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**Arnaud Dupuy**
*University of Luxembourg and IZA*

**Morgan Raux**
*Aix-Marseille School of Economics and IZA*

**Sara Signorelli**
*CREST - Ecole Polytechnique and IZA*

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**IZA – Institute of Labor Economics**

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

# ABSTRACT

## Digitalization, Change in Skill Distance between Occupations and Worker Mobility: A Gravity Model Approach

The recent digital revolution has significantly broadened the scope of IT-related tasks in most occupations in the labor market. In this paper, we document these changes, we propose a novel conceptual framework for thinking about the effect of technological change that incorporates the changing task distance between occupations, and we investigate its impact on worker mobility using a gravity equation approach. Our results reveal that the evolution of skill distance between jobs significantly affected mobility patterns, disproportionately favoring workers with preexisting knowledge of digital tools. Finally, we micro-found our gravity equation through a matching model to evaluate mobility in counterfactual scenarios without technological change.

**JEL Classification:** J23, J24, J62

**Keywords:** occupation mobility, technological change, search and matching

**Corresponding author:**
Sara Signorelli
CREST
5 Avenue Henry Le Chatelier
91120 Palaiseau
France
E-mail: sara.signorelli@polytechnique.edu

# 1 Introduction

The 2010s marked the advent of the Fourth Industrial Revolution, characterized by the widespread diffusion of digital technologies such as artificial intelligence, cloud computing, and the Internet of Things across most sectors of activity. This decade also saw the proliferation of basic IT literacy requirements across a broad range of occupations, including low-skilled roles.[1] This new wave of technological change brought significant transformations to the essential skill sets required in the labor markets of adopting countries (Acemoglu et al., 2022). These changes manifest themselves in changes in demand for different occupations and changes in tasks required within occupations (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019; Acemoglu et al., 2022; Spitz-Oener, 2006). For example, machine learning-assisted tools are now widely employed in various occupations, including data scientists, marketing specialists, and academic economists. Similarly, digital applications for real-time order tracking have become ubiquitous in industries such as hospitality, food delivery, logistics, and more. The convergence of occupational skill content along the digital dimension has created new job opportunities for workers proficient in these skills, allowing them to explore a broader set of professions. In contrast, workers who lack proficiency in digital tools may face increased challenges in securing employment in occupations that are becoming increasingly IT-intensive.

The literature on skill-biased technological change initiated by Katz and Murphy (1992) and the one on routine-biased technological change that originated with Autor, Levy and Murnane (2003) consider individuals as unidimensional in terms of their skill endowments, and model the effect of technological shocks as shifters of skill-specific productivity.[2] In

[1] Bergson-Shilcock and Taylor (2023) find that 92% of jobs in the US require some digital skills, while about one third of current workers lack even basic knowledge of digital tools. Appendix Figure A1 shows that Microsoft Office is the skill with the highest growth in demand during this period, while the majority of the 25 skills with the highest growth in demand can be classified as digital.

[2] Katz and Murphy (1992) distinguish between low- and high-skill workers and model technological shocks as increasing the productivity of high-skill workers. Autor, Levy and Murnane (2003) distinguish three types

this paper, we introduce a novel framework for analyzing the effects of technological change, viewing both individuals and occupations as multidimensional bundles of skills and tasks. Our framework attributes two primary effects to shifts in skill demand driven by technological advancements: (i) changes in the distribution of jobs across occupations due to variations in occupational demand, and (ii) changes in the relative productivity of skill bundles as a result of shifts in the skill distance between occupations. For example, considering the case of machine learning technologies, we anticipate an increased demand for data science roles. In addition, we expect these technologies to enhance the relative productivity of data scientists in a range of other occupations that increasingly require their expertise.

Given that in our conceptual framework the labor market is affected by digitalization through both changes in employment size of occupations and changes in the distance between occupations, it is particularly suited to be studied empirically with the help of a gravity model. We use the quasi-universe of online job postings advertised in the U.S. between 2010 and 2019 to precisely measure the skills required in each occupation at any given point in time. We construct a measure of digital skill distance between any pair of occupations by comparing their relative euclidean distance with respect to a set of reference IT occupations, assumed to reflect the relevant bundle of skills needed to work with digital technologies. We also construct a measure of the overall skill distance between occupations computed as the Euclidean skill distance between each pair. Finally, we match these measures with information on workers' mobility across occupations observed in France during the same period[3] which we obtain using employer-employee data covering the universe of the French labor force.

of workers – manual, routine, and cognitive – and model technological shocks as increasing the productivity of cognitive workers and decreasing the one of routine workers, thus resulting in employment and/or wage polarization.

[3] There are two reasons behind the choice of using vacancy data from the U.S. to measure changes in skill distance between occupations in France. The first is data-driven : Burning Glass Technologies began to collect data in Europe only recently, and their quality and coverage remains much lower than the one achieved in the U.S. The second and most important one is that we want to isolate changes coming from technological factors, abstracting away from any change driven by institutional determinants. Although technological shocks typically affect all industrialized countries with little difference in timing, any change in skill content observed in the U.S. is expected to be exogenous to the French institutional context.

Our empirical investigation yields three main findings: (i) the skill distance and the digital skill distance between occupations underwent significant changes between 2010 and 2019, with occupations, on average, becoming closer to one another; (ii) these changes significantly influenced patterns of occupational mobility in the French labor market; and (iii) while changes in the overall skill distance symmetrically affect mobility within a given occupation pair, changes in digital skill distance predominantly favor mobility from occupations initially more intensive in digital skills to those that experienced a recent increase in digital intensity. This latter finding suggests that the ongoing digitalization of the labor market has enhanced career opportunities for workers already equipped with IT skills, while offering fewer benefits to those lacking such competencies at the beginning.

Gravity estimations are well suited to study the determinants of workers' flows across occupations. However, without a clear micro-foundation, they are limited in their ability to investigate the underlying mechanisms, interpret the magnitude of the results or assess the aggregate effect of digitalization on workers' mobility over the decade. To address these issues, we micro-found the determinants of workers' flows across occupations with a discrete version of the two-sided matching model presented in Dupuy and Galichon (2022). This micro-foundation has three advantages. First, the model provides a structure to the estimation that supports our interpretation of the results. Second, it enables us to simulate counterfactual scenarios and quantify the share of additional workers' mobility resulting from changes in digital skills distance between occupations and changes in occupation demand brought about by the digitalization shock. Third, the model enables us to investigate the mechanisms underlying the observed changes in worker flows, distinguishing between mobility resulting from changes in amenities and mobility resulting from changes in productivity (Dupuy and Galichon, 2022). For this last point, we take advantage of the detailed information on wages contained in the French administrative data allowing us to compute the average wage change associated with each occupational move.

Our counterfactual exercises reveal that, in the absence of technological change over the past decade, long-run occupational mobility would have been 3.3% lower than observed. In particular, 15% of this effect can be attributed to changes in digital distances between occupations, rather than shifts in demand within individual occupations. Furthermore, our simulations confirm that the impact of reducing digital distances between occupations is asymmetric between workers with varying levels of initial digital literacy. Workers with high baseline digital literacy would have experienced a 5% reduction in mobility without technological change, with 30% of this effect driven by changes in digital distances between jobs. However, workers with low baseline digital literacy would have moved more over the decade in the absence of changes in digital distance. This disparity is also evident when considering flows into non-employment: technological change reduces non-employment transitions for digitally skilled workers while increasing them for the others. Finally, the additional mobility facilitated by changes in digital skill distance is driven two-thirds by productivity effects (higher wages) and one-third by nonwage amenities. Overall, these findings underscore that evolving skill distances between occupations play a substantial role in mediating the effects of technological change on employment outcomes.

This paper first relates to the literature studying the effect of technological change on the labor market, and in particular to the articles studying the recent digitalization shock and the articles studying the effect of technological change on workers' flows.[4] Our contribution lies in proposing a novel conceptual framework for analyzing the effects of technological change, which justifies the use of dyadic data to disentangle the impact of changes in demand within an occupation from the effects of evolving skill distances between occupations due to shifts in task content. Furthermore, we advance the literature on technological change and mobility by simultaneously considering the full set of potential dyadic transitions, rather than focusing

[4] Among the papers studying the effect of digital technologies we find Acemoglu et al. (2022); Deming and Noray (2020); Webb (2019). Papers focusing on worker flows include Adao, Beraja and Pandalai-Nayar (2022); Battisti, Dustmann and Schönberg (2023); Bessen et al. (2023); Cortes (2016); Edin et al. (2023).

solely on predefined "exposed" occupations, such as those initially characterized by high routine intensity, and examining mobility changes only for workers in those roles. Lastly, our framework accounts for the possibility that rapid technological advancements can render current workers' skills obsolete, a mechanism highlighted by Lise and Postel-Vinay (2020) and Deming and Noray (2020). We show that our results remain robust when incorporating the potential for skill obsolescence among workers who remain in the same occupation, but face significant changes in the task content of their jobs.

Secondly, our work contributes to the literature on the skill content of jobs and the associated mobility costs (Cortes and Gallipoli, 2018; Gathmann and Schönberg, 2010; Lazear, 2009; Lise and Postel-Vinay, 2020; Poletaev and Robinson, 2008; Yamaguchi, 2012). Following the same principles of these studies, we conceptualize occupations as multidimensional bundles of tasks and reject the notion of distinct labor markets. Instead, we emphasize that occupations are interconnected through worker flows, which are larger between occupations with more similar skill requirements. Third, our analysis aligns with the literature that employs gravity models to examine individual flows. In particular, numerous studies on international migration have applied this framework to quantify the costs of distance, using a micro-foundation based on random utility models (Beine, Bertoli and Fernández-Huertas Moraga, 2016; Beine et al., 2021). Carlier et al. (2023), like our study, employ a two-sided one-to-one matching model to provide a micro-foundation for migration flows.

