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Transitions From Offline to Online Labor Markets: The Relationship Between Freelancers' Prior Offline and Online Work Experience

Transitions from Offline to Online Labor Markets: The Relationship between Freelancers' Prior Offline and Online Work Experience

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Abstract: An emerging stream of research from various disciplines studies online labor market (OLM) platforms as an alternative way of accomplishing work compared to traditional (offline) labor markets. Although prior work has increased our understanding of how OLM platforms function, we so far know very little about the relationship between what workers have done before entering the platform and the skill content of their online jobs. However, the question of why workers do the jobs they do in an online context and what drives their decision is fundamental to understanding how these markets function and are used by workers. Using data on 4,771 freelancers working on Upwork.com, the world's leading freelancing website, we compare the skill content of their online jobs with their last reported offline prior to platform entry. Based on prior work on occupational mobility (Gathmann & Schönberg, 2010) and human capital investments (Becker, 1962), we hypothesize and find that workers with more valuable skillsets adjust their skill portfolios less while working online, i.e. the distance between their offline and online skill portfolio is lower. We further show that being female, coming from

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an advanced economy and reporting having current offline employment moderates the relationship between skill value and skill distance.

Keywords: Online labor markets, gig economy, labor mobility, occupational mobility, human capital, task-based approach, digital platforms, knowledge work.

JEL class: J24, J6, J44.

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1 From Offline to Online Labor Markets: The Relationship between Freelancers' Prior Offline and Online Work Experience

1.1 Introduction

Research on workers' mobility and careers has so far studied how workers cross job, occupational, organizational, and geographical boundaries to advance their careers (Bidwell & Briscoe, 2010; DeFillippi & Arthur, 1994; Feldman & Ng, 2007; Peri & Sparber, 2011; Robinson, 2018; Rosenfeld, 1992) but have overlooked a novel type of work boundary: Moving from offline (local) to online (global) labor markets. Such digital marketplaces refer to a new and technology-enabled form of accomplishing work that enables a global set of workers to complete (knowledge) tasks remotely and on-demand as independent contractors (Agrawal *et al.*, 2015; Horton & Chilton, 2010).

Given the distinct features of OLMs, the transition from offline to online labor markets generally represents a major shift in workers' careers. In fact, workers cross multiple boundaries simultaneously: Working online implies organizational changes – in fact, multiple new employing firms and moving towards self-employment – but also geographical changes by working for clients across the globe. However, no study has yet explored whether these transitions further entail changes in the types of jobs workers accomplish. Specifically, it is not clear whether workers simply continue their prior job and transfer their existing skillset to an online context or shift their careers entirely by learning new and applying different skills. On the one hand, moving to jobs with similar skill requirements is beneficial in terms of wage outcomes, i.e. returns to prior human capital investments (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008). On the other hand, OLMs are characterized by a large degree of flexibility due to the job heterogeneity and short-oriented nature of work. Thus, workers may use OLMs to learn skills on-the-job (Becker, 1962) and as a stepping-stone to new careers. Although a growing number of workers decides to work online (Kässi & Lehdonvirta, 2018), we know surprisingly little about the relationship between workers' offline and online jobs. However, the question of why workers do the jobs they do in an online context and what drives their decision is fundamental to understanding how these markets function and are used by workers. Thus, we ask: *What drives changes in workers' skill portfolios when working online compared to their prior (offline) job? What are the boundary conditions?*

To examine our question empirically, we study whether transitions entail changes in workers' skill portfolios[2] compared to their prior (offline) job. This can also be referred to as occupational change, which is defined as fundamental changes in skills, training and routines (Feldman & Ng, 2007). We use data on 4,771 freelancers working on Upwork.com, the world's leading freelancing website, and compare the skill content of their online jobs with their last reported offline prior to platform entry. Based on prior work on occupational mobility (Gathmann & Schönberg, 2010) and human capital investments (Becker, 1962), we hypothesize that the decision to move will depend to on the value of their current skill portfolio in an online context. Specifically, we hypothesize and find that workers with more valuable skillsets adjust their skill portfolios less while working online, i.e. the distance between their offline and online skill portfolio is lower. Since online workers are very diverse in terms of their background and motivations to enter the platform (Manyika *et al.*, 2016), we also consider that some workers may respond differently to the value of their skills. We show that being female, coming from an advanced economy and reporting having current offline employment moderates the relationship between skill value and skill distance.

We contribute to a number of research streams. First, we contribute to research on OLMs by being the first to study how work experience acquired prior to platform entry affects the jobs workers accomplish online. Given that a growing number of workers enters digital markets to offer their services, it is important to study how both labor markets interrelate. Second, we add

[2] Skills refer to practical skills as well as theoretical and practical knowledge that is applied to tasks to produce output (Acemoglu & Autor, 2011; Eggenberger *et al.*, 2018).

to the current discussion on reskilling, referring to activities aimed at “learning new sets of competencies to transition to a completely new role” (World Economic Forum, 2019: p. 4). Due to continuous technological innovation and rapidly changing skill requirements, it is predicted that workers have to adjust their skillsets more frequently in the future (Autor *et al.*, 2003; Autor & Dorn, 2009). Our study shows that some workers already seem to use OLMs as a stepping stone to new career paths. Such platforms can thus become a powerful tool to enable and smooth job transitions in the future by learning skills on-the-job in short-term assignments. Third, we add to the literature on boundaryless careers (DeFillippi & Arthur, 1994) by adding a new type of work boundary that workers can span. Finally, we add to the literature on occupational mobility by studying occupational changes at a very fine-grained level and for a global set of workers.

1.2 Occupational Change in Offline Labor Markets

Since we are interested in the occurrence of changes in workers’ skill portfolios, we build on prior work studying occupational mobility at the individual level.

The occupational mobility literature has been growing in recent years, focusing both on the rates of occupational mobility and on the implications of occupational transitions for individuals’ human capital and wages. In general, occupational mobility appears to be not random; from a given occupation, transitions to some occupations are more likely than to others (Kambourov & Manovskii, 2008; McCall, 1990; Papageorgiou, 2014; Shaw, 1987). This distinction is important because both human capital and wage losses should be lower if workers move to related occupations.

A growing body of literature thus studies occupational mobility at the level of the task to describe the relatedness of occupations instead of using changes in two- or three-digit occupational codes (e.g. Acemoglu & Autor, 2011; Autor *et al.*, 2003; Autor & Handel, 2013). By characterizing an occupation as a bundle of tasks demanding certain skills, one can study the relationship of different occupations and provide a more nuanced view on workers' human capital and mobility patterns (Poletaev & Robinson 2008; Gathmann & Schönberg 2010; Yamaguchi, 2012). Researchers using a task approach thus allow looking inside the "black box" of census occupation codes and descriptions (Yamaguchi, 2012).

For example, Gathmann and Schönberg (2010) propose the concept of "task-specific human capital" (opposed to occupation-specific human capital) to measure the transferability of skills across occupations, i.e. the distance between occupations. They find that worker's current occupation affects future occupational choices. More specifically, by distinguishing between manual, interactive and analytical tasks, they show that human capital is more portable across occupations than previously considered. For example, a baker who moves to another occupation relying on manual tasks does not experience a huge loss in human capital. They further show that individuals moving to a rather distant occupation suffer a larger wage loss. Likewise, Poletaev and Robinson (2008) and Robinson (2018) find that a large amount of occupational mobility involves little or no specific human capital loss when taking the distance between occupations in terms of their task and skill requirements into account.

These studies suggest that first, researchers have to study mobility at a fine-grained level to accurately portrait mobility and human capital losses and second, that workers generally have an incentive to move to occupations matching their existing skills because of potential human capital and wage losses.

1.3 Online Labor Markets

1.3.1 Defining Online Labor Markets

OLM platforms such as Amazon Mechanical Turk, Upwork, Fiverr, and Freelancer.com facilitate the allocation of labor across global economies (Agrawal *et al.*, 2015). OLMs are markets "where labor is exchanged for money, the product of that labor is delivered over a wire and the allocation of labor and money is determined by a collection of buyers and sellers operating within a price system" (Horton, 2010: 516). We study spot markets for (more high-skill) tasks, a particularly powerful new way of accomplishing work online (Horton, 2010). In these markets, employers can "buy discrete chunks of labor from a global pool of workers at a market price, similar to how they obtain any other factor of production" (Chen & Horton, 2016: 414).

