Regular gig workers are therefore unlikely to fake their profiles. But even if the data collected contained fake profiles or fake information regarding educational degrees or work experience, the data still make it possible to test the signalling strength of (fake) gig worker characteristics on their income levels, simply because work requesters need to base their hiring decisions on the same information – also not knowing whether, or not, it is reported truthfully. In addition to these self-reported characteristics of gig workers, we control for, and thus collected data on, the years a gig worker was registered on the platform, as well as the industry and country in which she offers her services. Data collection took place between July 2017 and February 2018.

More concretely, we operationalized the various variables as follows: In line with previous studies (Graham et al., 2017), the dependent variable (***income level*** of a gig worker) was measured as the *hourly wage* (in US Dollars) that the gig worker asked for at the day we studied her profile. Since this variable was positively skewed, we log transformed it before using it in the below OLS regression analyses.

In line with the labour economics literature (Miller, 1960, Mincer, 1975, Day and Newburger, 2002, Wadensjö & Andersson 2004), a gig worker's ***educational credentials***, the core independent variable assessed in H1, is measured as the highest educational degree the worker reports to have completed.[4] In order to distinguish between different educational degrees, we carefully investigated the education systems of the 14 economies included in the sample and took their different educational trajectories into account. Accordingly, we distinguish between a high school degree (1), a vocational degree (2), a bachelor degree (3), a master degree (4), and a PhD (5).

The years of relevant ***work experience***, the second independent variable assessed (see H_2), was measured as the number of years that a gig worker had worked in the same (or a closely related) field as the one in which she was offering gig services on the platform. Importantly, we did not only count work experience as a gig worker towards the years of relevant experience, but all work experience gained – also during dependent employment, traditional freelancing, or temp agency work. To give an example, the 5 years during which a gig worker was employed as a high school teacher in French language and mathematics was *not* counted towards her relevant work experience if she was offering programming services; but they *were* counted, if the gig worker offered translation services from or into French language.[5] Since the variable 'relevant work experience' was positively skewed, we log transformed the variable before using it in the below OLS-regressions.

The ***review*** score obtained, the third income predictor analysed (see H_3), indicates the platform rating of the gig worker's performance on a scale from 1 (extremely poor performance) to 5 (highest possible performance). This score is calculated by the platform and indicates the average evaluation that a gig worker received from all the previous requesters for whom she completed a service. Given that the performance of most gig workers is highly appreciated, this variable is strongly left-skewed (i.e. close to 5). High evaluations are a frequent phenomenon of online platforms with a review system (Hu et al., 2009; Kokkodis and Ipeirotis, 2016). They can be explained through the effects of low ratings, because gig workers with a poor score are less likely to be hired again and, thus, leave the platform (see Jerath et al., 2011). To normalize the review distribution, the scores were first reversed, implying that the review scores became right- skewed, and were then log transformed.

The ***gender*** of a gig worker, the fourth independent variable considered (see H_4), is dichotomous and can take on two values: male or female. We manually coded this variable for each gig worker by identifying his/her gender on the basis of the worker's name, profile description, and picture added. Those cases, where the gender could not be unambiguously identified, and where multiple people operated under the same account or promoted a company, were not taken into account.

In addition to these predictors of income levels, we also control for possible country-, industry-, and time-effects. We operationalize these control variables as follows: To control for possible ***country***-specific differences in income levels, we recorded from which country each gig worker was offering her services.

While only high-skill gigs are transacted on the platform studied, salary levels may differ between ***industries*** because the demand for (or supply of) some industries is higher (or lower) than for others. When registering on the platform, gig workers indicate which skills they possess in offering specific services (such as Javascript, legal research, SAP, French language, or blog writing). Each of these skills is part of a broader industry, such as information and communication technologies (ICT), writing, design, administration, translations, or marketing and sales. To provide just one example: in the design industry, skills can range from architectural, furniture, and graphic design to interior, as well as sticker design – to name just a few. Both industries and skills are pre-defined by the platform. While gig workers may indicate that they possess skills in different industries, the platform allocates each gig worker to that one industry for which she indicated to have most skills of high proficiency. On the platform in question, gig work is mostly offered in four industries, namely ICT, writing, language (translations), and design. We control for possible industry effects by focusing on these four industries and indicating for each gig worker in which industry she is active.

Finally, the income levels of gig workers may systematically increase, or decrease, as ***time*** goes by. The reason may, for example, be that gig workers learn how to promote themselves, so that income levels increase with time, or that competition amongst gig workers increases, so that income levels go down. To control for such temporal effects, we recorded when each gig worker registered on the platform and counted the months since registration. As the variable 'time on platform' was positively skewed, we log transformed it.

Table 1 provides an overview of the aforementioned dependent, independent, and control variables and their operationalisation.

3.2.2. Qualitative measures

To discern the causalities underlying the quantitative analyses, the eight gig workers selected were interviewed in their native language (i.e. German or, respectively, English). Each interview lasted about 30 min, was performed online via Zoom, recorded digitally and then transcribed.

More specifically, these semi-structured interviews (Merton and Kendall, 1946; Richards and Morse, 2013) were organized as follows. After obtaining informed consent, the interviewer posed the same set of questions: first, about the first and, then, about the last gig job that the interviewee had completed on the platform in question. These question sets asked: to describe the first/last gig job; how the interviewee had

[4] To understand whether a gig worker had correctly indicated the degree/s obtained, we manually compared the degree information provided by the gig worker with the degree information provided by the respective institute of (higher) education. In the rare cases of inconsistencies, we considered the degree as not completed.

[5] To distinguish relevant from irrelevant work experience, we manually compared the information provided by the gig worker about her previous work experience with the field in which she was offering gig services.

Table 1
Operationalisation of Dependent, Independent, and Control Variables.

Variable name	Operationalisation
Income	Hourly wage asked for (in US $)
Educational attainment	Highest degree reported:
	1 = High School
	2 = Vocational training
	3 = Bachelor[a]
	4 = Master
	5 = PhD
Experience	Years worked in relevant field
Review rating	Average performance rating of platform on a scale from 1 (poor performance) to 5 (excellent performance)
Gender	Female (0)[a] or Male (1)
Country	Canada[a]
	France
	Germany
	Greece
	Hungary
	Italy
	Netherlands
	Poland
	Portugal
	Romania
	Spain
	Sweden
	UK
	US
Industry	ICT[a]
	Design
	Language
	Writing
Time on platform	Years registered on the platform

[a] Reference category in the following OLS regression analyses.

obtained the respective job; how and why she obtained it; and how educational credentials were important for obtaining and, respectively, completing the job. If this had not been mentioned by the gig worker by then, the interviewer also asked about how work experience and reviews were important for completing the first/last gig job and how the gig worker obtained the necessary skills for completing that job. The interviewer ended with asking about how well-paid gig jobs in general are obtained: What skills are necessary to this end, and how did the gig worker acquire these skills? Through systematic case comparisons, this interview structure made it possible to discern whether the importance attributed to educational credentials, work experience, reviews, and other explanators of well-paid gig work changed over time.

3.3. Analyses

3.3.1. Quantitative OLS regressions

Before conducting regression analyses using the software R, we first explored the data by means of descriptive statistics and correlation analyses. To test the above hypotheses, we estimated several ordinary least squares (OLS) regression models for which we used list-wise deletion of cases with missing values. This, in turn, limited the size of our dataset from 2327 to 1607 gig workers.[6] We checked for multicollinearity (VIF < 10), homoscedasticity and normal distribution of the error terms. These assumptions were not violated in our models.