To the best of our knowledge, the closest paper to ours is Cortes and Gallipoli (2018), which is the first to quantify the costs associated with skill distance between occupations using a gravity model approach. In their setting, skill distance is fixed over time and measured at baseline. We extend their work by showing that changes in skills distance largely affect worker's mobility, especially in periods characterized by rapid technological change. Our main objective is in fact to quantify how these changes affect mobility patterns. Furthermore, our paper focuses on a specific dimension of skill distance, capturing the effect of the diffusion of digital technologies. Finally, we diverge from their work by proposing another type of micro-foundation for the gravity model. Our micro-foundation builds on a two-sided one-to-one matching model with transfers following Dupuy and Galichon (2022) and has two main advantages relative to the random utility model used in Cortes and Gallipoli (2018): First, we model workers' mobility resulting from an equilibrium between supply of and demand for workers in the various occupations, which allows us to consider mobility due to changes in occupation-specific demand and to take into account congestion effects.[5] Second, our framework includes predictions that directly allow us to disentangle between the two possible channels behind the mobility patterns: differences in productivity, and differences in amenities.[6]

The remainder of the paper is organized as follows. Section 2 presents our conceptual framework for thinking about the effects of technological change. Section 3 presents the data. Section 4 presents the gravity estimation. Section 5 presents the empirical results. Section 6 presents the matching model micro-founding the gravity equation. Section 7 presents the counterfactual exercises and distinguishes the mechanisms at play. Section 8 concludes.

## 2 Conceptual framework

In this section, we formalize our conceptual framework for thinking about the effects of technological change on the labor market. At the center of our framework is the notion of skills distance and, in particular, the distance between the skills a worker possesses and the skills required for a job.

[5]In the random utility model used in Cortes and Gallipoli (2018), workers who want to move to a given occupation can do so without restrictions. In other words, there is no competition among workers to secure a finite set of jobs.

[6]This exercise further speaks to the recent contributions trying to disentangle mobility driven by wage differentials versus non-wage amenity differentials (Sorkin, 2018; Lehmann, 2023), and more generally to evaluate how important are non-wage amenities in determining workers' utility (Mas and Pallais, 2017).

Let $z^p$ be a vector of $Z$ skills a worker possesses, where $p$ stands for possessed, and group workers into discrete types so that all workers of type $i$ have skills $z^p = z_i^p$. Similarly, let jobs be defined by their vector $z^r$ of $Z$ required skills, where $r$ stands for "required", and group jobs into discrete types of occupations so that all jobs of type $j$ have required skills $z^r = z_j^r$.[7]

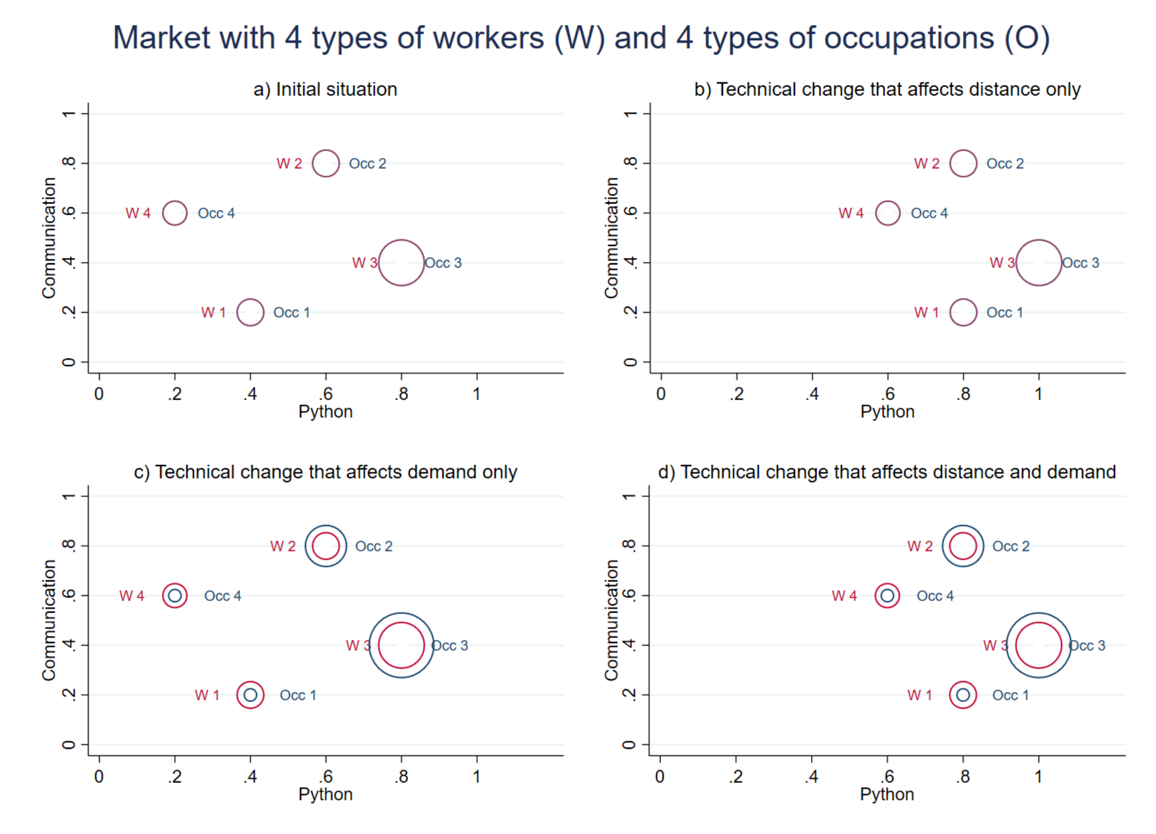
Although the skills possessed and the skills required are two distinct concepts, there is a clear mapping between the two. The first relates to the knowledge and know-how possessed by individuals. The second relates to the activities to be performed on the job. In particular, the bundle of skills possessed by each individual determines its relative productivity in each occupation. Optimal productivity in an occupation $j$ that requires skills $z_j^r$ is assumed to be obtained with workers whose skills perfectly match those requirements. Consider, for example, workers of type $i$ with skills $z_i^p$. If $z_i^p = z_j^r$, then the skills of workers of type $i$ match perfectly those required in the occupation $j$. In contrast, if $z_i^p \neq z_j^r$, the skills of workers of type $i$ do not perfectly match those required by occupation $j$, i.e. the skills distance between the skills possessed by the worker and those required by the occupation is greater than 0. We denote the distance between the skills of the worker and those required by the occupation by $d\left(z_i^p, z_j^r\right)$.[8]

Figure 1 shows a simplified version of our conceptual framework with only two skills ($Z = 2$), communication (vertical axis) and the Python programming language (horizontal axis). There are four types of workers (W1-W4) and four types of occupations (Occ1-Occ4) represented by circles, in red for workers and blue for occupations. The coordinates of the center of each circle correspond to the (required) skills of the associated group. For example, workers of type 1 have skills $z_1^p = (0.4, 0.2)$, while occupation 2 requires skills $z_2^r = (0.6, 0.8)$. The distance between the skills possessed by a worker of type 1 and those required in the

[7] Implicit in this setting is the idea that required skills are associated to tasks. For instance, a required skill might be to program in Python. The task "programming in Python" is associated with the required skill of the same name. For all practical matters, we use required skills and tasks interchangeably.

[8] In the next section we introduce the metric used to compute these distances.

Figure 1: Visualization of the conceptual framework




**Notes:** Circle's size reflects mass of jobs/workers. The figure sketches the two distinct effects of technological change in the context of our conceptual framework.

occupation of type 2 is then $d\left(z_1^p, z_2^r\right)$ which is best understood using the Euclidean distance in this example. The size of each circle indicates the employment weight of the associated type of worker/occupation in the economy.

Panel a) of Figure 1 represents our baseline scenario and corresponds to a situation before the advent of technological change. As drawn, it is assumed that there is a perfect match between the skills possessed by workers of type $i$ and the skills required by the occupations of type $i$ and there are as many jobs of type $i$ as workers of type $i$ (circles of the same size). Hence, at baseline, we assume that workers of type $i$ are matched with occupations of type $i$ and the distance between workers' skills and those required in their occupations is 0. It is important to notice that, even in the absence of technical change, over time, some workers might change occupation because of idiosyncratic shocks. We call this mobility "natural",[9] and expect it to occur predominantly between occupations close to each other in terms of required skills, i.e. small distance $d\left(z_j^r, z_k^r\right)$ for two occupations $j \neq k$. For example, we expect more "natural" mobility between occupations Occ1 and Occ4 than between occupations Occ4 and Occ3.[10]

With this framework in mind, we can now conceptualize technological changes as bringing about two major effects. First, technological change can trigger changes in the skills required in each occupation. In panel b) of Figure 1 we see that while communication requirements remain unchanged in all occupations, all occupations face a growing requirement for python, and more so in occupations that had low python requirements at baseline. It is also important to note that, as depicted, we make the assumption that workers' skills evolve with the skills requirements of their matching occupation at baseline. Hence, workers of type $i$, who are employed in the occupation of type $i$ at baseline, see their skills evolve as the skills requirements of the occupation $i$. This assumption is valid when workers learn on-the-job and firms invest in constant training to keep their workers up to date.[11] Importantly, as depicted, technological change results in occupations getting closer to each other, i.e. the distance $d\left(z_j^r, z_k^r\right)$ for each pair of occupations is smaller in panel b) than in panel a). Since our framework predicts that workers move more towards occupations whose required skills are close to their own skills, we can expect some additional mobility of workers of type 2 (W2) towards occupations of type 4 (Occ 4), and some additional mobility of workers of type 3 (W3) towards occupations of type 1 (Occ 1) compared to the baseline situation (without

[9]We herewith make a reference to the "natural" rate of unemployment which occurs because of idiosyncratic shocks (search frictions for instance).