Work processes on OLM platforms are as follows. Clients register by providing contact details and basic information. Then, they can post any number of jobs and hire as many freelancers as they like, in general and for a single project. Postings include a task description, the client's location, the type of contract offered (fixed price or hourly-pay), and other job features. Freelancers register by giving contact details, name and location as well as setting up a profile page. Profiles are very detailed and include a description of skills, education, skill test scores, certifications, agency affiliation, portfolio items, platform work history and feedback scores. Importantly for our study, freelancers can add work experience outside the platform, including the respective job title, timeframe, company name and a free text on their tasks and responsibilities. To get hired, freelancers apply by submitting cover letters and bids and are eventually interviewed by clients before hiring. Freelancers then complete tasks remotely. Submission of deliverables and payments are via the platform which charges a fee. After completion, both client and freelancer evaluate the project with a score from 1 to 5 on a number of process- and outcome-related criteria.

As evident from the description above, OLMs differ from traditional markets in several ways. First, work takes place online rather than by physically collocated workers (Chen & Horton, 2016). Another distinct feature is the feasibility of hiring on demand and outsourcing smaller jobs instead of entering a long-term employment contracts (Agrawal *et al.*, 2015). In addition, most OLMs broker highly heterogeneous tasks, enabling workers to work in diverse task categories and on tasks requiring different skill levels. Likewise, employers are flexible in which tasks to outsource and how to specify each job (e.g. contract type, engagement level, skills required, hiring multiple workers). OLMs are further characterized by a large degree of market transparency since prices, demand and supply are visible to both freelancers and employers (Horton & Tambe, 2020). Finally, given the global nature of OLMs and low entry barriers, digital workers are diverse in their motivations to enter the platform, geographical locations, education, and professional background (Manyika *et al.*, 2016).

1.3.2 Related Work

Existing work on OLMs mostly studies how to overcome challenges arising from the digital nature of transactions: The lack of high-bandwidth information on workers at the time of the hiring decision and the difficulty to monitor and control workers after hiring due to spatial and time differences. Thus, a large body of research on OLMs examines hiring decisions and focuses on identifying quality signals (Agrawal *et al.*, 2016; Chan & Wang, 2017; Hong & Pavlou, 2017; Kanat *et al.*, 2018; Kokkodis & Ipeirotis, 2016; Leung, 2014, 2017; Pallais, 2014; Stanton & Thomas, 2016). Another body of research explores drivers of workers' task performance, e.g. by studying the effect of different pay schemes (Mason & Watts, 2010; Shaw *et al.*, 2011; Yin & Chen, 2015). However, an emerging stream of literature and the closest to ours has begun to explore mobility patterns of workers *on* platforms (Anderson, 2017; Leung, 2014; Kokkodis & Ipeirotis, 2016; Horton & Tambe, 2020). For example, they find that web developers build their careers strategically and react to skill shocks by learning new skills (Horton & Tambe, 2020). However, prior work studies only what workers do once they have entered the platform and not the relationship between workers' prior offline experience and online jobs. Put differently, whether the web developer has worked as a web developer before. We address this missing piece to shed light on how these markets are used by workers. To our knowledge, the only paper so far studying the relationship between offline and online labor markets was conducted by Borchert and colleagues (2018). Using data from a large U.S. platform for microtasks, the authors examine how local unemployment affects participation and work intensity online. Nevertheless, they do not explore whether workers apply their existing expertise to online jobs or switch to completely new tasks. At the same time, jobs on micro-task platforms differ fundamentally from traditional jobs (e.g. image tagging to train artificial intelligence or participating in marketing or academic surveys) and it might be difficult to substitute their prior job with online work.

1.3.3 Transitions from Offline to Online Labor Markets

When workers enter OLMs, they have to make a choice: Sticking to their existing or changing their skillset compared to their prior job. On the one hand, and as mentioned before, moving to jobs with similar skill requirements is beneficial for workers in terms of wage outcomes and human capital accumulation (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008). By utilizing their existing skillsets, they can maximize the returns to their skills on the platform. Then, workers simply substitute their offline job with online work and their skillset should not change dramatically to reduce losses.

On the other hand, workers may move to tasks requiring different skills. First, OLMs make switching easy due to the flexibility and task-based nature of these markets. Workers can bundle their tasks themselves (opposed to working on firm- or occupation-specific task bundles), so that skill portfolios might deviate from prior (offline) jobs. The entry barriers to novel and potentially distant skill families is further low due to the short-term nature of jobs and varying skill levels. Since skills are in part acquired by engaging in on-the-training (Becker, 1962), workers may follow an earn while you learn strategy (Tambe *et al.*, 2020) and use OLMs as a stepping-stone to new careers. Reskilling (i.e. learning new sets of skills) in an OLM context is not as risky as switching jobs offline because it requires lower commitment. Workers can simply use online work as a testing ground. Second, online jobs are typically in areas of high demand (e.g. Data Science or Web Development). Prior work finds that high industry growth rates not only reduce barriers to entry but also increase workers' expectations that they can successfully shift into a new career path (Feldman & Ng, 2007). Finally, individuals may also possess skills not captured by their current occupation. Due to mismatches, the labor market may not always fully utilize the available skills (Borghans, Green, & Mayhew, 2001), so that workers "exploit" these underutilized skills online.

In sum, the relationship between prior work experience and online jobs is not straightforward and it remains unclear whether worker predominantly change career paths in OLMs or continue their offline careers.

1.4 Hypotheses

1.4.1 Baseline Effect

Based on prior work on occupational mobility (Gathmann & Schönberg, 2010) and human capital investments (Becker, 1962), we hypothesize that the decision to move will depend on the value of worker's current skill portfolio in an online context. Specifically, we hypothesize that the value of one's prior skills affects the degree of skill change.

Prior work highlights that the market value of skills varies; for example, the increasing value of information and communication technology and computer skills (Autor, 2001), engineering (Rock, 2019) or more broadly STEM skills (Deming & Noray, 2019), and artificial intelligence skills (Alekseeva *et al.*, 2020) on the labor market. The value of skills, i.e. the wage premium employers are willing to pay, generally increases with its demand and a perceived skill shortage on the labor market (i.e. limited supply). This is particularly the case in areas with fast changing skill requirements, creating a sense of worker shortage, although its rather the *skills* that are scarce but not the workers themselves (Deming & Noray, 2018). Skill shortage is driven by certain investment costs that are necessary to acquire the respective skill, e.g. intensive on-the-job training and education (Becker, 1962). For example, if a skill (such as programming) becomes easier to acquire (e.g. through easy-to-use programming packages) so that more workers pick up the skill as a result of reduced investment costs, the market value of the skill decreases (Rock, 2019). Investments costs also depend on the specificity of skills, i.e. their transferability across tasks (Djumalieva & Sleeman, 2018). Investments in specific human capital are considered to be risky because workers may spend more time without an assignment while waiting for more lucrative (specialized) tasks (Eggenberger *et al.*, 2018). Even though skills may be in high-demand, this can change rapidly and specific skills reduce workers' flexibility to change jobs. However, job-related risks are typically compensated with higher mean earnings (Azmat & Petrongolo, 2014). In sum, skills vary in their market value due to investment costs and risks.

In OLMs, freelancers can gather detailed information on the value of their skills because of the transparency of the market, i.e. price tags for jobs are visible to market participants. In fact, pay transparency is a distinct characteristic of OLMs since offline workers lack this fine-grained and real-time information on prices for skills. Furthermore, Upwork publishes a quarterly "Skills Report", including a list with high-demand skills, so that workers should have an idea about the demand of their skills. Consequently, workers may strategically decide to adjust their skillset or not when entering OLMs based on their current skillset. Due to this transparency, we argue that workers base their decision to change their skill portfolio on the present value of their current compared to an alternative career path. Workers who already possess skills in valuable areas face higher opportunity costs of switching to different skill families. At the same time, the return to investments in a particular skill increases with its subsequent rate of utilization (Rosen, 1983). Consequently, a worker who already invested in acquiring valuable skills, should have an incentive to "exploit" this skillset as extensively as possible to maximize returns. This also applies to workers who do not possess the exact skill that is in high demand in a certain area (e.g. artificial intelligence) but related skills (e.g. more broadly knowledge in statistics). Remaining within their prior skill boundaries is superior to moving because learning costs should be lower for skills in the same skill family. Conversely, workers with skills in less valuable areas have two choices: If they choose to switch, they can either learn new skills or work with another skill they already possess. Investments in learning new skills might be compensated by expected income growth and applying an already existing skills bears no investment costs, increasing the likelihood of skill change. If they choose to stay in their prior area, they face low wages and limited opportunities for career progression. Consequently, these workers may generally be more likely to adjust their skill portfolio due to lower opportunity costs and move further away from the skill content of their prior jobs. In sum, we argue that with an increasing value of workers' skill portfolio, they tend to move less.