In the first model, we only included the control variables (country, industry, and years active on the platform), in the subsequent four models we added one independent variable per model. In model 6, we estimated the full model and included all control and independent variables.

3.3.2. Qualitative case comparisons

To analyse the interview data collected, we applied Eisenhardt's (1989) guidelines on comparative case studies. Accordingly, the answers obtained were grouped by topic, i.e. according to the potential explanators of gig income levels. In a next step, all representative quotes on how educational credentials, work experience, and reviews influence the chances of obtaining well-paid gig jobs were listed. While a complete list of these quotes is provided in the appendix (in original language, i.e. German, where applicable), the most insightful quotes are reported in the results section (translated into English language, where needed). In the case of contradictory views about similar causal relationships, it is also reported in the results section how often the respective causalities were mentioned to highlight their relative importance.

4. Results: on the limited impact of education on the income of gig workers

4.1. OLS regression results

Table 2 presents the descriptive statistics of the interval variables included in the final dataset, consisting of 1607 gig workers. The table reveals that the average gig income was just above 27 US dollars per hour. The minimum amount asked for was 2 US dollars, whereas the maximum was 300 US dollars. The average work experience in a relevant field was 5.49 years, while the average time registered on the platform was 5.12 years. Overall, the gig workers received very positive reviews, with a minimum score of 3 points and mean of 4.91 points (on a scale of 1 to 5 points).

For the sake of simplicity, the following descriptive statistics are reported and discussed in Appendix A: Table A1 provides insights into the categorical and ordinal variables included in the dataset, while Table A2 shows the average income of gig workers by educational attainment, as well as by gender. Finally, Table A3 provides an overview of the correlation analyses conducted.

Table 3 reports the results of the OLS regression analyses. All models are statistically significant. The model with only the control variables (model 1) explains 11 % of the variation in the income level of gig workers, whereas the full model (model 6) explains 17.6 % of the variation. When looking at the F-change and its significance, we see that – compared to model 1 including only the control variables – model 2, which additionally includes the educational attainment dummies, does not lead to a statistically significant improvement. For the other independent variables, a significant improvement is observed whenever they are individually added to the control variables. In other words, the reported educational attainment does not add to the explanation of gig

Table 2
Descriptive statistics of interval variables.

Variable	Minimum	Maximum	Mean	Median	Std. deviation
Income (in US$ per hour)	2.00	300	27.13	20.00	22.20
Income (log)	0.30	2.48	1.33	1.30	0.29
Experience (in years)	0	42	5.50	4.00	5.70
Experience (log)	0.00	1.63	0.67	0.70	0.36
Review rating (on scale 1–5)	3.00	5.00	4.91	5.00	0.20
Review rating (reversed and log)	0.00	0.48	0.03	0.00	0.06
Time on platform (in years)	0	16	5.15	5.00	2.92
Time on platform (log)	0.00	1.23	0.74	0.78	0.22

[6] This decrease in cases is primarily due to missing data for the variable *relevant work experience* (708 cases). To ensure that this data limitation does not bias the results obtained when all cases with missing data are excluded list-wise, we also performed a robustness check based on all cases excluding only the variables with missing data pair-wise. This robustness check did not lead to significantly different results (see Appendix B).

Table 3
OLS regression results on hourly income of gig workers.

	Dependent variable					
	Hourly income gig worker (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on the platform (log)	0.167***	0.170***	0.131***	0.165***	0.142***	0.106***
	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)	(0.032)
France	−0.115*	−0.113*	−0.100	−0.111*	−0.123*	−0.103*
	(0.053)	(0.053)	(0.052)	(0.053)	(0.053)	(0.051)
Germany	−0.020	−0.018	−0.014	−0.022	−0.024	−0.018
	(0.050)	(0.050)	(0.049)	(0.050)	(0.049)	(0.048)
Greece	−0.277***	−0.275***	−0.264***	−0.278***	−0.281***	−0.267***
	(0.051)	(0.051)	(0.050)	(0.051)	(0.051)	(0.049)
Hungary	−0.118*	−0.118*	−0.117*	−0.121*	−0.122*	−0.124*
	(0.060)	(0.060)	(0.059)	(0.060)	(0.059)	(0.058)
Italy	−0.232***	−0.226***	−0.216***	−0.228***	−0.216***	−0.192***
	(0.046)	(0.046)	(0.045)	(0.046)	(0.045)	(0.044)
Netherlands	−0.023	−0.018	−0.011	−0.020	−0.015	0.003
	(0.059)	(0.059)	(0.057)	(0.059)	(0.058)	(0.057)
Poland	−0.176***	−0.175***	−0.165***	−0.177***	−0.179***	−0.168***
	(0.049)	(0.049)	(0.048)	(0.049)	(0.048)	(0.047)
Portugal	−0.133*	−0.132*	−0.136**	−0.132*	−0.137**	−0.140**
	(0.053)	(0.053)	(0.052)	(0.053)	(0.053)	(0.051)
Romania	−0.224***	−0.220***	−0.207***	−0.223***	−0.222***	−0.201***
	(0.040)	(0.040)	(0.039)	(0.040)	(0.039)	(0.038)
Spain	−0.129**	−0.128**	−0.136**	−0.128**	−0.122**	−0.126**
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.043)
Sweden	−0.039	−0.044	−0.027	−0.038	−0.027	−0.018
	(0.067)	(0.067)	(0.065)	(0.067)	(0.066)	(0.065)
UK	−0.065	−0.064	−0.056	−0.064	−0.064	−0.054
	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)	(0.041)
US	−0.012	−0.005	−0.017	−0.011	−0.007	−0.005
	(0.038)	(0.038)	(0.037)	(0.038)	(0.038)	(0.037)
Writing	0.006	0.006	−0.001	0.008	−0.003	−0.008
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Design	−0.004	−0.004	−0.010	−0.005	−0.019	−0.026
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)
Language	−0.064**	−0.064**	−0.070***	−0.061**	−0.067**	−0.070***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
High School		−0.089*				−0.058
		(0.041)				(0.040)
Vocational		−0.024				−0.016
		(0.028)				(0.027)
Master		0.007				0.007
		(0.016)				(0.015)
PhD		0.047				0.045
		(0.046)				(0.044)
Experience (log)			0.165***			0.161***
			(0.019)			(0.019)
Review Rating (reversed and log)				−0.288*		−0.246*
				(0.112)		(0.108)
Gender					0.088***	0.092***
					(0.015)	(0.015)
Constant	1.325***	1.320***	1.241***	1.334***	1.287***	1.205***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)
Observations	1607	1607	1607	1607	1607	1607
R^2	0.110	0.114	0.151	0.114	0.129	0.176
Adjusted R^2	0.101	0.103	0.142	0.104	0.119	0.164
F Statistic	11.600***	9.749***	15.745***	11.362***	13.086***	14.084***
F change (compared to model 1)		1.783	76.799***	6.612*	34.218***	18.005***

Note: Standard errors are presented in parentheses.
Reference category = Canada (Country); ICT (Industry); Bachelor (Education).
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

workers' income, whereas their reported experience, review scores and gender do. This is also supported by the coefficients. While we base our interpretations of the results on the full model, the results are robust for the different models.

Given that the dependent variable is log transformed, the coefficients of the interval variables that are also log transformed can be interpreted in percentages. Accordingly, an increase of 1 % in the independent variable x_n, relates to a change with a percentage equal to B in the dependent variable y.