[10]Figure A6 provides evidence supporting this hypothesis.

[11]Our framework can accommodate the opposite assumption : that workers possess the skills required in the occupation at the moment they are hired, but that their skills become obsolete when the required skills of their occupation evolves (Deming and Noray, 2020). Appendix Figure A2 shows how the diagram would change under this assumption. In our empirical analysis, we present robustness tests where the distance between occupations, including once own, is defined using the initial bundle of required skills in the origin occupation and the final bundle of required skills in the destination occupation.

technological change). Finally, note that the size of the circles has remained constant, so that the demand in each occupation and the supply of each type of worker have not changed. This means that the mobility observed in this scenario would be merely the result of 1) "natural" mobility (idiosyncratic shocks) and 2) changes in the skills requirements between occupations.

The second major effect of technological change is that it varies the demand for different occupations and thus their relative size in the labor market. This effect is depicted in panel c) of Figure 1. In this example, while the supply of workers is the same as in the baseline situation (same size of red circles), the demand in occupations of types 2 and 3 has increased (larger blue circles) while the demand in occupations of types 1 and 4 has declined (smaller blue circles). However, note that the skills requirements are the same as in the baseline situation. Everything else equal, we expect increased mobility of workers away from shrinking occupations towards growing occupations, and more so towards growing occupations that are closer. The mobility observed in this scenario would be simply the result of 1) "natural" mobility and 2) changes in demand.

Finally, the total effect of technological change is shown in panel d) of Figure 1, where both the distribution of occupations and the skills requirements have changed. The observed mobility would then combine the three effects: 1) "natural" mobility, 2) changes in the required skills, and 3) changes in demand.

Our conceptual framework differs in several aspects from the canonical model presented in Autor, Levy and Murnane (2003); Acemoglu and Autor (2011) and refined in Acemoglu and Restrepo (2019). First, in our framework, workers and occupations are multi-dimensional in their skills and tasks (required skills), and thus cannot be ranked on a linear scale. In this aspect, we are closer to the empirical literature on the skill content of jobs (Gathmann and Schönberg, 2010; Lazear, 2009). This feature allows us to consider the multidimensional nature of the distance between workers and occupations, which defines their relative productivity. Second, in our framework, technological change modifies both the employment distribution of occupations and the occupation-specific productivity of workers. This contrasts with their model where the distribution of jobs is homogeneous and the only effect of technological change is to vary the total productivity of worker types (and not the occupation-specific one). We believe that this conceptualization makes it possible to derive some additional interesting conclusions on the effects of technological change, including the disentangling of the role of the distribution channel from the skill distance channel, and the quantification of their role for productivity and amenity changes. Finally, the structure of the effects of technological change in our framework, operating through both a change in skills distance and a change in relative size, is particularly suitable for studying through the lenses of a gravity model.

# 3 Data

## 3.1 Measuring skills distance

Our skills distance measures start by measuring the time-varying skills requirements by occupation. For this, we rely on data from Burning Glass Technologies (BGT) collected in the United States between 2011 and 2019. The primary advantage of this data source is that BGT compiles the quasi-universe of online job ads by daily web-scraping around 40 thousand job boards and company websites. As a result, they can identify around 3.4 million active postings at any given point in time, which is believed to be close to the entirety of vacancies posted online in the United States over that period. They also apply text-analysis algorithms to drop duplicate postings of the same vacancy and classify some of the add characteristics into standardized codes. Of particular interest to us is the fact that they extract 13 thousand distinct skills required in job postings, and they associate each to a SOC occupation code. For more details on the data, see Carnevale, Jayasundera and Repnikov (2014). Given these appealing characteristics, a number of papers have used BGT to study job characteristics and changes in skill demand.[12]

An advantage of using data from the United States to capture technology-driven changes in occupational mobility patterns in France is that they are exogenous to any change driven by French institutional factors. Our hypothesis is that the changes in skills requirements in each occupation measured using U.S. job ads only affect French occupational mobility through technological shifts common to all industrialized countries, and we believe are exogenous to domestic skill availability and wage levels. We thus map US SOC codes to French PCS codes in order to apply our measures of skill distance to the French employer-employee data.

We are mainly interested in measuring digital skills distance and the changes in the demand for digital skills. However, our gravity estimations require us to control for skill distance in all dimensions of skills. We thus construct two distinct measures and distinguish between an overall skill distance and a more specific distance in digital skills.

To measure the overall skills distance, we consider each occupation $j$ as a vector of $Z$ required skills in year $t$ denoted $z_j^{r,t} = \left(z_{j,1}^{r,t}, z_{j,2}^{r,t}, ..., z_{j,Z}^{r,t}\right)$ where $z_{j,k}^{r,t}$ corresponds to the share of ads for occupation $j$ requiring skill $k$ in year $t$. To avoid well-known issues when comparing vectors, for each occupation $j$, we normalize vector $z_j^{r,t}$ by its Euclidean norm $\left\|z_j^{r,t}\right\|$, so that $z_j^{r,t}$ is of unit length for all $j$ and $t$.

Our next step is to measure the skills possessed by the workers. Ideally, we would like to observe the exhaustive set of actual skills possessed by any French worker included in the data. This information is unavailable. Workers do not even explicitly report this information

[12]See for instance Bloom et al. (2021); Dillender and Forsythe (2022); Acemoglu et al. (2022); Braxton and Taska (2023).

on their CVs. As an alternative, we approximate the skills possessed by workers by combining information on their employment history and the skills required in each occupation. This approximation relies on the following set of assumptions.

*Assumption 1: In the baseline year t, the type of worker is defined by her occupation at t and her skills correspond to those required in that occupation.*

*Assumption 2: workers' skills evolve over time with the skills requirements of their matching occupation at baseline.*

Assumption 1 implies that if at baseline $t$ a worker is working in the occupation $i$, then her skills perfectly match those required in her job, and we say that this worker is of type $i$ and has skills $z_i^{p,t} := z_i^{r,t}$. Assumption 2 is valid when workers learn on-the-job and firms invest in. We make the assumption that workers' skills evolve with the skills requirements of their matching occupation at baseline. Together, assumptions (1-2) indicate that workers of type $i$ have skills $z_i^{p,t} := z_i^{r,t}$ at baseline (Assumption 1) and skills $z_i^{p,t+1} := z_i^{r,t+1}$ at a later date (Assumption 2).[13]

Skills distance between a worker of type $i$ and an occupation of type $j$ at baseline is thus obtained by computing:

$$\begin{aligned} SD_{ij}^t &= d\left(z_i^{p,t}, z_j^{r,t}\right) \\ &= d\left(z_i^{r,t}, z_j^{r,t}\right). \end{aligned}$$

Under assumption 1, our measure of skills distance at baseline $t$ is simply the overall skills distance between occupations $i$ and $j$ which we compute using the Euclidean distance between

[13]As mentioned in the previous section, we replace this assumption in Appendix Figure A2 where we assume instead that workers' skills remain as at baseline, i.e. there is no learning on-the-job and no training. We construct these alternative measures of skill distance and show in the empirical analysis that the main findings remain unchanged.

the vectors $z_i^{r,t}$ and $z_j^{r,t}$ as follows:

$$d\left(z_i^{r,t}, z_j^{r,t}\right) = \left(\sum_k \left(z_{i,k}^t - z_{j,k}^t\right)^2\right)^{1/2}. \tag{1}$$

Assumption 2 allows us to derive the skill distance at $t+1$ in a similar fashion to obtain the following:

$$\begin{aligned} SD_{ij}^{t+1} &= d\left(z_i^{p,t+1}, z_j^{r,t+1}\right) \\ &= d\left(z_i^{r,t+1}, z_j^{r,t+1}\right). \end{aligned}$$

Our measure of digital skills relies on the assumption that IT occupations are the most intensive in digital skills. We therefore consider the list of IT occupations as a composite reference category and denote this digital occupation $j = d$, where $d$ stands for digital. We consider required skills $z_d^{r,t}$ as the reference digital skills at $t$. In order to quantify the degree of digitalization of an occupation $j$ we construct the scalar $q_j^t$ as minus the Euclidean distance in required skills between that occupation $j$ and the required skills in the typical digital occupation $d$:

$$\begin{aligned} q_j^t &= -d\left(z_j^{r,t}, z_d^{r,t}\right) \qquad (2) \\ &= -\left(\sum_k \left(z_{j,k}^{r,t} - z_{d,k}^{r,t}\right)^2\right)^{1/2}. \end{aligned}$$

An occupation $j$ is therefore fully digital whenever $q_j^{r,t}$ attains a maximum value of 0 which occurs whenever $z_j^{r,t} = z_d^{r,t}$, and small when the euclidean distance between the two vectors $z_j^{r,t}$ and $z_d^{r,t}$ is large.

Following Assumptions (1-2), a worker of type $i$ has digital skills $q_i^{p.t} = q_i^{r,t}$ at baseline and

$q_i^{p,t+1} = q_i^{r,t+1}$ at $t+1$. We can then proceed and compute the digital skill distance between a worker of type $i$ and an occupation of type $j$ for any $t$ as the Euclidean distance between the scalars $q_i^{p,t}$ and $q_j^{r,t}$.