Baseline Hypothesis (H1): *The value of a worker's skill portfolio in an online context is negatively related with the skill distance between offline and online jobs.*

1.4.2 Moderating Effects

On top of understanding how the market value of one's skills in an online context drives the degree of skill change, it is also meaningful to consider the conditions under which this relationship is strengthened or weakened. Since online workers are very diverse in terms of demographics, motivations, and geography (Manyika *et al.*, 2016), some workers may react stronger or weaker to different levels of skill value. Particularly, we argue that being female, coming from an advanced economies and reporting having current offline employment moderates the relationship between skill value and skill distance.

Females. We hypothesize that women are less sensitive towards the value of their skills when deciding on which tasks to work in an online context for two reasons. First, evidence from experiments consistently shows that women are more risk-averse than men (Azmat & Petrongolo, 2014). More valuable skills are likely to be more specific and less broadly applicable. Since OLMs are much more volatile than offline labor markets because the demand for certain skills can change rapidly (Horton & Tambe, 2019), women might tend to shy away from this risk. Specifically, if women are more risk-averse than men, they will also care more about income stability than high average returns. So instead of maximizing mean wages, females may tend to hedge their risk towards different skill clusters with an increasing skill value than men. Second, prior work suggests that females tend to benefit more from the flexibility that internet-based working offers than males (Dettling, 2011), e.g. due to childcare. If they also enter for the flexible work schedule and less to maximize mean earnings, they should be less sensitive towards the value of their skill portfolio. Likewise, online work is considered as a way for stay-at-home mothers to reenter the labor market (Agrawal *et al.*, 2015). These women might be generally more open towards a career change and more likely to experiment with jobs different from their prior work than men.

Hypothesis 1a: *Being female weakens the negative relationship between the value of a worker's skill portfolio in an online context and the skill distance between offline and online jobs.*

Advanced economy workers. OLMs are global labor markets so that workers come from both high- and low-income countries (Agrawal *et al.*, 2015). Thus, workers differ in their local outside (offline) options and living costs. Workers participating from lower-income countries may be more constrained in terms of (local) outside opportunities, so that OLMs increase the pool of jobs for them. Particularly, they have access to jobs from high-income countries, so that workers from less developed economies often earn significantly more than local minimum wages (Agrawal *et al.*, 2015). Thus, OLMs generally represent an attractive alternative to offline jobs for them. Conversely, workers from advanced economies face higher living costs and on average, better local outside opportunities. As such, they might only be willing to work online if they earn sufficient wages. Given that the competition from low-cost countries puts pressure on market prices, working in some areas may become (financially) very unattractive for advanced economy workers. When possessing a less valuable skill portfolio, workers from advanced economies may be particularly likely to switch to different jobs instead of remaining in a low-paid skill cluster compared to workers from less developed countries. For them, working in these areas might still be an attractive alternative so that they are less likely to move.

Research on occupational choices of highly educated immigrants and native-born workers also suggests that an overrepresentation of one group in an occupation can lead to occupational mobility of the other group to new occupations with different skill content (Peri & Sparber, 2011). Particularly, native-born workers sort into jobs they have a comparative advantage such as communication-intensive jobs when more immigrants enter the labor market. In our setting, workers from advanced (and mostly Western) can be seen as equivalent to native-born workers because most employers come from advanced economies (Agrawal *et al.*, 2015). In sum, workers from advanced economies should be more sensitive towards the value of their skill portfolio because if differences in local outside options and living costs.

Hypothesis 1b: *Coming from an advanced economy strengthens the negative relationship between the value of a worker's skill portfolio in an online context and the skill distance between offline and online jobs.*

Current employment status. Many freelancers also have a parallel offline job and thus a second stream of income (Manyika *et al.*, 2016). Research on dual job-holding suggests that workers have two dominant motives to take a second job (Panos, Pouliakas, & Zangelidis, 2014): First, employees may be hours constrained, i.e. willing to work more but not having the opportunity in their primary job (Perlman, 1966). As the willingness to work more hours is related to earning low or insufficient wages in the first job, this is also often referred to as the financial motive. However, employees may also decide to get a second job in order to smooth their consumption, or to build savings, even if they are not experiencing an immediate financial need (Guariglia & Kim, 2004). Second, workers may aim at learning new skills or gaining experience in alternative occupations. By taking a second job in another area they can gain relevant training, or acquire new credentials that may foster subsequent job transitions (Panos *et al.*, 2014). Based on these motives, we argue that dual jobholders react stronger to different levels of skill value compared to workers with no current offline employment. Dual job-holders with lowly valuable skill portfolios may be more likely to reskill completely compared to those with no offline job. First, they should have an incentive to move to a career path promising higher earnings. Second, their offline income enables them to buffer against earnings volatility when making the shift Conversely, workers with no current offline employment may often rely on jobs they already have experience in to ensure some income stability. However, with an increasingly valuable skill portfolio, dual jobholders may be more likely remain in their area of expertise and simply wait for (lucrative) jobs to arise to smooth their offline consumption or build savings. To sum up, we hypothesize that currently employed workers react stronger to the value of their skills than those with no current offline employment.

Hypothesis 1c: *Being currently employed offline strengthens the negative relationship between the value of a worker's skill portfolio in an online context and the skill distance between offline and online jobs.*

1.5 Data and Methods

1.5.1 Data & Sample

We focus on *Upwork*, one of the world's largest freelancing website. Upwork facilitates transactions ranging from administrative support and graphic design to software and web development. We rely on Upwork data because of their focus on more high-skill, long-term oriented work (Pofeldt, 2016), e.g. developing an online marketing strategy, porting an Android app from an iOS app and adding features to an existing (Web or Mobile) app. Consequently, workers on Upwork generally have the opportunity to work in their prior field of expertise and simply substitute their offline with online jobs.

To identify a worker's prior job and respective skill content, we use freelancers' self-reported job titles. Workers can list their prior work experiences on their profiles (section "Work Experience"), i.e. job title, company, and a comment on their tasks and responsibilities. The original dataset includes 594,909 reported job titles of 234,930 freelancers with a minimum of one job on the platform. Since our original dataset includes 254,495 freelancers, the vast majority of workers has reported at least one prior job.

Since the section "job title" is a free text field, standardizing self-reported job titles and matching them with occupational data is a nontrivial task. We applied fuzzy string matching[3] to compare self-reported job titles with official job titles associated with each occupation. Particularly, we used the Python package *FuzzyWuzzy*, which can overcome complex issues such as typographical mistakes, reordered words or items, prefixes and suffixes. The function *processExtractOne* was used to extract the best string match out of a list of 59,457 alternate job titles linked to occupational categories. This helps us to standardize job titles and identify a worker's prior job title and occupation.[4] The resulting similarity scores between pairs of strings lie between 0 and 100, where 100 represents a perfect match. The library of job titles used as a comparison was downloaded from The Occupational Information Network (O*NET).[5] Since the computational time for string comparisons is quite high, we extracted a random sample of 200,000 observations from our original dataset on off-platform experience.

After identifying the occupation associated with self-reported job titles, we included only the last job reported before the worker entered Upwork. First, the skills of one's prior job are the most salient and recently used skills. Second, to assess career continuity versus career change, we only need the last job prior to OLM entry because a career is defined as a sequence of jobs within an individual's work history (Spilerman, 1977). We deleted all observations that were reported to have been accomplished on common OLM platforms (mentioned in "company"), i.e. oDesk, Elance, Freelancer.com, Guru, Fiverr, and Amazon Mechanical Turk, to ensure that

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[3] Fuzzy String Matching is the process of finding strings that approximately match a pattern. The algorithm is based on the Levinsthein distance measure and calculates the similarity of two strings. In non-technical terms, the Levenshtein distance between two strings is the minimum number of single-token edits (insertions, deletions or substitutions) required to change one string into the other.

[4] Although we do not use occupational data directly in our analysis, we provide some descriptive statistics on occupations of Upwork freelancers in our *Appendix A.2*.

[5] The Occupational Information Network (O*NET) is a publicly available database and the primary source for occupational information in the U.S. (e.g. Autor & Handel, 2013; Yamaguchi, 2012). O*NET databases cover hundreds of standardized and occupation-specific descriptors on almost 1,000 occupations. Information on how O*NET collects alternate job titles can be found here: https://www.onetcenter.org/dl_files/AltTitles.pdf.

jobs indeed refer to offline jobs. Job titles "Founders" were also excluded because their skillset is not clear. We further took a conservative approach and excluded observations that had a similarity score below 95 with one of the job titles provided in the library, resulting in a sample of 33,627 freelancers and jobs. We finally reduced the sample to freelancers with a minimum of 10 jobs on the platform to ensure a certain career trajectory, resulting in a sample of 10,507 freelancers and observations.