Most strikingly, model 6 indicates that – compared to the reference category (bachelor degree) – different educational degrees are not significantly related to the income level (at a 5 % significance level). Importantly, the same results are obtained if we select any of the other educational degrees as reference category. Higher educational degrees do not translate into higher hourly gig income. These results run counter to the expectations of hypothesis H1. We therefore reject H1 and conclude that signalling higher levels of educational attainment does not have a statistically significant influence on the income levels of gig workers in online labour markets.

Signalling work experience is positively related to gig income levels, indicating that the more experience a gig worker has in the field in which she offers her services, the higher her income. Considering that both the dependent and the independent variable are log transformed, we can conclude that a 1 % increase in years of work experience is related to a 0.165 % increase of the hourly gig income. Therefore, H_2 is supported at a 0.001 significance level.

At first sight, the review scores of gig workers seem to be negatively related to their income levels. Importantly, though, the review scores needed to be reversed in order allow for their log transformation, so that low scores indicate pleased employers – and vice-versa. Therefore, the negative coefficient indicates a positive relation between ratings and income levels. More concretely, a 1 % increase in review scores is related to a 0.288 % increase of the hourly gig income (significant at a 0.05 significance level). These results confirm H_3: Better references translate into higher income levels.

Finally, gender is also significantly related to income levels. Given that female gig workers form the reference category, the positive coefficient implies that men have a significantly higher hourly income than women (significant at a 0.001 significance level). Like in all traditional labour markets, female gig workers experience income discrimination as men earn significantly more than women in the gig economy for doing the same job. Compared to women, men earn 0.088 points more on the log transformed income variable. Therefore, the expectation of H_4 that "male gig workers have a higher income than female gig workers" is corroborated.

With respect to the control variables, we see a statistically significant relation between the time that gig workers are registered on the platform and their income levels. Furthermore, we see that gig workers in France, Greece, Hungary, Italy, Poland, Romania, and Spain, earn significantly less than gig workers in Canada. This is noteworthy to the extent that the online gig economy is a global labour market, for which proponents of convergence arguments would expect income levels to become increasingly homogenous. Finally, gig workers completing language and translation tasks earn significantly less than gig workers completing ICT tasks.

To cross-check the robustness of the above results, we conducted several additional analyses, which are presented in Appendix B.

4.2. Causal insights of qualitative case comparisons

The qualitative insights provided by the gig workers interviewed corroborate and explain the regression results obtained. A complete list of quotes on the causalities identified is provided in Appendix C. Without exception, the gig workers interviewed highlighted that good ***references*** (in the form of 5-star ratings and written reviews) are key to obtaining well-paid jobs. This is particularly remarkable, because all interviewees stressed the importance of good references when they were asked what was important for obtaining their (first/last) gig job(s). That is, references were mentioned although gig workers were not directly asked about them:

> "I think the biggest thing is just to getting yourself established, because that takes quite a bit of patience. Often times clients won't want to hire you, if you have no reviews." (Interviewee #2, p. 70, lines 1-2)[7]

> "Eventually as time processes, your feedback [obtained] speaks for itself." (Interviewee #4, p. 78, line 19)

> "I'm sure the references help a lot." (Interviewee #4, p. 80, line 18)

When asked about their first gig job, it was furthermore remarkable how the interviewees systematically pointed out that they sold their work below value, simply, to obtain good references.

> "So, I sold myself short at the time to get the job and then also the review." (Interviewee # 1, p. 62, lines 33-34)

> "So, they want to kind of pay less, because you don't have (…) the reviews. How it worked for me, I couldn't get anything which seems to take forever. I was trying for a month or two and nobody would reply on any of my postings. So, I got to the point where I took some low-priced jobs. Even though they were not worth it, just to get some reviews. (…) [W]ithout that, it seems impossible to get any jobs, I would say." (Interviewee #2, p.70, lines 2-8)

> "(…) I was willing to work cheap because I wanted to gain some feedback." (Interviewee #6, p.91, line 21)

Several interviewees also reported that they experienced a moment, when their gig work started to take off, which coincided with the moment when gig workers had built a reliable portfolio of positive reviews. This, in turn, also allowed the gig workers interviewed to ask for higher prices:

> "I now have 100 reviews, which is why my hourly rate is higher. I no longer sell myself short." (Interviewee #1, p. 62, lines 40-41)

> "After you have 500 plus reviews (…) [p]eople will think "Wow that guy is a superstar, he has completed 1000 projects and what not. I want him [even if his rates are more expensive]." (Interviewee #8, p. 102, lines 28-30)

In sum, the narratives of the interviewees clearly confirm the causal mechanism proposed by signalling and, respectively, screening theory about how references translate into labour market success: Gig workers signal their qualities, while gig requesters screen worker qualities, via the references (i.e. the ratings and reviews) written by previous work requesters. The more positive reviews a gig worker has, the more are gig requesters inclined to pay high rates.

As laid out in the theory section, labour economists as well as labour sociologists propose different causal explanations for the same correlational link between ***educational credentials*** and labour market success. On the one hand, human capital theory argues that higher formal education leads to higher income levels, because workers have simply learned more and are, accordingly, better skilled. On the other hand, signalling (and, respectively, screening) theory argues that workers have often acquired the necessary skills outside their educational trajectories but can use their educational credentials to signal their commitment and work quality. Given that we did not find a correlation between higher educational degrees and hourly gig income, it was revealing how gig workers talked about their formal education – and its limited importance for obtaining well-paid gig jobs, because educational credentials are neither essential for acquiring the necessary gig skills nor for signalling gig qualities.

Only two out of eight interviewees confirmed the idea of ***human capital theory*** that higher educational credentials help to acquire the skills needed for gig jobs.

> "Yes, my education is helpful. (…) I learned PHP through my degree in one of my classes". (Interviewee #2, p. 67, lines 17-19)

> "Well, since I was studying creative writing, that was kind of like perfect. Just knowing how to describe something. In creative writing, we talked a lot about scenically writing. Being able to look and describe what you are seeing with your eyes. I think that was very helpful". (Interviewee #6, p. 90, lines 27-30)

[7] The page numbers refer to the original interview transcriptions, which are available on request from the corresponding author.

The other six interviewees explicitly refuted the idea of human capital theory and explained that their educational credentials were not useful for acquiring the necessary gig skills:

> "I have a lot of specialist knowledge, but I really acquired or found out about all the specialist knowledge myself." (Interviewee # 3, p. 75, lines 28-30)

> "I have to say that [my studies are] irrelevant. Even though I did learn negotiating as a lawyer and debate when I came out of law school, it wasn't until I started my own [IT] business since I came out of my shell." (Interviewee # 4, p. 80, lines 31-33)

> "[Running a business] helped me much more than university ever did." (Interviewee # 4, p. 80, lines 39-40)

Importantly, and as the above quotes also suggest, the limited importance of higher education for acquiring gig skills does ***not*** mean that gig workers would require no skills. On the contrary, gig workers need a variety and often fairly specific skills. However, all but one gig worker (interviewee #2) explained that they obtained the necessary skills (beyond their general literacy) almost exclusively outside their formal educational trajectories, thereby contradicting human capital theory:

> "It was Amazon Web Services that I used and they have a lot of tutorials that they supply on their website for that. That's what I used to learn, how to do it." (Interviewee #2, p. 68, lines 17-18)

> "I took a course back then. A Photoshop course, a beginner's course and the rest I learned through [YouTube] tutorials." (Interviewee #5, p. 84, lines 18-21)

> "It was kind of self-training, if you will. I have not gotten any formal training in graphic design and I went into YouTube, into Shaw Academy, edX. (…) And another one is W3Schools." (Interviewee #8, p. 103, lines 38-44)

In sum, these interview insights explain why our quantitative results revealed no significant relationship between educational degree and hourly gig income: because (beyond some general reading and writing ability) gig workers chiefly obtain the necessary skills outside their educational trajectories, namely through self-study, online tutorials (e.g. on YouTube), learning-by-doing, and trial-and-error processes. This, in turn, suggests that human capital theory, arguing that formal education provides the necessary skills for future jobs, is hardly applicable to the gig economy.