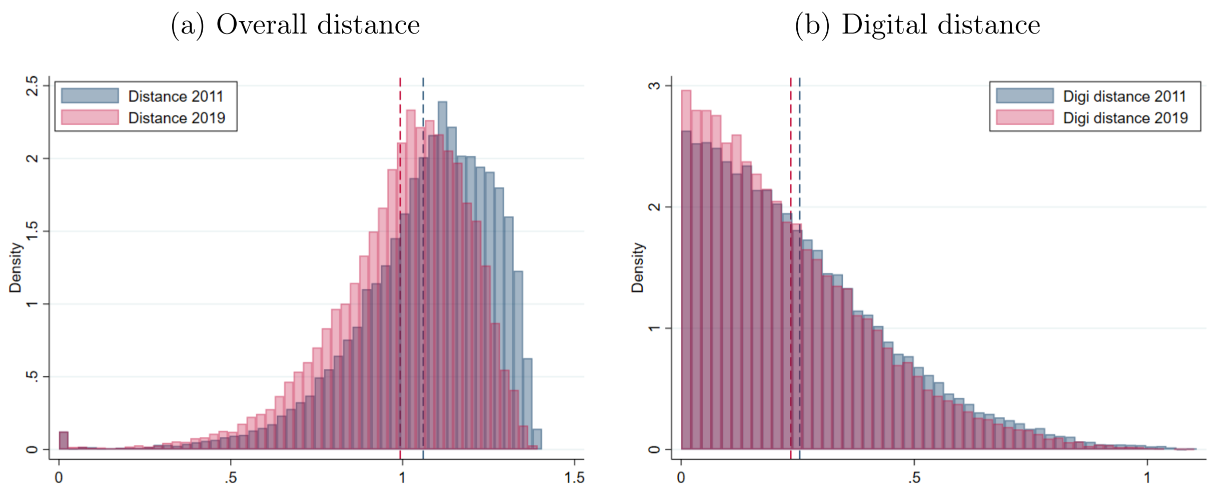
$$\begin{aligned} DSD_{ij}^t &= d\left(q_i^{p,t}, q_j^{r,t}\right) \\ &= d\left(q_i^{r,t}, q_j^{r,t}\right) \\ &= d\left(-d\left(z_i^{r,t}, z_d^{r,t}\right), -d\left(z_j^{r,t}, z_d^{r,t}\right)\right), \end{aligned} \tag{3}$$

for all $t$.

An alternative approach would have been to use the same expression as in equation 1 restricting the list of skills to those that are explicitly linked to IT, but such a procedure would have confounded occupations that are very similar because they demand the same types of digital skills, and occupations that are very similar because they both do not demand any digital skills. In addition, our approach considers that, in order to perform digital tasks, workers also need to possess a set of complementary skills that might not seem digital at first glance, but that are essential for performing the job. Being agnostic about which set of tasks might be complementary, we adopt a data-driven approach consisting of considering the bundle of tasks demanded in "fully digital" occupations as the optimal mix of skills. The appendix Table A1 presents the list of such reference occupations, which in short includes all jobs in the category of IT engineers and IT technicians. In total, they represent 2% of the occupation codes and 3% of total employment. In order to validate this choice, we manually classify the Burning Glass listed skills into digital and non-digital, where in the first we include all tasks that are linked to any software and hardware related to IT. We then summarize the share of digital skills observed in our "fully digital" occupations and in all the others. The results are presented in the Appendix Figure A3. We can see that our digital occupations count on average 48% of IT-related skills, while the average within other occupations is around 9%. This observation also highlights how, even in occupations directly related to IT, 50% of the skills demanded are actually not directly related to IT but rather complementary to it.

Figure 2 shows the distribution of distance and digital distance between all pairs of occupation, both at the beginning and the end of our period. What we can highlight is that occupations have gotten closer to each other, since the overall distance decreased by 8% between 2011 and 2019 and the digital distance decreased by 7%.

Figure 2: Evolution of skill distance over the period




The figure shows the distribution of distance and digital distance across all occupation pairs, both in 2011 (the beginning of our period) and in 2019 (the end of our period). Vertical dashed lines represent the yearly averages.

This finding is further confirmed and precised by several additional analyses. Appendix Figure A4 shows two scatter plots correlating the level of overall distance and digital distance in 2011 and their respective level in 2019. The picture shows that most of the dots are located below the 45-degree line, indicating that the distance was greater in 2011 relative to 2019. The correlation coefficient between the overall distance measured in the two points in time is 0.94, while it is 0.90 for the digital distance. Furthermore, the fitted polynomial reveals that occupation pairs that were farther away from each other have decreased their distance relatively more than pairs that were closer. This fact is confirmed in Figure A5, which shows the change in distance as a function of the initial level of distance. For both the overall distance and the digital distance, the change is larger in pairs that were further away from each other in 2011. We take all of these observations as evidence of the extent to which the decade of 2010s has been subject to important changes in the task-content of occupations, making this period particularly suitable to study the effect of these changes on worker flows.

## 3.2 Occupation mobility

Information about occupational mobility and associated changes in wages is derived from French registry data. In particular, we rely on the Payroll Tax records called *DADS poste*, which collect information on all employees active in the French labor market, including their annual salary, the total number of hours worked in the year and the occupation in which they are employed. Although the version made available by the French statistics office INSEE does not include individual worker identifiers that can be followed over time, except for a sub-sample of 1/12th of the employees, a recent contribution by Babet, Godechot and Palladino (2022) explains how to re-construct the quasi-entirety of the worker panel using the information available in the registry.[14] Using this reconstruction of the worker panel, we build three distinct datasets: i) baseline mobility, measuring all occupation flows observed between 2011 and 2012, ii) end-line mobility, measuring all occupation flows observed between 2018 and 2019, and iii) long-run mobility, measuring all occupation flows observed between 2011 and 2019. For all of the three datasets we further compute the average origin and destination

[14] In short, each dataset reports individual level information relative to the activity in the current year $t$ as well as information relative to the year that preceded it $(t-1)$. As such, the same information is reported twice for two consecutive years, once for year $t$ and once for year $t-1$ for the wave afterward. Babet, Godechot and Palladino (2022) show that the match on the available overlapping information is unique for 98% of the individuals, thus allowing to reconstruct a worker-level panel for the quasi-universe of the observations. The only caveat that exists is for individuals who remain out of employment for more than one year and who are therefore considered a new individual once they return.

wage relative to all occupation pairs, we include all pairs of stayers, defined as the flows of workers that remained in the same occupation during the period, and we include flows towards and from non-employment to obtain a complete picture of employment in the labor market.

Figure A6 in the appendix shows a matrix with all occupation pairs ranked according to the French PCS classification. Broadly speaking, the rank follows socio-professional categories, going from executives and engineers, to professionals and technicians, to clerical office workers, to skilled, and finally unskilled blue collar workers. To improve readability, diagonal pairs, corresponding to stayers who remain in the same occupation over the period, have been dropped. What we can observe is that mobility patterns cluster around similar occupations, and that this is especially true among higher ranked professions. Descriptively, this picture validates that skill distance matters when it comes to mobility patterns.

### 3.3 Final sample

Given that we want to portray the entirety of the French labor market to take into account all general equilibrium effects of changes in distance between occupations, our data cleaning is restricted to the bear minimum. In particular, for workers with multiple jobs, we only consider the main one, defined as the one that paid the highest total salary over the year, and we further drop workers with incomplete occupation codes and with hourly wages below the statutory minimum wage. Finally, we only keep workers in prime age, defined between 20 years old and 60 years old. In contrast, we do not apply any sectoral or occupational restriction. In total in our final sample we have 385 occupation codes plus one non-employment category, which give rise to 148,996 pairs of occupations. In roughly 35% of the occupation pairs, we observe zero flows, which is not surprising given the wide variety of jobs included.

Table 1: Summary statistics

| | All pairs | | | | Pairs of occupational switches | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Minimum | Maximum | Mean | Standard deviation | Minimum | Maximum |
| Digital distance in 2011 | 0.252 | 0.196 | 0.000 | 1.11 | 0.254 | 0.195 | 0.000 | 1.11 |
| Digital distance in 2019 | 0.233 | 0.184 | 0.000 | 1.10 | 0.235 | 0.184 | 0.000 | 1.10 |
| Change in digital distance (2011-2019) | -0.019 | 0.084 | -0.539 | 0.660 | -0.019 | 0.084 | -0.539 | 0.660 |
| Distance in 2011 | 1.060 | 0.220 | 0.000 | 1.41 | 1.068 | 0.200 | 0.011 | 1.41 |
| Distance in 2019 | 0.988 | 0.217 | 0.000 | 1.39 | 0.996 | 0.200 | 0.006 | 1.39 |
| Change in distance (2011-2019) | -0.072 | 0.075 | -0.536 | 0.470 | -0.072 | 0.075 | -0.536 | 0.470 |
| Initial share of digital skills | 0.095 | 0.093 | 0.000 | 0.613 | 0.096 | 0.093 | 0.000 | 0.613 |
| Share of occ. with high digital skills | 0.539 | 0.499 | 0.000 | 1 | 0.539 | 0.498 | 0.000 | 1 |
| Mobility 2018 - 2019 | 172 | 4072 | 0 | 538008 | 23 | 189 | 0 | 21515 |
| Mobility 2011 - 2019 | 223 | 4294 | 0 | 413237 | 33 | 306 | 0 | 44865 |
| Number of observations | 148,994 | | | | 147,840 | | | |
| Number of occupations | 385 | | | | 385 | | | |

**Notes:** The table summarizes the main variables of interest for the analysis. On the left, statistics are obtained from all pairs of occupations, including pairs where the occupations of origin and destination are the same (stayers). On the right, statistics are obtained from a subset of pairs that involve a switch in occupation, thus excluding stayers.