1.5.2 Approach to Measuring the Skill Content of Jobs

To study changes in the skill portfolio of workers when transitioning into OLMs, we have to find a measure to compare both offline and online jobs on the same dimensions to assess their similarity. Prior work using a task approach constructs measures of different task types to compare two jobs, e.g. abstract (analytical or interactive), routine (cognitive or manual), and nonroutine manual tasks; analytical, interactive, and manual tasks (Gathmann & Schönberg, 2010); or science, math, interactive, mechanical, and verbal tasks (Speer, 2017). An occupation is then similar if it relies heavily on the same task type. This approach is based on the assumption that these tasks require similar skills, however, the actual skills are not observed. We take advantage of the fact that employers on the platform include the skills required to perform a task in their job description. Specifically, we use the skill tags attached to job postings to describe the skill content of jobs freelancers accomplished.[6] We are thus able to capture the multidimensionality of skills (Speer, 2017). At the same time, tasks on OLMs are knowledge tasks and thus mostly abstract (i.e. analytical or interactive tasks). By measuring the skill content, we can distinguish between different types of abstract tasks.

Since we have to describe offline jobs in a similar way and there is no public database providing such fine-grained skill data on jobs, we rely on a skill taxonomy developed by Djumalieva and Sleeman (2018) for NESTA using U.K. offline job advert data provided by Burning Glass

[6] As described in chapter 3, missing values for skills were predicted using a neural network.

Technologies. The six skill families (top layer) of their data-driven taxonomy are: 1) education, sales and marketing, 2) information technology, 3) science and research, 4) engineering, construction, and transport, 5) health and social care, and 6) business administration.[7] We rely on their taxonomy for two reasons: First, the authors report the skill content of the 200 most common job titles in their dataset, e.g. ranging from cleaner to architect and web developer. Specifically, they report the weight the job titles put on each skill family or more specifically, the average share of skill tags in every skill family attached to offline job adverts for the 200 job titles. Second, the authors provide an extensive and publicly available list of skill tags associated with the identified skill families.[8] This data enables us to match their taxonomy with our skill data to calculate the share of skill tags attached to online jobs falling into each of the six skill families. We can thus compare the skill content of online to offline jobs in terms of how much weight they put on the six top layer skill families. As such, these two skill vectors will be similar if workers put similar weights on skill families both online and offline. Examples of the skill content of job titles can be found in our *Appendix A.2*. Since their list includes only data on 200 different job titles and because of missing values on freelancer characteristics, our final sample includes 4,771 freelancers and observations.

1.5.3 Variables

Dependent variable. To measure the *skill distance* between offline and online jobs, we calculate the cosine similarity between the skill vector of a worker's prior job and across all online jobs. For the latter, we calculated the share of skill tags attached to job postings falling into one of the six top layer skill families for every task accomplished on the platform. For this exercise, we restricted the number of attached skills to 10, assuming that those are the most

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[7] Their taxonomy overlaps with other taxonomies to a large extent. For example, Anderson (2017) relies on OLM data and identifies the following 11 distinct skill clusters: Administrative, Art/Design, Writing, Translation, Marketing, General Programming, IT administration, Mobile Development, Engineering, Data & Statistics, and Testing.

[8] A detailed description of each skill cluster and respective skill tags as well as some examples of the skill content of the reported job titles is provided in *Appendix A.2*.

central ones. Then, we took the average percentage of skills in each skill family across all online jobs. Thereby, we are able to identify the weights workers put on the skill families in an online context. Once we have vectors that represent both online and prior offline jobs as a combination of the skill families, we measure the skill distance between them as:

$$\textit{Skill Distance}_i = 1 - \cos(\theta) \text{ with } \cos(\theta) = \frac{\vec{J_t} \cdot \vec{J}_{t+1}}{\|J_t\| \|J_{t+1}\|}$$

where $\vec{J_t}$ is the last job performed by a freelancer *i* prior to OLM entry represented as a vector of skills, and $\vec{J}_{t+1}$ the average skill vector of all jobs accomplished on the platform. Values are between 0 and 1, where 0 indicates a perfect overlap of both skill vectors, i.e. the worker does not adjust her skill portfolio when working online. The further a worker moves from her prior skill portfolio, either by putting different weights on skill families or by moving to other skill families, the higher the value gets. Workers who change the skill content of their jobs completely have a score of 1.

Independent variables.

Skill value. To capture the *skill value* of a worker's offline skill mix in an online context, we ran a simple linear wage regression at the transaction level[9] of the following form to predict the value of each skill family:

$$\hat{y}_i = \beta_0 + \beta_1 * BusinessAdmin + \beta_2 * IT + \beta_3 * EducSalesMarketing + \beta_4 * HealthSocialcare + \beta_5 * EngConstrTransp + \beta_6 * ScienceResearch + \varepsilon$$

where $\hat{y}$ is the predicted hourly rate of transaction *i* in USD and each skill family a dummy variable turning 1 if the job description includes a minimum of one skill tag from the respective skill family. The resulting fitted values for the six job families are (in descending order): Science & research: 24.82; Engineering, construction, & transport: 17.89; Information technology: 17.24; Health & social care: 17.40; Education, sales & marketing: 14.48; Business

[9] We used our original sample of Upwork (hourly pay) transactions to estimate skill prices across jobs. We thus assume constant average prices across time. Although this is not a perfect approach, it seems reasonable to assume that the ranking of skill families has remained relatively constant over time. For example, engineering skills have very likely been more valuable than business admin skills across years.

administration: 8.80. We weighted the predicted values of each skill family with the respective share in the skill portfolio of each job title to capture the overall value of offline skill portfolios in an online context. For example, the value of the skillset of the job title "assistant store manager" is 10.82 (62% Business Administration; 34% Education, Sales, Marketing).[10] We then subtracted the lowest value of a skill portfolio occurring in our sample (around 8.80) from all skill value variables so that a value of 0 corresponds to individuals with the least valuable skill portfolios. Thus, the constant in our regression refers to the skill distance of a person with the least valuable skillset.

Moderating variables. The variable *female* is a dummy variable, turning 1 for females. The gender was identified by matching a worker's first name[11] with an extensive global names list including associated gender. Missing values were manually coded by checking alternate name lists online. Our binary variable *advanced economy* refers to the economic situation of a freelancer's location (advanced vs. emerging/developing economy), where 1 refers to being located in an advanced economy (Agrawal *et al.*, 2015). The economic situation is based on data by the International Monetary Fund (World Economic Outlook, 2017), dividing countries into these two major groups. The dummy variable *employed* captures whether workers' report to have current offline projects on their profiles. It turns 1 if workers have not indicated an end date to their last job before entering the platform. This is also in line with prior work (Agrawal *et al.*, 2016).

Controls. We further control for a variety of factors potentially affecting our results. The variable *offline tenure* is the logarithm of the number of months since they started their first reported job offline. With more experience, workers may be generally less likely to move because "sunk costs" are high. Prior work suggests that the distance of moves, as well as the propensity to switch occupations, declines sharply with labor market experience (Gathmann &

[10] The reported percentages by Djumalieva and Sleeman (2018) do not sum up to 100% but range between 90-97%. We divided the weighted value of a job titles by the total sum of the shares of a given job title.
[11] Our data does not include worker's family names for data protection.

Schönberg, 2010). Since the time horizon for returns to new skill investments falls with a worker's age, mobility might be lower. We do not include job tenure (i.e. tenure in the last prior job) because roughly half of freelancers have reported only one prior job so that these variables are highly correlated. We further include *high education* to control for a worker's general ability. It is a dummy equal 1 if the freelancer reports having undergraduate, graduate, or PhD education. Educational attainment is the most widespread used proxy for general skills (Autor & Handel, 2013; Gathmann & Schönberg, 2010). Since Upwork is a global platform and most employers come from Western countries (Agrawal *et al.*, 2015), the business language is English. Prior work shows that language proficiency is related with occupational change (e.g. Chiswick & Taengnoi, 2007), thus we include *English proficiency* as a control. The variable turns 1 if a freelancer is located in a country in which English is the official language (The World Factbook, 2020). To also capture that some non-native speaking countries tend to have high proficiency levels, workers that come from countries that are listed as having very high or high English proficiency based on English test results, e.g. Netherlands and Sweden, also have a value of 1 (Education First, 2019). We further include the variable *offline mobility*, the logarithm of the number of prior job switches divided by the tenure on the offline labor market in years. The variable captures average yearly changes of workers in their offline work history and thus controls for innate preferences for mobility (Shaw, 1987). Finally, workers entered the platform at different points of time. Thus, we include *year dummies* to account for time effects. For example, the platform may have attracted different types of freelancers when the platform was still young or that different types of jobs were available at the beginning of their career.