Similarly, the qualitative insights gained explain the limited applicability of ***signalling*** (and, respectively, screening) ***theories*** for explaining why gig workers obtain well-paid jobs. Only two interviewees suggested that their degrees are perceived as quality signs by gig requesters and, therefore, useful for obtaining well-paid gig jobs:

> "[I]t's a mixture of both, studies and my work experience." (Interviewee #2, p.69, line 2)

> "I think, I didn't have my degree [as an English translator] yet. [But] I was already going to school for it, so yes, that played a [role]. The fact that I just told them that I'm going to school to do a master's degree in English. So that did play a part [for getting my first gig job], yes." (Interviewee #6, p. 90, lines 23-25)

This statement was particularly insightful as it suggests that higher education can be used as a quality signal even if the degree is not yet completed.

And yet, six out of eight interviewees pointed out that the degrees they obtained are, simply, irrelevant to signal the qualities of their gig skills:

> "In freelancing, [formal qualifications are] not so important. What matters in freelancing is, that you can do the job." (Interviewee #4, p. 78, lines 18-19)

> "What I found out in the gig economy is that no one cares about your formal education, if you have a bachelor's degree, a master's degree[, or even] a PhD (…)." (Interviewee #8, p. 101, lines 43-45)

Taken together, these insights explain our quantitative findings, i.e. why educational credentials in the form of higher educational degrees are not correlated with hourly gig wages: Educational degrees are typically not considered important by gig workers as a way to signal their qualifications – thereby contradicting the core idea of signalling theory.

Contrary to higher educational degrees, relevant ***work experience*** constitutes another key device for all gig requesters to gain and signal their gig qualities which, in turn, allows them to obtain well-paid gig jobs. This is true both for work experience gained in a 'traditional job' (as an employee or freelancer) and for work experience gained through gig work. More specifically, and in line with the argument of ***human capital theory*** that (not only formal education but also) work can provide workers with the qualifications needed, gig workers repeatedly stressed how they gained the necessary skills via their work experience outside the gig economy:

> "You learn a lot [working as a salaried web developer], just by having so many colleagues who can give you lots of tips. You see best practice examples of how to do something in the best possible way from the senior staff." (Interviewee #1, p. 64, lines 5-7)

> "My first professional programming jobs were traditional jobs, for 4-5 years, before I started freelancing [on the platform]. I kind of dipped my toe in it back then. (…) [So,] I had 4 or 5 years of traditional programming experience before I started trying to freelance." (Interviewee #4, p. 79, lines 28-31)

> "(…) I spent a lot of time in the sales field. I worked in the sales department. So, I had a bit of experience. I always feel like that helped (…)." (Interviewee #6, p. 91, lines 11-12)

In line with ***signalling theory***, gig workers also pointed out how their traditional work experience helped in marketing their qualities.

> "I actually think that might have made me stand out since I teach. And actually, I happened to teach English to children in China. Even though it is not specifically related to the job, it may have had an influence." (Interviewee #6, p. 92, lines 5-7)

> "(...) he [was] looking for someone who can write and who has prior medical knowledge. I don't have this prior medical knowledge at all, but if you enter that into the [platform] search, I also seem to appear there. (...) That was one of the reasons why he chose me and wrote me." (Interviewee #7, p. 97, lines 30-35)

Taken together, these insights explain why work experience on traditional labour markets is positively correlated with labour market success in terms of hourly gig income: Gig workers benefit from their work experience both as a source to acquire the necessary gig skills and as a way to signal their qualifications.

In addition, and as shown by the positive correlation between the ***time worked on the gig platform*** and the workers' income levels, also the experience gained during gig work helps both to acquire the necessary skills (in line with ***human capital theory***) and to signal skill qualities (corroborating signalling theory). Accordingly, gig workers highlighted how they learned the necessary skills on the platform over time:

> "You have to talk to the customer, just like now. You have to write to them, you have to trade, you have to negotiate prices, and you learn how it works [over time]." (Interviewee #5, p. 84, lines 9-11)

Similarly, gig workers used their gig experience to ***signal*** their qualities:

> "[The gig requester] knew me, I have already completed a few projects with him. It basically comes down to what you have done in the past. Nothing else really matters." (Interviewee #8, p. 103, lines 16-17)

Together, these statements explain how gig workers obtain well-paid jobs by acquiring the necessary skills and signalling their qualities via their gig work over time: They corroborate our quantitative findings that gig wages go up the longer gig workers are active on the platform.

5. Conclusions: contributions, implications, limitations

The rise of the so-called 'platform economy' and, in particular, of digital labour platforms has led to the creation of new labour markets and employment practices. We are still in the early stage of understanding the potential impact of these developments on established theory and paradigms. Based on principal-agent theory, we here shed light on the educational credentials–income nexus, one of the most widely acknowledged relationships in labour-economic and labour-sociology studies of *traditional labour markets*. Given that gig workers can access jobs without needing any educational credentials, our study is the first to address the question whether educational attainment also is a significant predictor of income levels *in the gig economy*. Contrary to the established literature investigating traditional labour markets, (Miller, 1960, de Wolff and van Slijpe, 1973, Lazear, 1976, Card, 1999, Day and Newburger, 2002, Wandesjö & Andersson 2004), we find that educational attainment is not related to the income levels of gig workers.

In view of this unexpected result, it is striking that our findings, simply, corroborate the core result of gender studies of income inequalities (Baroudi and Igbaria, 1994; Booth et al., 2002; Gill, 2002; Bobbitt-Zeher, 2007): Also in the gig economy, women experience income discrimination as they earn significantly less than men for completing the same type of task. This pay gap between male and female gig workers is particularly noteworthy because the (physical) contact between gig requesters and gig workers in the online gig economy is extremely limited. If at all, gig requesters and workers only meet virtually. This seems to lend support to the explanation of Barron (2003) that men earn systematically more than women, simply, because they ask for a higher remuneration – and do so more frequently.

Our findings thus contribute to principal-agent theory by indicating how adverse selection is prevented in online labour markers (Spence, 1973; Jensen and Meckling, 1976). More precisely, they support the idea that signalling mechanisms, addressing information asymmetry to reduce adverse selection problems in work relationships, are important for workers' income levels also in the gig economy. Importantly though, in the gig economy, the main signalling mechanism no longer consists in educational credentials, but rather in the gig workers' previous work experience, gender and, most importantly, ratings and reviews. The particular importance of reviews in obtaining well-paid gig jobs corroborates earlier findings on self-branding strategies of gig workers (Scolere et al., 2018; Rahman, 2021; Blyth et al., 2022). To stand out from the crowd of competitors, online gig workers need to signal their qualities by highlighting their own capabilities, as well as the reviews and references obtained for previous jobs.

Our findings have several implications for platform work(ers) and beyond. Overall, they indicate that the gig economy operates, at least partly, in a different way than traditional labour markets. This, in turn, implies that the gig economy may require separate regulation, which becomes particularly visible with regard to the review systems of platforms.