Table 1 describes our main sample. As already visible from Figure 2, occupations have gotten closer to their skill requirements on average, both overall and only in the digital dimension. When we manually classify the Burning Glass listed skills into digital and non-digital, we find that, on average, 9.5% of the skills listed in occupation ads in 2011 are digital, while the median is at 7%. As shown in the appendix Figure A3 this share is much higher for our digital occupations of reference. Finally, on average the pairwise flow size is of 172 moves at endline and 223 moves if we look at long-term moves between 2011 and 2019. However, these flows include stayers and movers in and out of unemployment. If we only consider occupation switchers, the average flow goes down to 23 at baseline and 33 for long-term changes.

# 4 A gravity model approach

Gravity models are mostly used to study how different measures of distances between two entities affect bilateral flows, net of any origin-specific and destination-specific factors that are common to all bilateral pairs. Gravity models are commonly used in the trade and migration literatures. Cortes and Gallipoli (2018) are the first to apply this estimation approach to study occupation mobility within labor markets. Our work builds on this approach but differs from theirs in several dimensions. We first relax the assumption made by the authors that skills required in occupations are fixed and explore how changes in skills distance over time affect mobility flows. We also differ by focusing on changes in digital skills that have become increasingly demanded on labor markets.[15] Finally, we adopt a different micro-foundation which is based on a discrete version of the two-sided matching model presented in Dupuy and Galichon (2022).

The gravity model that we consider for measuring the effect of skill distances on mobility is the following:[16]

$$Mob_{ij} = \beta_0 + \beta_1 Dist_{ij} + \beta_2 DigiDist_{ij} + \alpha X_{ij} + \gamma_i + \gamma_j + \epsilon_{ij}. \tag{4}$$

Where $Mob_{ij}$ captures the total flows between origin $i$ and destination $j$, including pairs where $i = j$ (stayers) and pairs where $i = 0$ or $j = 0$ (movers to and from non-employment). $Dist_{ij}$ and $DigiDist_{ij}$ represent our measures of skill distance and digital skill distance described in Section 3. Both measures are standardized to have mean zero and standard deviation one to facilitate the interpretation of regression coefficients. The multilateral resistance parameters $\gamma_i$ and $\gamma_j$ absorb all the determinants of mobility flows that are driven by origin and destination factors, thus absorbing all the effects driven by changes in their own labor demand and labor supply. As such, this part of our analysis can be seen as fully complementary to the literature on technological change that studies the effects of changes in own occupation demand on employment and wages. Here we absorb all the changes driven

[15] Figure A1 highlights how digital skills have experienced the largest increase in labor demand over the years 2011-2019.

[16] This gravity equation is similar to the one used by Cortes (2016), with the difference that we include a specific measure of digital distance.

by own demand factors and we focus on the indirect effects of changes in skill demand in a given occupation through changes in it's distance relative to other occupations.[17] Finally, $X_{ij}$ controls for additional bilateral factors affecting occupation flows. In particular, we control for an indicator for stayers, which takes into account the fact that there are some additional fix costs associated with switching occupation that go beyond the simple effect of skill distance. In addition, we include a dummy equal to one for all occupation switches that involve a change in socioeconomic status, which are expected to be more costly than changing jobs within a given status.[18] Finally, standard errors are double-clustered at the level of origin occupation $i$ and destination occupation $j$, and the model is estimated using pseudo-poisson maximum likelihood (PPML), as is standard in gravity models to avoid biases coming from the large portion of zeros in bilateral flows (Silva and Tenreyro, 2006).

Equation 4 is suitable for estimating the effect of distances measured at a given point in time on contemporaneous mobility flows. However, the main objective of this paper is to capture the effect of changes in digital skill distance over the past decade on mobility patterns. Thus, we decompose the skill distance measured in 2019 into a baseline measure of the skill distance in 2011 and a measure of change between 2011 and 2019 for each pair of occupations. Our main specification is thus the following:

$$\begin{aligned} Mob_{ij} = \beta_0 + \beta_1 Dist_{ij}^{11} + \beta_2 DigiDist_{ij}^{11} \\ + \beta_3 \Delta Dist_{ij}^{11-19} + \beta_4 \Delta DigiDist_{ij}^{11-19} + \alpha X_{ij} + \gamma_i + \gamma_j + \epsilon_{ij}, \end{aligned} \quad (5)$$

[17]In the counterfactual exercise presented in section 7 we disentangle which portion of total changes in mobility are driven by direct changes in own occupation demand versus indirect changes through evolving skill distance to other occupations.

[18]These switches might involve additional institutional constraints such as the need for a higher education diploma. In practice, we define changes of socioeconomic status using the French occupational classification, which divides occupations into 5 categories: CEOs and business owners, executives and engineers, intermediate professionals and technicians, clerical workers, and blue collar workers.

where $\beta_4$ is expected to capture the digital distance channel of the effect of technological change on mobility, controlling for changes in all other dimensions of the skill distance that might be due to many other factors. We estimate the effect on two mobility outcomes ($Mob_{ij}$): end-line mobility between 2018 and 2019 and long-run mobility between 2011 and 2019. The first has the advantage of capturing the total effect of the changing distances since all moves occur at the end of the period. The second also includes some changes that happened early in the 2010s, but has the advantage of capturing longer career trajectories.

Finally, we investigate the presence of asymmetric effects. The changes in digital distance that occurred over the last decade were driven by the generalization of digital technologies, initially used in few high-digital jobs, to many other occupations in the labor market. If in 2010 only IT engineers and data scientists were required to know how to code in different software languages, by 2019 many more jobs require some coding ability, including marketing, sales, management strategy and financial positions, among others. A similar expansion of digital skills took place within low-skill jobs. In fact, Appendix Figure A1 shows that among the 25 skills that saw the largest change in share of ads mentioning them, all occupations combined, the vast majority involve the use of some digital software. It is also striking that the single skill that saw the highest change in demand is Microsoft Office, which signals that this shift might not only concern highly skilled occupations requiring complex coding abilities, but also more middle- to low-skill occupations that now require some basic computer knowledge. Given these characteristics of the change in digital skill distance, we expect that it affected mobility flows in an asymmetric way, favoring workers initially employed in occupations that were already digitally intensive at the beginning of the period, by giving them access to a variety of new opportunities outside of their initial occupations. We test this hypothesis in the data by interacting the changes in the digital distance ($\Delta DigiDist_{ij}^{11-19}$) estimated in Equation 5 with the digital intensity of the origin occupation $i$ measured in 2011, which is just the share of digital skills observed within the ads of that occupation.

# 5 Empirical results

Table 2 presents the main results obtained from the estimation of equations (4) and (5). Columns (1) to (4) have end-line mobility between 2018 and 2019 as outcome, while columns (5) to (8) show the robustness of the results in using long-run mobility as outcome. Coefficients are obtained from the PPML estimation and are thus presented in exponentiated form. As such, coefficients larger than 1 signal a positive effect, and coefficients smaller than 1 signal a negative effect. The coefficients in column (1) reveal that a 1 standard deviation higher skill distance is associated with 50% less occupational mobility, and a 1 standard deviation higher digital skill distance is associated with 15% less occupational mobility. Both coefficients are highly significant and highlight how mobility declines rapidly along these dimensions. The size of the flows of stayers in the same occupation are 36 times higher than the flows to other occupations after controlling for skill distance, highlighting the presence of inertia in occupation choices possibly due to high switching costs. Column (2) shows the coefficients obtained if the distances are measured with error and, in particular, if the flows in 2018-19 are related to the distances measured in 2011. The effect of digital distance does not show large changes, while the effect of overall distance becomes slightly smaller (a 1 standard deviation higher skill distance is associated with 46% less occupational mobility).

More interestingly, columns (3) and (4) directly test whether distance changes observed over the decade have an impact on mobility flows. In column (3), we can see that a 1 standard deviation larger increase in distance decreases mobility by 23%, while changes in digital distance do not present a significant effect, consistent with the fact that the coefficients on digital distance are very similar in columns (1) and (2). The fact that changes in digital distance make no difference to mobility during the period may seem at odds with the premises of the paper, but, in fact, this may be due to the presence of important asymmetries in the effect.

Table 2: Effects of distance and digital distance on mobility flows

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Mobility 2018 - 19 | | | | Mobility 2011 - 19 | | | |
| | Distance in '19 | Distance in '11 | | | Distance in '19 | Distance in '11 | | |
| Distance | 0.507*** | 0.535*** | 0.502*** | 0.503*** | 0.477*** | 0.504*** | 0.470*** | 0.471*** |
| | (0.0154) | (0.0153) | (0.0159) | (0.0159) | (0.0145) | (0.0153) | (0.0148) | (0.0148) |
| Digital distance | 0.845*** | 0.834*** | 0.837*** | 0.833*** | 0.952 | 0.947 | 0.954 | 0.950 |
| | (0.0331) | (0.0338) | (0.0364) | (0.0365) | (0.0340) | (0.0351) | (0.0372) | (0.0373) |
| Change in distance | | | 0.771*** | 0.774*** | | | 0.739*** | 0.742*** |
| | | | (0.0341) | (0.0343) | | | (0.0324) | (0.0324) |
| Change in digital distance | | | 0.983 | 1.044 | | | 1.000 | 1.054 |
| | | | (0.0445) | (0.0484) | | | (0.0422) | (0.0579) |
| Change in digital distance for digital intensive occ. | | | | 0.884** | | | | 0.896* |
| | | | | (0.0456) | | | | (0.0555) |
| **Controls :** | | | | | | | | |
| Stayers | 36.46*** | 35.83*** | 36.76*** | 36.87*** | 5.166*** | 5.179*** | 5.315*** | 5.325*** |
| | (4.551) | (4.474) | (4.536) | (4.539) | (0.576) | (0.532) | (0.556) | (0.553) |
| Level switch | 0.474*** | 0.432*** | 0.473*** | 0.473*** | 0.631*** | 0.583*** | 0.633*** | 0.634*** |
| | (0.0398) | (0.0382) | (0.0397) | (0.0395) | (0.0517) | (0.0506) | (0.0523) | (0.0522) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The table summarizes the results obtained from estimating equations 4 and 5 with pseudo-poisson maximum likelihood (PPML). All regressions include origin and destination occupation fixed effects and control for a dummy for stayers and a dummy for occupational switches involving a change in socio-economic status. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form (larger than 1 signals a positive effect and smaller than 1 signals a negative effect). Columns (1) to (4) show results using endline mobility as outcome, while columns (5) to (8) use long-term mobility as outcome. Column (4) and (8) interact change in digital distance between 2011 and 2019 with the initial share of IT skills observed in the origin occupation i.