1.5.4 Empirical Framework

We estimate an ordinary least square (OLS) model using robust standard errors. The decision making entity are individuals. Since our independent variable captures heterogeneity between job titles, we do not include dummies for job titles in our analysis.

1.6 Results

1.6.1 Descriptive Statistics

Table 1.1 gives descriptive statistics, *Table 1.2* the top 20 job titles and *Table 1.3* pairwise correlations for all variables in the sample we used in our regression analysis.

Table 1.1: Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Skill Distance	0.221	0.301	0	1
Skill Value	15.03113	2.592492	8.800092	17.89194
English Proficiency	0.698	0.459	0	1
Employed	0.431	0.495	0	1
Log(OfflineTenure)	3.770	0.955	0	6.190
High Education	0.791	0.407	0	1
AdvEconomy	0.223	0.416	0	1
Log(OfflineMobility+1)	0.169	0.244	0	2.773
Female	0.316	0.465	0	1

Note: The number of observations for all variables is 4,771.

Freelancers have an average cosine similarity score of 0.22 between offline and online skill vectors, suggesting that freelancers change their skill portfolio on average not fundamentally when working online. Indeed, a list with the most common job titles in our sample (*Table 1.2*)[12] indicates that freelancers tend to come from areas that have an obvious substitute, e.g. web developers, graphic designer, or customer service representatives. Nevertheless, we find all sorts of job titles in our sample, ranging from carpenters to nannies, nurses and electricians. Our dataset includes 116 different job titles.

[12] See for comparison also Appendix 2, Table A.2.C for the top 20 job titles in our original sample of 33,627 freelancers as well as descriptives on their prior job family and occupation.

Table 1.2: Top 20 Job Titles in our Sample

Job Title	Freq.	Percent	Cum.
web developer	831	17.42	17.42
graphic designer	732	15.34	32.76
software engineer	354	7.42	40.18
front end developer	305	6.39	46.57
project manager	303	6.35	52.92
developer	282	5.91	58.83
software developer	203	4.25	63.09
customer service representative	133	2.79	65.88
designer	130	2.72	68.60
administrative assistant	114	2.39	70.99
marketing manager	67	1.40	72.40
teacher	63	1.32	73.72
english teacher	57	1.19	74.91
business development manager	52	1.09	76.00
data analyst	50	1.05	77.05
marketing executive	50	1.05	78.10
architect	49	1.03	79.12
account manager	44	0.92	80.05
executive assistant	44	0.92	80.97
accountant	41	0.86	81.83

The skill value[13] of prior jobs ranges from 8.8 (job title "administrative assistant") to 17.89 (job title "mechanical engineers"). Roughly 40% of workers report having current offline projects. Thus, many workers still derive an income from offline jobs. The vast majority of freelancers comes from less developed economies (78%). This is in line with prior work on OLMs, showing a tendency towards North-South trade: Employers from high-income countries hire workers from less developed countries (Agrawal *et al.*, 2015). However, workers are primarily located in countries in which English proficiency is high (70%). Given that basic knowledge in English is necessary to participate in a global labor market, this is not surprising. The educational level of workers is also high with 79% reporting having a Bachelor's degree or higher. This supports

[13] Note that we show the original range. For our analysis, we subtract the value of the least valuable skill portfolio (8.8) from all values.

the fact that Upwork is a platform for more high-skill work. Prior work also shows that OLM workers are relatively well-educated (Agrawal *et al.*, 2015). Our sample further includes 31% females, which is comparable with samples of other studies conducted in OLMs. For example, Chang and Wang (2018) study hiring decisions in OLMs and have 30% females in their sample. Freelancers entered the platform between 2005 and 2017.

Overall, our independent variables show considerable variance and the correlation matrix indicates generally low pairwise correlations.

1.6.2 Regression Results

Table 1.4 reports the regression results of our OLS model. We include all controls in column 1. We add our main independent variable *skill value* in column 2, and then separately our three interaction terms in columns 3 to 5. Column 6 shows the full model.

As evident from column 6, we find support for our baseline hypothesis as freelancers with valuable skill portfolios move less or put differently, an increase in their skill value by one USD (note that a value of 0 corresponds to workers with the least valuable skill portfolios), decreases the distance between the skill portfolio of their offline and online job by 0.0331 ($p<0.001$). H1a predicted that being female mitigates the effect of skill value on skill distance, and our results support this ($\beta=0.0236$, $p<0.001$). Women thus seem to be less sensitive towards high values of their skill portfolios. We find also support for our H1b that coming from an advanced economy strengthens the negative effect of possessing valuable skills on skill distance ($\beta=-0.0256$, $p<0.001$). An increase in the skill value by one unit (USD), reduces the skill distance of an advanced economy freelancer by 0.0587 [-0.0331+(-0.0256)]. Finally, H1c is supported; current offline employment strengthens the negative effect of skill value on skill distance as shown by the negative sign of the interaction coefficient (ß=-0.00865, $p<0.05$). However, the effect is not very strong, an increasing skill value reduces the skill distance for those with current employment only marginally.

Table 1.3: Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Skill Distance	1.000								
(2) Skill Value	-0.277***	1.000							
(3) Female	0.087***	-0.307***	1.000						
(4) Advanced Economy	0.022	-0.188***	0.166***	1.000					
(5) Employed	0.002	0.078***	-0.025*	-0.032**	1.000				
(6) English Proficiency	0.074***	-0.095***	0.111***	0.251***	0.035**	1.000			
(7) log(OfflineTenure)	0.067***	-0.225***	0.098***	0.174***	-0.078***	0.087***	1.000		
(8) log(OfflineMobility+1)	-0.005	-0.073***	0.040***	0.090***	-0.029**	-0.041***	-0.031**	1.000	
(9) HighEducation	0.033**	0.088***	-0.029**	-0.075***	0.026*	0.104***	-0.055***	0.005	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Table 1.4: Regression Results

VARIABLES	(1) Skill Distance	(2) Skill Distance	(3) Skill Distance	(4) Skill Distance	(5) Skill Distance	(6) Skill Distance
SkillValue		-0.0331***	-0.0410***	-0.0280***	-0.0296***	-0.0331***
		(0.00210)	(0.00260)	(0.00226)	(0.00257)	(0.00304)
Female#SkillValue			0.0195***			0.0236***
			(0.00418)			(0.00412)
AdvancedEconomy #SkillValue				-0.0204***		-0.0256***
				(0.00465)		(0.00470)
Employed#SkillValue					-0.00881*	-0.00865*
					(0.00396)	(0.00390)
Female(=1)	0.0524***	0.00384	-0.109***	0.000378	0.00474	-0.136***
	(0.00983)	(0.0103)	(0.0272)	(0.0103)	(0.0103)	(0.0267)
Employed (=1)	0.00413	0.0137	0.0121	0.0130	0.0692*	0.0654*
	(0.00883)	(0.00854)	(0.00852)	(0.00853)	(0.0280)	(0.0276)
AdvancedEconomy (=1)	-0.00734	-0.0256*	-0.0228*	0.0889**	-0.0266*	0.120***
	(0.0119)	(0.0113)	(0.0113)	(0.0298)	(0.0113)	(0.0299)
Log(OfflineTenure)	0.0189***	0.00352	0.00369	0.00391	0.00352	0.00420
	(0.00475)	(0.00464)	(0.00463)	(0.00462)	(0.00464)	(0.00459)
HighEducation (=1)	0.0222*	0.0357***	0.0338**	0.0369***	0.0351***	0.0342**
	(0.0107)	(0.0105)	(0.0105)	(0.0104)	(0.0105)	(0.0104)
EnglishProficiency (=1)	0.0366***	0.0288**	0.0296**	0.0298**	0.0303**	0.0326***
	(0.00972)	(0.00936)	(0.00934)	(0.00935)	(0.00939)	(0.00934)
Log(OfflineMobility+1)	-0.0103	-0.0313+	-0.0267	-0.0292+	-0.0312+	-0.0230
	(0.0166)	(0.0165)	(0.0164)	(0.0164)	(0.0165)	(0.0163)
Year dummies	YES	YES	YES	YES	YES	YES
Constant	-0.0487**	0.288***	0.353***	0.243***	0.259***	0.282***
	(0.0165)	(0.0264)	(0.0288)	(0.0273)	(0.0293)	(0.0317)
Observations	4,771	4,771	4,771	4,771	4,771	4,771
R-squared	0.021	0.089	0.095	0.095	0.091	0.105

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure 1.1 to 1.3 illustrate our interaction effects. It shows the linear prediction of our dependent variable skill distance for different levels of skill value and males vs. females (*1.1*), advanced vs. less developed economy (*1.2*), and offline employment vs. no employment (*1.3*).