Given that review systems are a central tool to signal gig worker quality, they also constitute an essential mechanism in relation to income levels. Importantly, review systems in the gig economy are unilaterally designed and governed by platforms, which decide about the criteria through which scores are weighed, aggregated, and assigned to gig workers. This is striking if one considers the massive efforts that institutes of (higher) education are undertaking to get their education programmes accredited (and regularly re-accredited) by the state. Otherwise, students would hardly enrol. While education programmes are governed and monitored by the state through accreditation systems, review systems are exclusively designed by platforms. The key role that good reviews play for obtaining well-paid gig jobs therefore indicates that more information is needed about how platforms design their review systems in order to understand whether, or not, also review systems ought to be accredited by the state.

Furthermore, the limited importance of educational attainment for gig income levels challenges the current education-income paradigm, which is based on the assumption that higher educational credentials are a route to – and a *conditio* sine qua non for – economic wealth. The interviews with gig workers have shown the importance of self-study and continuous learning in the gig economy to learn and keep up to date with the required gig skills. Accordingly, and contrary to traditional employment, higher educational credentials do not necessarily translate into higher gig income. Should the gig economy indeed develop into one of the major labour markets of the future, the limited importance of educational attainment may have major implications for the current design of education systems – and their consequences.

First, it might imply that adolescents become less burdened with debts related to the enrolment in formal education programmes. Recent studies demonstrate that obtaining higher education increasingly means substantial financial investments and debts for graduates across Europe (Johnson et al., 2012; Dämon, 2016; Chamie, 2017). Next to loans for paying tuition fees, higher education requires students to pay for their accommodation, board, and insurances without having time to earn a substantial income. Adolescents therefore often accumulate debts to afford higher education. If gig work constitutes a viable alternative to earn an income without needing to gain a higher education degree, this can not only prevent a substantial number of adolescents to run into debts that may in the end not pay off. It can also empower young people to pursue their own professional interests early on. They may consider alternative training options rather than to commit themselves to the current paradigm, which considers formal higher education as the major prerequisite for a financially comfortable and secure life. However, starting a gig work career also seems to require some investment upfront, namely to sell one's labour for much less than competitors do in order to build a portfolio of references and reviews. If the number of gig workers rises, it is likely that competition amongst them will rise as well – and so would the cost of this initial investment.

Second, the limited importance of educational attainment in the gig economy may also have important implications for skilled, yet unemployed workforces, especially for those people without a degree in higher education. It may empower those workforces to earn a living and find - even demanding and sophisticated - gig work without having to invest into higher educational credentials first. In this regard, the results of our study seem positive. We are aware of (discussions on) potential negative conditions of gig work, such as the lack of social security (Graham et al., 2017; Van Doorn, 2017; Athreya, 2020; Schor et al., 2020). The focus of our study, however, is on the education-income nexus in the high-skill online (rather than the low-skill on-site) gig economy. Future research might want to take a broader focus by including on-site gig jobs and comparing different outcomes.

Third, our findings also imply that institutes of higher education may consider adapting their programmes. This is particularly true for programmes that are closely linked to the type of those high-skilled jobs which, in the future, may increasingly be completed by gig workers. In these areas, educational institutes may decide to modify their programmes in such a way that they better prepare for dependent employment on the one hand and for gig work on the other. The skills transmitted through such programmes could become better targeted to the needs of gig workers, e.g. by training communication and sales skills next to distinct gig skills or building-up a work portfolio, so that the resulting degrees re-gain their signalling strength. As a corollary, this may alter the spending decisions of governments. Rather than to invest into traditional education programmes only, governments may design and support specific programmes for gig workers.

Our study also has its limitations. Most importantly, it is based on the analysis of only one platform for high-skilled online services – including in particular programming, design, translations, and writing tasks. The extent of the aforementioned contributions and implications thus depends on the generalizability of our findings. More research is needed to investigate whether our findings regarding signalling mechanisms and gender pay gap also apply to other platforms, to gig workers from other countries, and to other types of gig jobs.

CRediT authorship contribution statement

Andrea M. Herrmann Conceptualization; Data curation; Funding acquisition; Methodology; Project administration; Supervision; Roles/Writing - original draft; Writing - review & editing

Petra M. Zaal Conceptualization; Data curation; Formal analysis; Methodology; Software; Roles/Writing - original draft

Maryse M.H. Chappin Conceptualization; Methodology; Formal analysis; Supervision; Writing - review & editing

Brita Schemmann Conceptualization; Project administration; Supervision; Writing - review & editing

Amelie Lühmann Conceptualization; Data curation; Formal analysis; Investigation; Validation; Writing - review & editing

Data availability

The data that has been used is confidential.

Appendix A. Descriptive statistics

Table A1 provides insights into the categorical and ordinal variables included in the dataset. These figures reveal that the dataset includes relatively few gig workers with a high school degree only (48 gig workers) and with a PhD degree (38 gig workers). The majority obtained a bachelor degree (903 gig workers). The others hold a degree in vocational training (118 gig workers) or a master degree (500 gig workers). Around 2/3 of the gig workers in the dataset are male (68.8 %), while 1/3 is female (31.2 %). Amongst all countries and industries covered in the dataset, most gig workers are active in the US (504 workers) and the ICT industry (548 workers).

Table A1
Descriptive statistics of categorical and ordinal variables.

Variable	Category	Frequency (number of gig workers)
Educational attainment	High School	48
	Vocational Training	118
	Bachelor	903
	Master	500
	PhD	38
Gender	Female	501
	Male	1106
Country	Canada	58
	France	50
	Germany	64
	Greece	57
	Hungary	33
	Italy	96
	Netherlands	35
	Poland	71
	Portugal	49
	Romania	294
	Spain	117
	Sweden	24
	UK	155
	US	504
Industry	ICT	548
	Writing	378
	Design	437
	Language	244

Table A2 shows the average income of gig workers by educational attainment, as well as by gender. The figures show that gig workers with higher degrees do, on average, not earn more. Interestingly, gig workers who report a vocational qualification, such as a formal training in a trade or another profession that does not require a degree in higher education, earn most on average. Gig workers who report to have a high school degree earn least. It is furthermore interesting to note that female gig workers earn on average less than male gig workers.

Table A2
Average income grouped by educational attainment and gender.

Variable	Category	Average income in US$
Education attainment	High School	23.02
	Vocational Training	29.86
	Bachelor	27.19
	Master	26.72
	PhD	27.73
Gender	Female	23.32
	Male	28.85

The correlation analyses, presented in Table A3, show that the income level of gig workers is positively correlated with all independent variables,[8] with the exception of educational attainment for which we do not observe a statistically significant correlation.

Table A3
Results of correlation analyses.

	Income (log)	Time on platform (log)	Experience (log)	Review rating (reversed and log)	Gender
Time on platform (log)	0.077**				
Experience (log)	0.243**	0.113**			
Review rating (reversed and log)#	−0.064*	0.027	−0.043		
Gender	0.147**	0.152**	0.003	−0.011	
Educational attainment+	0.006	−0.033	0.057*	0.005	−0.060*

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
# Since the review variable needed to be reversed before its log transformation, a negative correlation indicates a positive relationship – and vice-versa.
+ All correlations reported for the variable 'educational attainment' are Spearman correlations because of the ordinal nature of the data. All other correlations reported are Pearson correlations.

Appendix B. Robustness checks

The following robustness checks were completed: First, the above OLS regressions were re-run by excluding missing values of cases pair-wise rather than list-wise. Importantly, this procedure did not change the direction, nor the significance, of the respective regression coefficients.