Our hypothesis is that changes in digital skill distance favored mobility in an asymmetric way, from occupations that were already high in digital intensity at the beginning of the period towards occupations that saw a recent increase in demand for digital skills. We therefore estimate equation (5) which interacts the change in digital distance with a dummy for the 50% of occupations with the highest share of digital skills in 2011 (corresponding to more than 7.5% of all skills). The results are presented in columns (4) and (8). We see that changes in digital distance only impact mobility from jobs that were initially highly digitally intensive. The coefficients reveal that an increase in digital distance by 1 standard deviation decreases mobility from highly digital occupations by 22%, while it does not affect mobility leaving initially low digitally intensive jobs. Given that the period saw a general decrease in digital distance between occupations, the interpretation is rather that decreasing digital distances between occupations has generated higher mobility from historically digital occupations towards newly digital ones, and less mobility the other way around. Running these regressions on long-run mobility flows gives rise to very similar coefficients.

Before moving on to the robustness tests on our main specification of interest, we first test the linearity assumption of the econometric model. The fact that distances are included linearly assumes that mobility decays linearly with distance. In order to test whether this assumption is a good approximation of reality, we test an alternative specification of equation 4 with dummies for the ten deciles of the distance and digital distance distributions instead of the linear measures. The appendix Figure A7 plots the coefficients obtained, where the first decile is omitted and serves as a reference category. The effect of overall skill distance seems to decelerate after the fourth decile but then still sees a big jump at the 10th decile. The effect of digital skill distance looks rather linear, and if anything it accelerates towards later deciles. All in all, while not perfect, the linearity assumption does not seem too far from reality, and it has the advantage of simplifying the model enough to allow the inclusion of easily interpretable interaction terms.

One may wonder whether our results depend on the assumption that workers learn on the job, such that we can assume that their skill distance when moving from $i$ to $j$ in 2019 is equivalent to the difference in skill required in the two occupations at the end of the period. The opposite assumption would be that workers do not update their skills during the 2010s decade, such that their skill distance when moving from $i$ to $j$ in 2019 is equivalent to the difference in skill required between occupation $i$ in 2011 and occupation $j$ in 2019. Note that under this assumption, a positive skill distance appears even for stayers, due to skill obsolescence (Deming and Noray, 2020). We construct distance measures following this alternative assumption and present the results obtained in the appendix Table A2. In addition to the controls already included in the main results, we also control for the interaction between the dummy for stayers and all the measures of changes in distance and digital distance, since they now vary even within stayers. This is because we care mainly about the effect of changing distances on the movers. The results obtained are remarkably similar in magnitude and significance to those presented in the main table 2. In particular, we still observe that the effect of changes in digital skill distance is asymmetric in a way that favors workers with initially high levels of digital knowledge.

Table 3: Robustness of the effect of changes in digital distance on end-line mobility flows

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Mobility 2018 - 19 | | | |
| | top 50% digi-int | top 25% digi-int | Continuous digi-int | level switch FE | ctr for digipair | ctr for baseline mob |
| | PPML | PPML | PPML | PPML | PPML | PPML |
| Distance | 0.503*** | 0.503*** | 0.502*** | 0.498*** | 0.502*** | 0.497*** |
| | (0.0159) | (0.0159) | (0.0158) | (0.0150) | (0.0156) | (0.0138) |
| Digi distance | 0.833*** | 0.835*** | 0.833*** | 0.910** | 0.843*** | 0.854*** |
| | (0.0365) | (0.0368) | (0.0360) | (0.0336) | (0.0365) | (0.0345) |
| D distance | 0.774*** | 0.775*** | 0.772*** | 0.775*** | 0.778*** | 0.746*** |
| | (0.0343) | (0.0342) | (0.0341) | (0.0350) | (0.0345) | (0.0345) |
| D digi distance | 1.044 | 1.137** | 1.007 | 1.097** | 1.044 | 1.052 |
| | (0.0484) | (0.0712) | (0.0523) | (0.0472) | (0.0483) | (0.0481) |
| D digi distance x high-digi | 0.884** | 0.829*** | 0.755 | 0.892** | 0.896** | 0.882** |
| | (0.0456) | (0.0496) | (0.134) | (0.0447) | (0.0478) | (0.0476) |
| **Controls:** | | | | | | |
| Level switch | 0.473*** | 0.473*** | 0.473*** | | 0.471*** | 0.480*** |
| | (0.0395) | (0.0396) | (0.0397) | | (0.0394) | (0.0416) |
| Stayers | 36.87*** | 36.91*** | 36.80*** | 38.42*** | 36.54*** | 51.85*** |
| | (4.539) | (4.551) | (4.530) | (4.667) | (4.520) | (7.722) |
| digipair | | | | | 0.823 | |
| | | | | | (0.233) | |
| D distance x digipair | | | | | 0.719*** | |
| | | | | | (0.0914) | |
| D digi distance x digipair | | | | | 1.674* | |
| | | | | | (0.456) | |
| D digi distance x digipair x high-digi | | | | | 0.665* | |
| | | | | | (0.154) | |
| Mobility 2011 - 12 | | | | | | 1.000*** |
| | | | | | | (8.54e-07) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 |
| p-val interaction | 0.0174 | 0.00184 | 0.114 | 0.0237 | 0.0411 | 0.020 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
The table summarizes the results obtained from estimating equation 5 with pseudo-poisson maximum likelihood (PPML), where the change in digital distance is interacted with initial digital intensity at origin. All regressions include origin and destination occupation fixed effects. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form.

Table 3 presents a series of additional robustness tests for end-line mobility, while the appendix table A3 does the same for long-run mobility. Column (1) reproduces the baseline results from Table 2, for comparison. Column (2) defines the dummy for high initial digital intensity as the 25% of occupations with the highest share of digital skills required at baseline, while Column (3) uses the continuous measure of the share of digital skills at baseline for the interaction. These specifications test the robustness of the results to different definitions of the intensity of the initial digital skill. Column (4) goes back to defining digital intensity as in our main specification but controls for the full set of fixed effects for socioeconomic level switches instead of just a dummy. The latter takes into account that different hierarchical switches may have different fix costs associated with them, and effectively only captures the effect of skill distances within a given hierarchical layer. Column (5) computes the effect separately for pairs involving at least one "fully digital" occupation - the reference group used to define digital distance - thus testing whether these specific pairs are driving the results. Finally, column (6) controls for the bilateral mobility flows from baseline between occupation $i$ and $j$, which captures all unobservable determinants of bilateral flows at baseline. The bottom of the table reports the p-values associated with the interaction term (our main coefficient of interest).

Overall, the results are very robust to these alternative specifications. The interaction with the continuous measure of initial digital intensity is marginally not significant for the endline mobility outcome (p-value = 0.11) but it is for the long-term mobility outcome, while the opposite is true for the model with the complete set of fixed effects for hierarchical level changes. Nevertheless, the same patterns arise throughout these exercises and the magnitudes are very stable. A final interesting observation is that, in the model where the effects are estimated separately for pairs involving or not a fully digital occupation, we find exactly the same patterns in both groups: the effect of shortening digital distance disproportionately favors mobility from occupations that were initially digital intensive towards occupations that were not, and this is true both for pairs involving at least one IT job but also for pairs that do not involve one.

Additional robustness tests are presented in the appendix. The left-hand side of the appendix Table A4 tests the robustness of our results to excluding from the distance measures skills that can be considered "generic", defined as those skills that are required in more than 90%

of occupations.[19] In this list we find skills such as "time management", "problem solving", or "people skills", whose changes over time might reflect more changes in the style of writing ads rather than true fundamental changes in the content of jobs. The results are broadly consistent with those found in the main analysis. The interaction with the binary variable of high initial digital intensity is not significant, but the interaction with the continuous measure of initial digital intensity is significant and goes in the expected direction. The right-hand side of the appendix table A4 shows the robustness of the results to use a different level of aggregation for occupation codes. In particular, we consider the 3-digit classification of French occupations rather than the 4-digit one, which shrinks the number of occupation pairs from roughly 150 to roughly 15 thousands. Here, the coefficients are similar in magnitude to those found in the main analysis, and while the interaction with the binary variable of high initial digital intensity is not significant, the interaction with the continuous measure is. For conciseness, we only present the results for end-line mobility, but results using long-run mobility show similar patterns and are available upon request. Finally, appendix Table A5 tests that the long-run mobility effects are not biased by disappearing age cohorts.[20] By selecting the 20 to 60 years old in each wave, we effectively count all the young workers entering the labor market after 2011 in the flows from non-employment, and all the old workers leaving the labor market after 2011 in the flows to non-employment. To correct for this, in table A5 we keep workers who are 20 to 52 years old in 2011 and workers who are 28 to 60 years old in 2019, effectively following cohorts. The results remain very similar to our baseline coefficients.