Figure 1.1: Predictive margins for different levels of skill value for males and females

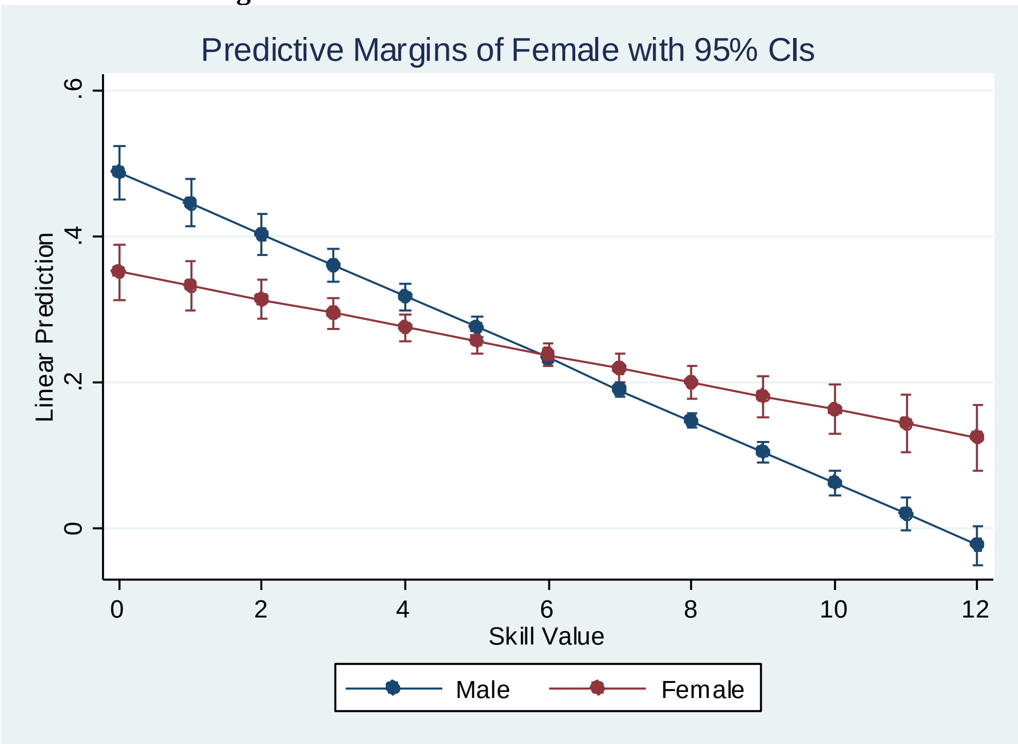


Figure 1.2: Predictive margins for different levels of skill value for workers from advanced and less developed economies

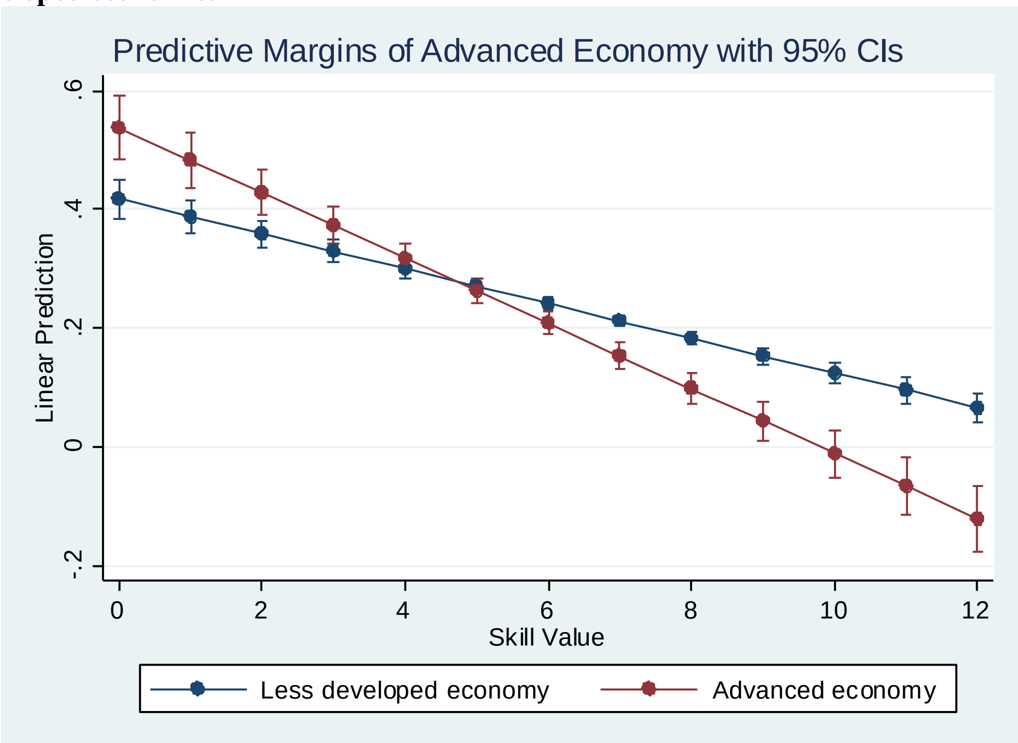
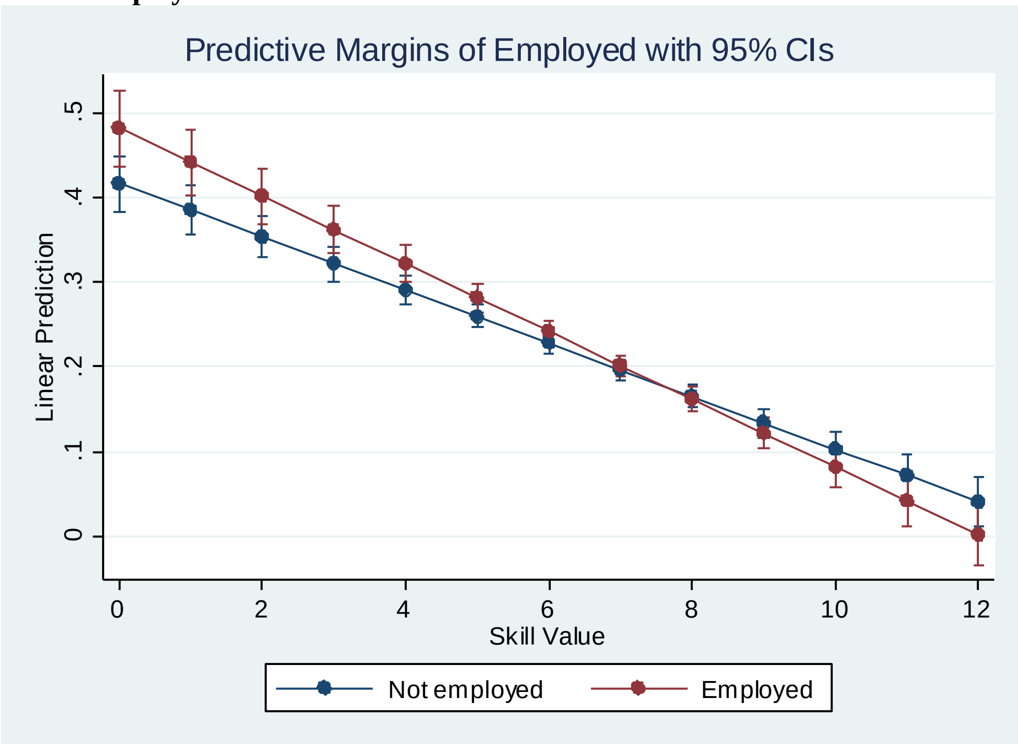


Figure 1.3: Predictive margins for different levels of skill value for workers with and without current offline employment



Our controls behave mostly as expected. The effect of more experience in offline labor markets on skill distance is positive and significant (p<0.001) in column 1 but turns insignificant once we include skill value. Older workers thus seem to have worked in jobs less valuable in an online context. Since online jobs often require state-of-the-art technical skills, older workers may simply lack these skills and are thus forced to move further away from their prior skills and follow an alternative career path. We further included high education as a control. Indeed, workers with high levels of education move further away from their prior job (ß=0.0342, p<0.01). This is in line with prior work suggesting that general human capital increases workers' job mobility. Similarly, proficiency in English increases the distance between offline and online jobs (ß=0.0326, p<0.001). English skills may offer alternative career paths (e.g. proofreading, translating, writing) while building on a skill the worker already possesses, reducing investments costs of switching paths. Finally, our control for preference towards mobility *log(OfflineMobility)* is not statistically significant. There seems to be no difference in movements between those that have switched jobs frequently before and those that did not.