Second, we estimated the same models by using the raw (i.e. the non-transformed) version of the respective variables. While the outcomes were similar, the R^2 obtained was lower. Furthermore, the assumptions of homoscedasticity and normal distribution of the error terms were violated, while multicollinearity was observed. These statistical flaws supported our earlier decision to run the analyses on the basis of the log-transformed variables.

Third, we also ran univariate models for each control, as well as for any of the independent variables. The outcomes for these variables turned out to be similar to the results in the full OLS regression model reported above: The only exception was educational attainment. When this variable alone was included in a model, gig workers in the first group (high school) turned out to earn statistically less compared to gig workers of the other educational groups. Nevertheless, we did not observe any significant results between the gig workers of the other four education groups.

Fourth, given that the review score was still skewed even after the log transformation of the variable, we also ran a model where the review score was transformed into a dichotomous variable. The latter assessed the impact of "low" review scores (i.e. of 4.8 and lower) as compared to high review scores (i.e. of 4.9 and 5.0 points) on income levels. But also then, the review scores continued to be positively and statistically significantly related to gig workers' income levels, whereas their educational attainment is not.

Last but not least, instead of just controlling for a gig worker's country and industry, we also estimated several multi-level OLS regression models in order to estimate the effect of being a gig worker in a specific country and/or industry. To do so, we used the lme4 package available in R. We included the group effects of a country, as well as of an industry, into the multi-level model (thereby estimating varying intercept models). Importantly, the results obtained from these multi-level analyses did not lead to a change of the independent variables – neither with regard to the direction, nor significance, of their respective regression coefficients.

Appendix C. Complete list of quotes on causalities identified[9]

Please note: Quotes in bold are used in main text.

On the important of ***references*** for obtaining gig jobs:

"(...) man wird gerankt. Je nachdem welche Bewertung man hat, umso besser wird man platziert bei den Angeboten. (...) [I]ch hatte noch keine Bewertungen, also war mein Ziel, erstmal Bewertungen zu sammeln, (…) deshalb [habe ich] auch Jobs angenommen für 20 Dollar, an denen ich 6-7 Stunden dran gesessen habe - für nichts." (Interviewee #1, p. 61, lines 5-10)

"[Der Auftraggeber] hat den Job gepostet und ich habe dann geschrieben, dass ich das machen kann. Inzwischen hatte ich ja gute Bewertungen (…) und dann kam man zusammen." (Interviewee #1, p. 63, lines 20-22)

"[M]y reviews that I have built up over the last couple of years is what, I think, helped as well. I have a pretty good rating on the websites through the good reviews of previous clients and, I think, that helped too." (Interviewee #2, p. 69, lines 25-27)

"I think the biggest thing is just to getting yourself established, because that takes quite a bit of patience. Often times clients won't want to hire you, if you have no reviews." (Interviewee #2, p. 70, lines 1-2)

"[Die Auftraggeber] gucken sich auch meine Referenzen an." (Interviewee #3, p. 74, line 39)

"Eventually as time processes, your feedback [obtained] speaks for itself." (Interviewee #4, p. 78, line 19)

"I'm sure the references help a lot." (Interviewee #4, p. 80, line 18)

"Ja, ich denke schon, dass die Kunden gucken, was man für Bewertungen hat und was man als Referenz drin hat. Das auf jeden Fall!" (Interviewee #5, p. 87, lines 9-10)

"Das war auch ganz am Anfang nicht sehr leicht, überhaupt an Jobs zu kommen, weil man natürlich noch keine Erfahrung und keine Bewertung hatte. Dann sind halt viele Auftraggeber erstmal skeptisch." (Interviewee #7, p. 95, lines 9-11)

"Solange ich noch keine Bewertung hatte, habe ich auch keinerlei Anfragen erhalten. Zumindest war das bei mir so. Das ist so ein bisschen, dass man komplett verschwindet in der Masse."(Interviewee #7, p. 95, lines 14-16)

[8] Note that the review scores needed to be reversed in order to log-transform them, so the negative correlation indicates a positive association with income levels.
[9] The page numbers refer to the original interview transcriptions, which are available on request from the corresponding author.

"But people really care about your portfolio. What you have done in the past. They want to see what employers have to tell about you. (…) [I]t's a mixture of your portfolio, your previous reputation, how you have handled previous projects and all that." (Interviewee #8, pp. 101-102, lines 46-4)

On the need to sell gig work below value at the beginning of a gig career in order to obtain good references:

"[Auf der Plattform zu arbeiten] war dann halt mein erster Job. (…) Bei mir war es halt so, dass ich versucht habe, die Konkurrenz zu unterbieten. **Ich habe mich also damals unter Wert verkauft, um den Job und dann auch die Bewertung zu bekommen** und ein wenig Geld zu bekommen." (Interviewee # 1, p. 62, lines 30-34)

Translated as: „So, I sold myself short at the time to get the job and then also the review." (Interviewee # 1, p. 62, lines 33-34)

"So, they want to kind of pay less, because you don't have (…) the reviews. How it worked for me, I couldn't get anything which seems to take forever. I was trying for a month or two and nobody would reply on any of my postings. So, I got to the point where I took some low-priced jobs. Even though they were not worth it, just to get some reviews. (…) [W]ithout that, it seems impossible to get any jobs, I would say." (Interviewee #2, p.70, lines 2-8)

"[Es war] am Anfang aber auch sehr zäh. Man muss doch sehr weit runtergehen. Mein erster Job war wirklich sehr niedrig von der Bezahlung her. Die allerersten Kunden habe ich auch nicht mehr, weil das Problem ist, wenn man bereits so niedrig ist, kann man auch nicht mehr höher gehen. Aber dann hat man irgendwann die Referenzen und dann kann man gucken, dass man neue Kunden bekommt, zu höheren Preisen. Aber am Anfang ist es hart." (Interviewee #5, p.87, lines 22-27)

"(…) [W]hen you start out, you don't have any feedback. So, that's a little handicap. So, I'm pretty sure I applied for 10 or 15 jobs actually. You know, it's just hard to get that first one to build up feedback. And then I got it, but in the very beginning, I had to work for very low rates because you don't have feedback. You know, you can't show that you are legit and all of that and do the job correctly." (Interviewee #6, p.90, lines 6-10)

"(…) I was willing to work cheap because I wanted to gain some feedback." (Interviewee #6, p.91, line 21)

Interviewees reporting how their gig work started to take off when they had built a reliable portfolio of positive reviews, which also allowed them to ask for higher gig rates:

"Inzwischen habe ich 100 Bewertungen, weshalb auch mein Stundensatz höher ist. Man verkauft sich nun nicht mehr unter Wert." (Interviewee #1, p. 62, lines 40-41)

Translated as: "I now have 100 reviews, which is why my hourly rate is higher. I no longer sell myself short." (Interviewee #1, p. 62, lines 40-41)

"(…) aber mittlerweile habe ich halt meine Referenzen und ich glaube nicht, dass da jetzt noch irgendwer [auf Bildungsnachweise] (…) guckt," (Interviewee #3, p. 72, lines 35-37)

"Nein, habe ich eigentlich nie gebraucht, formale Abschlüsse oder so, sobald man gewisse Referenzen vorlegen konnte. Der Anfang ist schwer, aber sobald man an gewisse Jobs rangekommen ist, hat es sich aufgebaut." (Interviewee #5, p. 83, lines 20-22)