All in all, given the robustness of these findings, we now turn to the micro-foundation that allows us to evaluate the magnitude of the effect of technological change on mobility relative to counterfactual scenarios where these changes did not happened.

[19]In order to consider that a skill is required in a given occupation, we define that it has to appear in at least 10% of the occupational ads.

[20]This is not an issue for the end-line mobility measure.

# 6 The model

As illustrated in section 3, we construct for each occupation a vector of required skills based on US job ads. Each entry in the vector indicates the relative importance of a different skill for this occupation. This corresponds to the share of ads in this occupation that require this specific skill. We further define a vector of skills possessed by each worker using the occupation of the job they initially held. The vector of skills of a worker is then simply the vector of required skills in the initial job of that worker. With this approximation in mind, the labor market we consider is a market where on both sides, workers and jobs are grouped into discrete types (occupations), and types are defined by a vector of (required) skills.

We use the two-sided one-to-one matching model with transferable utility a la Choo and Siow (2006) and Galichon and Salanié (2022*b*) to model this market.[21] In this model, there is a large number of workers of each type and a large number of jobs of each type. Both workers and employers aim to match up with one agent on the other side to maximize their utility. Transfers, in the form of wages, are possible, but the market being competitive and workers and employers being price-takers, transfers are determined in equilibrium.

## 6.1 Workers' and jobs' types

We denote by $O$ the list of occupations. We say that a job is of type $j \in O$ when this job's occupation is $j$. Let $X_j$ be the mass of jobs of type $j$ in the market so that there are $\sum_{j \in O} X_j$ jobs in the market.

Types of workers are also defined using occupations. A worker is of type $i \in O$ if the occupation of her previous job is $i$. Workers who were previously not employed are taken

[21] See also Galichon and Salanié (2022*a*) for a generalized version version and Dupuy and Galichon (2022) for a continuous type version of the model applied to the labor market for risky jobs.

into account by extending the set of occupations to include a category "0", i.e. $O_0 = O \cup \{0\}$, so that a worker who was previously not employed is said to be of type $i = 0$. Let $Y_i$ for all $i \in O_0$, be the mass of workers of type $i$ on the market, so that, for example, $Y_0$ indicates the mass of workers who were not previously employed. There are $\sum_{i \in O_0} Y_i$ workers on the market.

Note that we do not restrict the mass of workers $\sum_{i \in O_0} Y_i$ to be equal to the mass of jobs $\sum_{j \in O} X_j$, as workers can remain not employed. However, since our empirical analysis does not consider job vacancies, the model is such that all jobs must be matched to a worker. Therefore, it must be $\sum_{i \in O_0} Y_i \geq \sum_{j \in O} X_j$.[22]

## 6.2 Matching

Let $X_{ij}$ denote the mass of workers of type $i$ matched to a job of type $j$ and let $X_{i\emptyset}$ be the mass of workers of type $i$ that remain not employed. A feasible matching is then a tuple $\left\{ (X_{i\emptyset})_{i \in O_0, j \in O}, (X_{ij})_{i \in O_0, j \in O} \right\}$ satisfying the accounting constraints[23]

$$X_{i\emptyset} + \sum_{j \in O} X_{ij} = Y_i, \ \forall i \in O_0, \tag{6}$$

$$\text{and} \sum_{i \in O_0} X_{ij} = X_j, \forall j \in O. \tag{7}$$

The first accounting constraint indicates that the total mass of workers of type $i$ matched to

[22]In appendix B.1 we show an extension of the model where jobs may also remain vacant. Because of the logit structure of the model, i.e. the Independence of Irrelevant Alternatives applies, and excluding the possibility of vacant jobs does not affect the remaining log-odds and the main analysis remains unchanged.

[23]Underlying this notation and interpretation of the matching model is the assumption that there are no vacant jobs in the economy. The market clears with all jobs being filled. This is because we assume that $\sum_i X_{ij}$, the sum of all workers working in $j$ is also the mass of jobs in $j$, i.e. $\sum_i X_{ij} = X_j$. As shown in Appendix B.1, this could be accommodated within the same framework. Estimation of this model, however, requires one to observe the mass of vacant jobs by occupation, which typically is not observed in matched-employer-employee data. Note that one could circumvent this issue by collecting data on vacancies by occupation and appending that information to the matched data.

any type of jobs (not employed included) is exactly the mass of workers of type $i$ available on the market. The second accounting constraint indicates that the total mass of jobs of type $j$ filled by any type of workers is exactly the mass of jobs of that type available on the market.[24]

### 6.3 Match values and choices

Let $\alpha_{ij}$ be the systematic intrinsic utility derived by a worker of type $i \in O_0$ when working in a job of type $j \in O_\emptyset = O \cup \{\emptyset\}$ and $w_{ij}$ be the monetary transfer, typically the wage, paid in jobs of type $j \in O_\emptyset$ for workers of type $i \in O_0$, with the convention that when workers do not work, i.e. $j = \emptyset$, they receive no transfers, i.e. $w_{i\emptyset} = 0$.[25] Further, let $\varepsilon_j$ be a worker-specific, idiosyncratic taste for occupation $j \in O_\emptyset$, drawn from a (centered) Gumbel type I distribution with unit scaling factor.

A worker of type $i \in O_0$ maximizes her utility by choosing the appropriate occupation, i.e. solves the problem

$$\max_{j \in O_\emptyset} \left( \alpha_{ij} + w_{ij} + \varepsilon_j \right). \tag{8}$$

Let $\gamma_{ij}$ be the systematic productivity of a worker of type $i \in O_0$ in a job of type $j \in O$ and $\eta_i$ be the idiosyncratic productivity of the job / employer when matched with a worker of type $i \in O_0$. It is assumed that the job-specific productivity $\eta_i$ is drawn from a (centered) Gumbel type I distribution with unit scaling factor.

[24] Using our notation one then has that $X_{0j}$ is the mass of workers that previously were not employed, who are working in occupation $j$. Moreover, $\sum_j X_{0j} = Y_0$ is the total mass of workers that previously were not employed whereas $X_{i0}$ is the mass of workers that were previously employed in occupation $i$ and are currently not employed. Finally, $\sum_i X_{i\emptyset} = X_\emptyset$ is the mass of workers that are currently not employed. Note that since individuals who were previously not employed and are still not employed are typically not observed in our data, we simply add the restriction $X_{0\emptyset} = 0$.

[25] Note that $w_{0j}$ $\forall j \in O$ needs not be 0 as it corresponds to the transfer paid to a worker of type 0, i.e. that was previously not employed, who is currently working in a job of type $j \in O$.

An employer with a vacant job of type $j \in O$ maximizes her profits by choosing the type of the worker to match with that solves the following problem

$$\max_{i \in O_0} \left(\gamma_{ij} - w_{ij} + \eta_i\right). \tag{9}$$

By an application of the Williams-Daly-Zachary theorem, each of these problems yields a solution of the form

$$\begin{aligned} \log X_{ij}^S &= \alpha_{ij} + w_{ij} - s_i \quad \forall (i,j) \in O_0 \times O_\emptyset / (0, \emptyset), && (10) \\ \log X_{ij}^D &= \gamma_{ij} - w_{ij} - m_j \quad \forall (i,j) \in O_0 \times O. && (11) \end{aligned}$$

The first equation can be thought of as the supply of workers of type $i$ to jobs of type $j$, while the second equation can be thought of as the demand of employers with jobs of type $j$ for workers of type $i$.

## 6.4 Equilibrium

In equilibrium, supply equates demand, i.e. $X_{ij}^S = X_{ij}^D = X_{ij}$ for all $(i,j) \in O_0 \times O$, and it follows that, by rescaling and adding equations (10) and (11),

$$\begin{aligned} X_{ij} &= \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right), \forall (i,j) \in O_0 \times O && (12) \\ X_{i\emptyset} &= \exp\left(\alpha_{i\emptyset} - s_i\right), \forall i \in O && (13) \end{aligned}$$

where $\varphi_{ij} = \alpha_{ij} + \gamma_{ij}$ and with

$$\begin{aligned} \sum_{j \in O_\emptyset} X_{ij} &= Y_i, \ \forall i \in O_0, && (14) \\ \text{and} \sum_{i \in O_0} X_{ij} &= X_j, \forall j \in O, && (15) \end{aligned}$$

with $X_{0\emptyset} = 0$.

Clearly, this solution is of the form of a typical gravity equation, since it contains a bilateral component ($\varphi_{ij}$) and two unilateral components associated with both sides of the market ($s_i$ and $m_j$). Interestingly, the matching foundation offers an equilibrium transfer equation. Indeed, using $X^S_{ij} = X^D_{ij} = X_{ij}$ in equilibrium, solving equation (11) for $w_{ij}$ and substituting the equilibrium expression of $X_{ij}$ in equation (12) for $X^D_{ij}$, one obtains equilibrium outcome as[26]

$$\begin{aligned} X_{ij} &= \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right) \forall i \in O_0, j \in O, \\ X_{i\emptyset} &= \exp\left(\alpha_{i\emptyset} - s_i\right), \forall i \in O, \\ w_{ij} &= \gamma_{ij} - \frac{1}{2}\varphi_{ij} + \frac{1}{2}\left(s_i - m_j\right), \forall i \in O_0, j \in O. \end{aligned}$$

## 6.5 Identification

Assume that one has access to the data $\mathcal{D} = (X, W)$, that is, data on matches and transfers (i.e. wages). Then in what follows, we show that the productivity channel ($\gamma_{ij}$) is

[26]Note that this can also be written as

$$\begin{aligned} X_{ij} &= \exp\left(\frac{(\gamma_{ij} - m_j) + (\alpha_{ij} - s_i)}{2}\right) \forall i \in O_0, j \in O, \\ w_{ij} &= \frac{1}{2}\left((\gamma_{ij} - m_j) - (\alpha_{ij} - s_i)\right), \forall i \in O_0, j \in O. \end{aligned}$$

This notation makes the source of identification more transparent, as we show in the next section.

identified separately from the preference channel ($\alpha_{ij}$). The intuition is that while productivity increases both the flow and the transfer, preferences increase the flow but decrease the transfer.