1.6.3 Robustness Checks

We further conducted two robustness checks as shown in *Table 1.5*.

Online experience. Since we measure the skill distance between offline and across all online jobs, and workers have varying career lengths on the platform, we include a control for the number of jobs workers accomplished on the platform (i.e. online work experience). Sustaining a coherent work history across many jobs is more difficult than for only a few jobs. Yet, the control variable is not significantly related with skill distance and our results do not change.

Average feedback score. If workers with less valuable skill portfolios are simply less talented than other workers and thus forced to switch between different types of jobs, our results would be biased. We thus include freelancers' average feedback scores received across online jobs to control for differences in the quality of workers. However, the variable is not significantly related with skill distance and our results are robust.

Table 1.5: Robustness Checks

VARIABLES	(1) Skill Distance	(2) Skill Distance
Log(OnlineExperience)	-0.00985	
	(0.00606)	
AvgFeedbackScore		-0.0121
		(0.0183)
SkillValue	-0.0332***	-0.0329***
	(0.00304)	(0.00305)
Female# SkillValue	0.0239***	0.0235***
	(0.00414)	(0.00413)
AdvancedEconomy#SkillValue	-0.0257***	-0.0257***
	(0.00471)	(0.00471)
Employed#SkillValue	-0.00884*	-0.00868*
	(0.00391)	(0.00390)
Controls	YES	YES
Year dummies	YES	YES
Constant	0.308***	0.334***
	(0.0355)	(0.0827)
Observations	4,771	4,771
R-squared	0.106	0.105

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

1.7 Discussion and Conclusion

1.7.1 Discussion

In this study, we explore the relationship between offline and online jobs and the factors that drive adjustments in workers' skill portfolios as well as their boundary conditions. More specifically, we find that the value of workers' skill portfolios drives their decision to move away from their prior job. Workers possessing more valuable skills have a smaller distance between their online and offline skills, i.e. they move less. We further show that the relationship between skill value and skill distance is moderated by three factors: Women are less sensitive towards the value of their skill portfolio than men and workers from advanced economies and with current offline employment more sensitive compared to their counterparts. We argue that this is due to differences in individual preferences, outside options, and non-monetary incentives to enter the platform.

These findings, in addition to being the first to the relationship between the skill content of offline and online jobs, have some interesting implications. First, we observe that online workers come from all sorts of occupations and jobs. OLMs thus generally attract a broad range of workers who are willing to pursue a career online. Second, we find that workers on average do not adjust their skill portfolio fundamentally, suggested by the relatively low mean distance between jobs (0.22), but rather transfer their career to an online setting. This finding contributes to the discussion on the role OLMs may play in the future (Rahman *et al.*, 2016): On the one hand, some workers can substitute their prior job and may even earn more in online than offline jobs (e.g. workers from less developed countries). Then, OLMs may represent a meaningful alternative to traditional labor markets. On the other hand, there are workers that transition into completely different jobs and change career paths online. Given that workers will have to switch to new jobs more frequently in the future due to technological changes (e.g. Autor, 2003; Furman & Seamans, 2019), OLMs could become a powerful tool to learn new skills and gain experience in alternative occupations. Third, our findings suggest that online workers are in fact diverse in terms of their backgrounds, motives, and preferences and thus navigate their online careers differently. Finally, our paper contributes to the literature on occupational mobility (Gathmann & Schönberg, 2010) by studying mobility in a very nuanced way. By observing workers' skills, we are the first to portrait the transferability of skills across this novel type of labor market boundary (offline vs. online space).

1.7.2 Limitations and Future Research

Our study is not without limitations. First, job titles are self-reported and thus potentially biased. For example, workers may simply claim that they have experience in an area. Nevertheless, workers should have an incentive to accurately report their prior experience. First, reputation scores are very important in platform settings. If workers have lied and expectations of employers are consequently not met, employers will penalize them with low ratings. Second, employers may check LinkedIn or Facebook profiles of workers or require small test jobs before hiring. As such, we do not think this is a widespread phenomenon but future research may find a way to match OLM data with (offline) labor market data that is not self-reported.

Second, we do not observe the actual skills workers applied in offline jobs but rather the average skill content per job title. Although this is true for all studies on mobility using job or occupational categories, future research may find a more direct measure of workers' offline skill portfolios, e.g. surveys or matching with skills attached to LinkedIn profile.

Third, we use only the last occupation before a worker has entered the OLM platform. Although we are explicitly interested in the sequencing of jobs (viewing online work as "one big job"), future research may compare the skill content of all offline jobs to measure the distance between both skill vectors. Relatedly, future research could dig deeper into the types of skills workers switch to. In fact, we do not know whether workers in fact learn new skills (e.g. start learning programming) if they switch or whether they already possess these skills (e.g. a Finnish customer service representative works on Finnish translations instead of customer service jobs). Also, studying whether workers move from low-skill to more high-skill tasks or the reverse (upward vs. downward movements) would represent a promising line of research.

Finally, future research may study long-term wage and other career outcomes resulting from a shift of one's career path in an online context. For example, scholars could examine whether workers indeed switch occupations offline after gaining experience in the respective area online. Further, the stepping-stone argument clearly depends on the value of online work experience in offline labor markets. If OLMs should enable career transitions, it is important to understand whether employers actually value this specific type of work experience for traditional (long-term employment) jobs and under which circumstances. For example, prior work studies the value of different postsecondary degrees (including from online institutions) by observing call back rates to applications in a field experiment (Deming *et al.*, 2016). The authors find that a business bachelor's degree from a for-profit online institution is 22 percent less likely to receive a callback than one from a nonselective public institution. It would thus be interesting to see whether we observe similar dynamics for actual work experience from online versus offline jobs.

In sum, we think our study makes several contributions by studying a novel type of work transition and opens up several fruitful areas for future research.

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Appendix

A1.1 Examples Skill Content of Job Titles

Job Title	Skill Content (in %)
.net developer	(software development, 84.9), (web development, 11.5)
account administrator	(office administration, 45.2), (accounting admin, 25.0), (accounting and financial management, 8.0), (general sales, 5.4), (logistics administration, 4.8), (payroll and tax accounting, 1.7)
data scientist	(data engineering, 48.4), (marketing research, 31.5), (physics and math, 6.6), (bi and data warehousing, 3.4), (software development, 2.9)
design engineer	(design and process engineering, 57.0), (electronics, 11.5), (construction engineering, 7.0), (manufacturing methods, 5.9), (electrical engineering, 5.2), (civil engineering, 3.1), (structural engineering, 2.4)

Note that we aggregated the skill clusters for our analysis on a top layer level. The full list can be found in the appendix of Djumalieva and Sleeman (2018).

Table 2 and *3* report the job families and the top 20 job titles from our original dataset including the last prior job of all freelancers with a minimum of 1 job on the platform. The dataset contains 33,627 freelancers.

A1.2 Job Families (O*NET) of Workers' Last Prior Occupation (Full Sample)

Job Family	**Freq.**	**Percent**	**Cum.**
Computer and Mathematical	11,407	33.92	33.92
Management	5,896	17.53	51.46
Arts, Design, Entertainment, Sports, Media	5,506	16.37	67.83
Office and Administrative Support	3,012	8.96	76.79
Business and Financial Operations	2,219	6.60	83.39
Education, Training, and Library	1,322	3.93	87.32
Sales and Related	1,145	3.41	90.72
Architecture and Engineering	1,091	3.24	93.97
Life, Physical, and Social Science	585	1.74	95.71
Healthcare Practitioners and Technical	265	0.79	96.49
Legal	229	0.68	97.17
Healthcare Support	225	0.67	97.84
Personal Care and Service	136	0.40	98.25
Production	134	0.40	98.65
Food Preparation and Serving Related	133	0.40	99.04
Community and Social Service	82	0.24	99.29
Transportation and Material Moving	55	0.16	99.45
Protective Service	49	0.15	99.60
Construction and Extraction	46	0.14	99.73
Building and Grounds Cleaning and Maintenance	42	0.12	99.86
Installation, Maintenance, and Repair	41	0.12	99.98
Farming, Fishing, and Forestry	7	0.02	100.00
Total	33,627	100.00	

A1.3 Top 20 Job Titles (Full Sample)