"(…) [O]nce you complete that first job, you have a five-star review hopefully from your client, that kind of paves the wave for future jobs. The hardest thing I found, is that I needed almost five months to land my first project. But once that first project was completed and with a good review, I was landing probably a couple of projects every month. Before I had even 20 reviews, I was getting a 20% – 25% response rate back from my projects." (Interviewee #8, p. 102, lines 14-19)

"After you have 500 plus reviews (…) [p]eople will think *"Wow that guy is a superstar, he has completed 1000 projects and what not. I want him [even if his rates are more expensive]."* (Interviewee #8, p. 102, lines 28-30)

On the (limited) importance of ***educational credentials*** for acquiring the necessary gig skills…

"Yes, my education is helpful. (…) I learned PHP through my degree in one of my classes". (Interviewee #2, p. 67, lines 17-19)

"Well, since I was studying creative writing, that was kind of like perfect. Just knowing how to describe something. In creative writing, we talked a lot about scenically writing. Being able to look and describe what you are seeing with your eyes. I think that was very helpful". (Interviewee #6, p. 90, lines 27-30)

"Ich kann viel mit Fachwissen punkten, aber das Fachwissen habe ich mir wirklich alles selber angeeignet beziehungsweise herausgefunden." (Interviewee # 3, p. 75, lines 28-30)

Translated as: "I have a lot of specialist knowledge, but I really acquired or found out about all the specialist knowledge myself." (Interviewee # 3, p. 75, lines 28-30)

"[D]ann [habe ich das] Fachabitur angefangen. Das war dann auch lustigerweise in die IT Richtung. Aber auch da ist mir wieder aufgefallen, [dass das] was ich da gelernt habe, (…) nichts mit dem Beruf zu tun [hat].“ (Interviewee # 3, p. 73, lines 10-13)

“I have to say that [my studies are] irrelevant. Even though I did learn negotiating as a lawyer and debate when I came out of law school, it wasn't until I started my own [IT] business since I came out of my shell.“(Interviewee # 4, p. 80, lines 31–33)

“[Running a business] helped me much more than university ever did.” (Interviewee # 4, p. 80, lines 39-40)

“Tatsächlich [habe ich] nicht wirklich in dem Ausbildungsbereich [etwas für meine spätere Gig-Tätigkeit gelernt]. Nicht in den formalen Sachen. Mehr so, was ich nebenher noch gemacht habe, das glaube ich eher.” (Interviewee # 7, p. 96, lines 2-3)

“Ich war eine Zeit lang politisch recht aktiv und habe für den Ortsverein die Homepage gemacht und dort die Texte erstellt etc. Das hat mir Spaß gemacht (…). Ich glaube, dieses Sprachgefühl dafür zu entwickeln, hat mir meiner Meinung nach mehr geholfen als meine Ausbildung.“ (Interviewee # 7, p. 96, lines 5-10)

“[Die Weiterbildung] war komplett autodidaktisch.“ (Interviewee # 7, p. 96, lines 17-19)

… as most gig workers acquire the necessary gig skills autodidactically:

“[Die erforderlichen] Fertigkeiten habe ich mir nebenbei angeeignet. Mit dem Programmieren habe ich mit 14 oder 15 angefangen als Hobby. (Interviewee #1, p. 61, lines 29-30). (…) Ich habe damals viele Bücher gelesen. Alles mögliche, habe mir viele Bücher ausgeliehen und dann immer wieder versucht diese Hello World Dinger auszuprobieren.” (Interviewee #1, p. 62, lines 15-17)

“It was Amazon Web Services that I used and they have a lot of tutorials that they supply on their website for that. That's what I used to learn, how to do it.” (Interviewee #2, p. 68, lines 17-18)

“The majority of the time, when I want to learn a new technology, I will find a good walk-through, or a book that I can read through and get hands on experience or whatever it is. Occasionally, I go to YouTube to find stuff, but I feel like walk-troughs and books are more valuable when learning something new.“(Interviewee #2, p. 67, lines 31–34)

“Also, ich habe so 1-2 Onlinekurse gemacht auf Udemy. (…)Da habe ich wirklich in 40 Stunden Videomaterial, was es dort gab für 13 Euro (…), eigentlich all das gelernt, was ich brauche, um weiterzukommen in diesem Business. Den Rest lernt man durch Googeln. Also ganz viel Selbst-Recherche, auch heute noch, täglich. Ich weiß auch nicht, wie alles funktioniert und selbst Entwickler, die 30 Jahre arbeiten wissen das nicht. Und natürlich YouTube auf jeden Fall auch. Das ist auch ein tägliches Tool, welches ich benutze.“ (Interviewee #3, p. 73, lines 37-45)

“There weren't videos [back then], so it was books. Stuff I could read online. Regular books, not e-books. Just wherever I could find the information, I would just read it. I always had a giant technical book. Even when I was eating dinner, I would be reading this stupid book.“ (Interviewee #4, p. 79, lines 22-24)

“Ich habe einen Kurs damals besucht. Einen Photoshop Kurs, einen Anfängerkurs und den Rest habe ich über [YouTube] Tutorials gelernt.“ (Interviewee #5, p. 84, lines 18-21)

Translated as: “I took a course back then. A Photoshop course, a beginner's course and the rest I learned through [YouTube] tutorials.“ (Interviewee #5, p. 84, lines 18-21)

“Das war komplett autodidaktisch.“ (Interviewee #7, p. 96, line 19)

“Das war größtenteils über YouTube. Ich habe mir Videos angeschaut und dann die ein oder andere Studie gelesen. Die habe ich dann über Google gefunden. Das hat sich dann darauf beschränkt.“ (Interviewee #7, p. 98, lines 17-19)

“It was kind of self-training, if you will. I have not gotten any formal training in graphic design and I went into YouTube, into Shaw Academy, edX. (…) And another one is W3Schools. Even before I started school for computer science, I used to go on sites and kind of learned how WordPress, Java Scripts, CSS works. I learned from these various resources mostly free, sometimes 20-40 Dollars for a course. So, that's how I learned.“ (Interviewee #8, p. 103, lines 38-44)

On the (limited) importance of ***educational credentials*** for signalling gig worker qualifications:.

“[I]t's a mixture of both, studies and my work experience.” (Interviewee #2, p.69, line 2)

“I think, I didn't have my degree [as an English translator] yet. [But] I was already going to school for it, so yes, that played a [role]. The fact that I just told them that I'm going to school to do a master's degree in English. So that did play a part [for getting my first gig job], yes.” (Interviewee #6, p. 90, lines 23-25)

“Bisher hatte ich noch keinen [Auftraggeber], der irgendwelche Nachweise [über meine Abschlüsse] haben wollte.” (Interviewee #3, p. 72, lines 28-29)

“In freelancing, [formal qualifications are] not so important. What matters in freelancing is, that you can do the job.” (Interviewee #4, p. 78, lines 18-19)

“[Ich] halte [mein Studium hinsichtlich meiner Gig-Tätigkeit] für irrelevant (…).” (Interviewee # 7, p. 98, lines 1-3)

“Ich glaube auch, das sind wieder keine formalen Qualifikationen, [die zum Erhalt eines Gig-Jobs Führen]. [S] ondern ich glaube, dass Wichtigste dabei ist, dass man authentisch und ehrlich ist. ” (Interviewee #7, p. 98, lines 32–36)

“What I found out in the gig economy is that no one cares about your formal education, if you have a bachelor's degree, a master's degree [, or even] a PhD (…).” (Interviewee #8, p. 101, lines 43-45)

"I would say formal education doesn't matter, what matters, is your skill and training. That does not have to be formal training." (Interviewee #8, p. 102, lines 42-44)

"It basically comes down to what you have done in the past. Nothing else really matters. No one cares about your formal qualification. I do not have a bachelor's or master's degree in English." (Interviewee #8, p. 103, lines 16-18)

On the importance of ***work experience*** for gaining gig skills and for signalling gig worker qualifications:

"Man lernt [in der Arbeit als angestellter Webentwickler] sehr viel, allein schon durch die vielen Kollegen, die einem viele Tipps geben können. Man sieht Best-Practice-Beispiele, wie man etwas bestmöglich macht von den Senior-Mitarbeitern (Interviewee #1, p. 64, lines 5-7). (…) Auf der Arbeit nimmt man dann Techniken und Neuerungen mit. Deshalb hilft das viel." (Interviewee #1, p. 64, lines 15-16).

Translated as: "You learn a lot [working as a salaried web developer], just by having so many colleagues who can give you lots of tips. You see best practice examples of how to do something in the best possible way from the senior staff." (Interviewee #1, p. 64, lines 5-7)

"I had several years of programming experience in traditional jobs behind me. It's not like I was complete new at the field of programming. I knew how to talk." (Interviewee #4, p. 78, lines 24-25)

"My first professional programming jobs were traditional jobs, for 4-5 years, before I started freelancing [on the platform]. I kind of dipped my toe in it back then. (…) [So,] I had 4 or 5 years of traditional programming experience before I started trying to freelance." (Interviewee #4, p. 79, lines 28-31)

"[Y] es, you absolutely need to have technical skills to make decent money. I have a lot of different skills from the last 20 years. It makes me very different than a traditional employee." (Interviewee #4, p. 81, lines 24-26)

"[M]an muss mit dem Kunden sprechen, so wie jetzt auch. Man muss mit denen schreiben, man muss handeln, man muss Preise verhandeln und das kriegt man dann schon mit. Ich war nebenher beim Studium im Verkauf tätig und da habe ich das natürlich auch mitbekommen." (Interviewee #5, p. 84, lines 9-12)

"(…) I spent a lot of time in the sales field. I worked in the sales department. So, I had a bit of experience. I always feel like that helped (…)." (Interviewee #6, p. 91, lines 11-12)

"I think my work experience helped me the most in [getting lucrative gig jobs], because I have 8 years of python programming under my belt from that job." (Interviewee #2, p. 68, line 39-40)

"Coding styles I have picked up along the way of working and having other people critiquing my codes and stuff like that." (Interviewee #2, p. 69, lines 1-2)

"I actually think that might have made me stand out since I teach. And actually, I happened to teach English to children in China. Even though it is not specifically related to the job, it may have had an influence." (Interviewee #6, p. 92, lines 5-7)

"I think, the fact, that I was an English teacher probably helped though. You know, that I had experience as an English teacher, because I did not only do ESL, but before that, I was an English teacher to Americans. So, like a real English teacher." (Interviewee #6, p. 92, lines 28-31)

"(…) er [hat] nach jemanden gesucht, der einmal schreiben kann und der zum anderen medizinisches Vorwissen hat. Dieses medizinische Vorwissen habe ich gar nicht, aber wenn man das bei [der Plattform] in die Suche eingibt, schein ich da auch mit aufzutauchen. Man kann es nicht beeinflussen. Ich habe keine Ahnung, warum und weshalb. Aber **das war bei ihm ein Grund, warum er mich dann ausgewählt und angeschrieben hat." (Interviewee #7, p. 97, lines 30-35)**

Translated as: (…) he [was] looking for someone who can write and who has prior medical knowledge. I don't have this prior medical knowledge at all, but if you enter that into the [platform] search, I also seem to appear there. (…) That was one of the reasons why he chose me and wrote me. (Interviewee #7, p. 97, lines 30–35).

On the importance of ***time worked on the gig platform*** for acquiring the necessary gig skills in order to obtain well-paid gig jobs:

"[A]n employee is usually much lazier. They don't do what has to be done, because they are getting paid no matter what. You know, so [as a gig worker] I had to learn how to do lots of different things." (Interviewee #4, p. 81, lines 27-29)

"Man muss mit dem Kunden sprechen, so wie jetzt auch. Man muss mit denen schreiben, man muss handeln, man muss Preise verhandeln und das kriegt man [mit der Zeit] dann schon mit." (Interviewee #5, p. 84, lines 9-11)

Translated as: "You have to talk to the customer, just like now. You have to write to them, you have to trade, you have to negotiate prices, and you learn how it works [over time]." (Interviewee #5, p. 84, lines 9–11)

"[N]ow I have a lot of different gigs. Like tutoring, I teach and I write, but I always feel like that all of the different things from all of the different fields definitely have helped in that way." (Interviewee #6, p. 91, lines 13-15)

"[A]uf [der Plattform] ist es gut als Übersetzer, die [Plattform-] Zertifikate gemacht zu haben. Zumindest die ersten." (Interviewee #5, p. 88, lines 21-22)

"But people really care about your portfolio. What you have done in the past. They want to see what [other gig requesters] have to tell about you. (…) [I]t's a mixture of your portfolio, your previous reputation, how you have handled previous projects and all that."(Interviewee #8, pp. 102, lines 3–4)

"[The gig requester] knew me, I have already completed a few projects with him. It basically comes down to what you have done in the past. Nothing else really matters." (Interviewee #8, p. 103, lines 16-17)

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Andrea M. Herrmann is Professor of Sustainable Innovation and Entrepreneurship at Radboud University (Nijmegen). She holds a PhD from the European University Institute (Florence) and was a Visiting Researcher at Columbia University (New York) and the Max Planck Institute für Gesellschaftsforschung (Cologne). Andrea M. Herrmann obtained several renowned research funds, most recently an ERC Consolidator Grant. In her research, she investigates how incumbent firms and entrepreneurs innovate, how they are

helped (or hindered) in innovation by their institutional environment, and what lessons can be learned from it by policy-makers. Her research interests comprise the areas of political economy, institutional theory, innovation management, entrepreneurship, and online labour markets (gig economy).

Petra M. Zaal works as an innovation and strategy consultant at Monitor Deloitte. She holds a Master's degree in Sustainable Business and Innovation from Utrecht University, and uses this to help companies build towards a sustainable future by focussing on their strategy for 2040 and beyond. Her research interests range from shaping trends of the coming decades to decarbonisation of large incumbents to bringing new, innovative, solutions to the market.

Maryse M.H. Chappin is Associate Professor at the Innovation Studies group of the Copernicus Institute of Sustainable Development at Utrecht University. She holds a PhD in Innovation Studies from Utrecht University. Her research mainly focuses on gaining a better understanding of (the process of) sustainable innovation. She studies the success of inter-organizational collaborations and networks in the context of sustainable innovation as well as the collaborations themselves. She is also interested in the role of the institutional environment on the innovation process.

Brita Schemmann is Professor of Business Administration, in particular Innovation Management, at Bremen University of Applied Sciences. She holds a PhD in Innovation Studies from Utrecht University. Her research mainly focuses on developing a better understanding of open and platform-based innovation in particular its processes and implications.

Amelie Lühmann holds a Bachelor's degree in Business Studies / International Management from the University of Applied Sciences Bremen and is currently pursuing her Master studies in Marketing Management at the Berlin School of Economics and Law. During her studies, she particularly discovered the topics of strategic marketing, entrepreneurship and innovation management to be highly exciting. In parallel to her master studies, she works at Deloitte and supports the Tax Technology Consulting project and communication management.