Official Title	Freq.	Percent	Cum.
Web Developer	2,415	7.18	7.18
Graphic Designer	1,809	5.38	12.56
Software Engineer	1,190	3.54	16.10
Developer	937	2.79	18.89
Project Manager	860	2.56	21.44
Customer Service Representative	733	2.18	23.62
Software Developer	712	2.12	25.74
Senior Software Engineer	704	2.09	27.83
Web Designer	547	1.63	29.46
Administrative Assistant	434	1.29	30.75
Programmer	394	1.17	31.92
Team Leader	332	0.99	32.91
Translator	283	0.84	33.75
Front End Developer	271	0.81	34.56
Teacher	261	0.78	35.33
Executive Director	255	0.76	36.09
Assistant Manager	248	0.74	36.83
Manager	242	0.72	37.55
Designer	235	0.70	38.25
Management Consultant	229	0.68	38.93

A1.4 Skill Tags per Skill Clusters

List of skill tags per skill cluster that could be matched with online data (i.e. occurred in at least one online job posting)

Top Layer	Sub Cluster	Skill Tags
Business administration	accounting	general-ledger, account-reconciliation, hyperion, invoicing, tax-preparation, financial-reporting, bookkeeping, jd-edwards, payroll-processing, spreadsheets, accounting, nav-system-implementation, compliance, job-costing, bank-reconciliation, transaction-processing, financial-analysis
Business administration	admin and law	legal-research, document-review, internet-research, email-handling, typing, contract-drafting, google-searching, virtual-assistant, mediation, arbitration, legal-consulting, litigation, telephone-skills, administrative-support, calendar-management, data-entry, corporate-law, office-administration, intellectual-property-law, property-management, transcription
Business administration	finance	derivatives, risk-management, onboarding, portfolio-management, economics, acquisitions, international-business, internal-auditing, financial-modeling, mergers-and-acquisitions, investment-banking, capital-markets, stress-management, business-process-modelling, due-diligence, asset-management, policy-analysis, risk-assessment, corporate-finance
Business administration	logistics	negotiation, order-processing, sourcing, supply-chain-management, inventory-management, sap, order-entry, logistics
Business administration	mgmt and hr	performance-management, program-management, trend-analysis, human-resource-management, employee-engagement, staff-development, retail-ops-management, business-plans, workforce-management, strategic-planning, hris, employee-training, change-management, learnshare-learning-management-system, performance-appraisal, linkedin-recruiting, financial-management, hr-policies, process-improvement, leadership-development
Education, sales and marketing	design	music, game-development, adobe-acrobat, desktop-publishing, adobe-indesign, filemaker-pro, animation, cgi, music-producer, online-help, graphic-design, photography, art-direction, video-production, adobe-photoshop, microsoft-publisher, frontpage, interactive-advertising, audio-editing, photo-manipulation, wordpress-plugin, image-editing, print-design, audio-post-production, web-design, sound-editing, audio-mastering, instructional-design, adobe-premiere, wordpress, 2d-animation, illustration, voice-talent, proofreading, game-design, print-advertising, audio-engineering, logo-design, print-layout-design, website-wireframing, banner-design, photo-editing, content-management-system, voice-over, cartooning, audio-production, adobe-after-effects, copy-editing, typesetting, digital-photography, adobe-flash, music-arrangement, adobe-dreamweaver, motion-graphics, audio-mixing, music-composition, editing, 3d-animation, final-cut-pro, adobe-illustrator, actionscript-2, brochure-design, video-editing
Education, sales and marketing	education, languages, art	singing, spanish, translation-english-german, translation-english-spanish, english-proofreading, italian, teaching-english, yoga, french, dutch, portuguese, german, chinese, english-grammar, teaching-physics, curriculum-development, teaching-mathematics, translation-english-french, russian, polish, translation, tutoring, japanese

Education, sales and marketing	marketing	market-research, seo, link-building, tableau, b2b-marketing, sem, seo-keyword-research, advertising, sas, brand-consulting, email-marketing, ebay-listing-writing, marketing-management, brand-marketing, marketing-strategy, direct-marketing, data-mining, ab-testing, internet-marketing, google-analytics, facebook-marketing, digital-marketing, social-media-market, on-page-optimization, competitive-analysis, ebay-marketing, r, qualitative-research, twitter-marketing, market-analysis, social-media-marketing, media-buying, seo-writing, yahoo-search-marketing, web-analytics, media-planning, mobile-marketing, predictive-analytics, campaign-management, data-science, seo-backlinking, brand-management, google-adwords
Education, sales and marketing	pr and journalism	ghostwriting, rss, article-writing, technical-writing, public-relations, internal-communications, marketing-communications, creative-writing, content-writing, fundraising, content-development, blog-writing, web-content-management, copywriting, event-planning, editorial-writing, ebook-writing, media-relations, corporate-communications
Education, sales and marketing	sales	trade-marketing, sales-management, lead-generation, telemarketing, direct-sales, outbound-sales, product-management, appointment-setting, merchandising, business-development, visual-merchandising, business-writing, cold-calling, account-management, presentations, salesforce.com, international-sales
Engineering, construction, and transport	civil engineering and design	architecture, engineering-design, revit, construction-management, survey-design, civil-engineering, architectural-design, primavera, microstation-v8, interior-design, microsoft-project
Engineering, construction, and transport	construction, maintenance, transport	plumbing, corel-paint-shop-pro, welding
Engineering, construction, and transport	energy and environmental mgmt	report-writing, energy-engineering, geology, economic-analysis, urban-design, arcgis, proposal-writing, quality-control, gis, environmental-science, fortran, chemical-engineering, landscape-design
Engineering, construction, and transport	mechanical and electrical engineering	computer-aided-manufacturing-cam, autodesk, electronics, embedded-systems, root-cause-analysis, hvac-system-design, scada, industrial-engineering, systems-engineering, electrical-engineering, engineering-management, matlab, cad-design, simulations, 3d-modeling, robotics, labview, microcontroller-programming, electrical-drawing, iso-9000, mechanical-design, process-engineering, pcb-design, kaizen, catia, product-development, 3d-design, verilog, electronic-design, circuit-design, mechanical-engineering, lean-manufacturing, material-design, six-sigma, arduino, product-design, 3d-rendering
Health and social care	cardiovascular and respiratory healthcare	medical-imaging
Health and social care	caregiving and rehabilitation	cooking, community-development
Health and social care	healthcare admin	healthcare-management, word-processing, welsh, medical-transcription
Health and social care	primary care	nursing

Information technology	business intelligence and it systems design	technical-editing, talend-data-integration, crystal-reports, cobol, visual-basic, it-management, document-management-system, microsoft-visio, user-acceptance-testing, uml, data-migration, data-modeling, microsoft-access, information-architecture, solution-architecture, requirements-analysis, oracle-pl/sql, microsoft-dynamics, system-analysis, oracle-database, informatica, data-warehousing, sdlc, vsam, ibm-websphere, systems-development, business-intelligence, it-strategy, microsoft-sql-ce, winrunner, powerbuilder, data-management, business-analysis
Information technology	it security	cryptography, computer-engineering, information-security
Information technology	it systems and support	lotus-notes, helpdesk-support, firewalls, network-security, zoom-video-conferencing, recruiting, system-administration, cisco-routers, clustering, vmware-esx, linux-system-administration, database-administration, microsoft-windows-powershell, itil, network-engineering, ssl, vbscript, computer-networking, vendor-management-systems, network-administration, ospf, sw-configuration-management, dsl-troubleshooting, email-deliverability-consulting, avaya, cpanel, bash, microsoft-exchange-server
Information technology	software engineering	jboss, enterprise-software, git, zend-framework, xsl, salesforce-app-development, web-testing, web-crawler, website-development, voip-administration, usability-testing, ruby-on-rails, unix, psd-to-html, asp, voip-software, shopify, data-structures, amazon-ec2, angularjs, junit, android, apple-xcode, woocommerce, agile-software-development, chef, data-visualization, relational-databases, asp.net, jquery, big-data, wan-optimization, database-testing, php, jdbc, mysql, perl, c++, web-scraping, nosql, ajax, iphone-app-development, database-design, kanban, javascript, objective-c, version-control, postgresql, data-scraping, html, mongodb, mobile-app-development, sqlite, joomla, magento, json, weblogic, iphone-ui-design, hw-prototyping, soap, api-development, spring-framework, automated-testing, frontend-development, xml, xhtml, ui-design, scrum, localization, swift, manual-testing, functional-testing, drupal, css, c#, html5, ipad-app-development, android-app-development, jsp, software-qa-testing, software-testing, hibernate, saas, python, salesforce-apex, c, sql, ios-development, amazon-web-services, twitter-bootstrap, ruby, selenium, java
Information technology	windows programming	activex, pascal, microsoft-visual-c++, vxworks, delphi
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Science and research	general biology	bio-informatics
Science and research	molecular biology	molecular-biology
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