Formally, consider that the double difference operator $\Delta^2$ applied to a variable $Y_{ij}$ returns:

$$\Delta^2 Y_{ij} = [Y_{ij} - Y_{kj}] - [Y_{il} - Y_{kl}], \forall i \neq k, j \neq l.$$

Then, using the gravity equation note that

$$\begin{aligned}
\Delta^2 \log X_{ij} &= \frac{1}{2}\Delta^2 [\varphi_{ij} - s_i - m_j] \\
&= \frac{1}{2}\left(\Delta^2 \varphi_{ij} - \Delta^2 s_i - \Delta^2 m_j\right) \\
&= \frac{1}{2}\Delta^2 \varphi_{ij} \\
&= \frac{1}{2}\left(\Delta^2 \gamma_{ij} + \Delta^2 \alpha_{ij}\right).
\end{aligned}$$

However, note also that applying the operator on transfers one has

$$\begin{aligned}
\Delta^2 w_{ij} &= \Delta^2 \left[\frac{1}{2}\left((\gamma_{ij} - m_j) - (\alpha_{ij} - s_i)\right)\right] \\
&= \frac{1}{2}\left(\Delta^2 \gamma_{ij} - \Delta^2 \alpha_{ij}\right).
\end{aligned}$$

It follows that rearranging these two results to express unknowns in terms of data $\mathcal{D}$, one has the following identification result:

$$\begin{aligned}
\Delta^2 \alpha_{ij} &= \Delta^2 \log X_{ij} - \Delta^2 w_{ij}, \\
\Delta^2 \gamma_{ij} &= \Delta^2 \log X_{ij} + \Delta^2 w_{ij}.
\end{aligned}$$

The amenities and productivity can be identified separately using the data on flows ( $X$) and transfers ($W$).

## 6.6 Computation

A clear advantage of the micro-foundation of the gravity equation through our matching model is in providing us with an algorithm to compute the equilibrium associated with counterfactuals of interest. To see this, use the equilibrium expressions of $X_{ij}$ and $X_{i\emptyset}$ (equations 12 and 13) into the accounting constraints (equations 6 and 7), to obtain[27]

$$\begin{aligned} \exp\left(\alpha_{i\emptyset} - s_i\right) + \sum_{j\in O} \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right) &= Y_i,\ \forall i \in O_0, &(16)\\ \sum_{i\in O_0} \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right) &= X_j, \forall j \in O. &(17)\end{aligned}$$

By simple factorization, this system can be written as

$$\begin{aligned} X_{i\emptyset} + X_{i\emptyset}^{1/2} \sum_{j\in O} K_{ij} M_j^{1/2} &= Y_i,\ \forall i \in O_0, &(18)\\ M_j^{1/2} \sum_{i\in O_0} K_{ij} X_{i\emptyset}^{1/2} &= X_j, \forall j \in O, &(19)\end{aligned}$$

where $K_{ij} = \exp\left(\frac{\varphi_{ij} - \alpha_{i\emptyset}}{2}\right)$, $M_j = \exp\left(-m_j\right)$ and $X_{0\emptyset} = 0$.

The first equation of the system is a quadratic equation of the form

$$z^2 + 2Pz = Y$$

[27] Note that setting $\alpha_{0\emptyset} \to -\infty$, one has $X_{0\emptyset} = \exp\left(\alpha_{0\emptyset} - s_0\right) \to 0$.

for $z = X_{i\emptyset}^{1/2}$, $Y = Y_i$ and $P = \frac{1}{2}\sum_{j\in O} K_{ij} M_j^{1/2}$, whose solution[28] is

$$z^2 = \left(\left(Y + P^2\right)^{1/2} - P\right)^2. \tag{20}$$

It follows that the system can be expressed in terms of $X_{i0}$ and $M_j$ as follows:

$$X_{i\emptyset} = \left(\left(Y_i + \left(\frac{1}{2}\sum_{j\in O} K_{ij} M_j^{1/2}\right)^2\right)^{1/2} - \frac{1}{2}\sum_{j\in O} K_{ij} M_j^{1/2}\right)^2, \tag{21}$$

$$M_j = \left(\frac{X_j}{\sum_{i\in O_0} K_{ij} X_{i\emptyset}^{1/2}}\right)^2. \tag{22}$$

This system actually provides an IPFP algorithm that admits a fixed point (see Chen et al. (2021)) which can be achieved by solving successively the first set of equations for $X_{i\emptyset}$ given all $M_j$ 's and then the second set of equations for $M_j$ given the solutions for $X_{i\emptyset}$'s obtained at the previous step.

This means that for known quantities for $(\varphi_{ij}, \alpha_{i\emptyset})_{i,j}$ and $(Y_i, X_j)_{i,j}$, one can use the above algorithm to solve for an equilibrium $(X_{ij}, w_{ij})_{i,j}$. We use this algorithm to compute the equilibrium associated with each of our counterfactuals once the parameters of the utilities $(\varphi_{ij}, \alpha_{i\emptyset})_{i,j}$ have been estimated using the method outlined in the next section.

[28] The solution is obtained by completing the square, i.e.

$$\begin{aligned} z^2 + 2Pz \quad &: \quad = (z+P)^2 - P^2 = Y \\ &\Leftrightarrow \\ (z+P)^2 \quad &= \quad Y + P^2 \\ &\Leftrightarrow \\ z \quad &= \quad -P + \left(Y + P^2\right)^{1/2} \\ &\Leftrightarrow \\ z^2 \quad &= \quad \left(\left(Y + P^2\right)^{1/2} - P\right)^2 \end{aligned}$$

## 6.7 Estimation

Recall that jobs' types are defined by a vector of required skills, whereas workers' types are defined by a vector of possessed skills. For each occupation $j$ and each worker $i$ the distance between the required skills and the skills of the worker can be calculated using classical metrics (for example, Euclidean distance).

Let $D_{ij}^k$ be a measure of the distance between the skills required for a job of type $j$ and the skills of a worker of type $i$. For instance, one could define a measure of distance using the Euclidean norm

$$D_{ij}^1 = ||z_i - z_j||$$

where $z_i$ is the vector of skills of a worker of type $i$ and $z_j$ is the vector of skills required for a job of type $j$.

Suppose that we parametrize $\alpha_{ij}^a = \sum_{k=1}^K a_k D_{ij}^k$ and $\gamma_{ij}^b = \sum_{k=1}^K b_k D_{ij}^k$ so that $\varphi_{ij}^\beta = \sum_{k=1}^K \beta_k D_{ij}^k$ where $\beta_k = a_k + b_k$. and $D_{ij}^k$ are $K$ basis functions of the "distance" between workers' types and jobs' types. With this parametrization of the model, the gravity equation now becomes

$$\begin{aligned} X_{ij} &= \exp\left(\frac{\sum_{k=1}^K \beta_k D_{ij}^k - s_i - m_j}{2}\right) \forall i \in O_0, j \in O, \\ X_{i\emptyset} &= \exp\left(-s_i\right), \forall i \in O, \end{aligned} \tag{23}$$

assuming $\alpha_{i\emptyset} = 0$.

As recently shown in Galichon and Salanié (2022*b*) this parametric version of the Choo and Siow (2006) equation can be estimated using GLM models, and in particular Pseudo-Poisson Maximum Likelihood as for the classical gravity equation. The main difference lies in the specification of appropriate weights (all terms in the exponential are divided by a factor 2 for pairs (i,j) unlike for transitions to not employed).

We therefore estimate the parameters $(\beta, s, m)$, where $s$ and $m$ are workers' type fixed effects and jobs' type fixed-effects respectively, using the command ppmlhdfe in Stata. We herewith obtain estimates $\hat{\varphi}_{ij}^{\beta} = \sum_{k=1}^{K} \hat{\beta}_k D_{ij}^k$, $\hat{s}_i$ and $\hat{m}_j$ of the parameters of the model.

However, note that the model also provides a solution for the equilibrium transfers which given our parametrization now read as

$$w_{ij} = \gamma_{ij}^{b} - \frac{1}{2}\varphi_{ij}^{\beta} + \frac{1}{2}\left(s_i - m_j\right), \forall i \in O_0, j \in O. \tag{24}$$

Using the estimates from the gravity equation one can compute the variable

$$y_{ij} = w_{ij} - \left(-\frac{1}{2}\hat{\varphi}_{ij}^{\beta} + \frac{1}{2}\left(\hat{s}_i - \hat{m}_j\right)\right)$$

where $w_{ij}$ are observed (log) wages. It follows that the parameters $(b_k)_k$ can be estimated applying a simple OLS regression of $y_{ij}$ on the basis functions $\left(D_{ij}^k\right)_k$. This means that we recover estimates of the productivity parameters $\hat{b}_k$ and the amenity parameters $\hat{a}_k = \hat{\beta}_k - \hat{b}_k$. Appendix B.2 presents an extension in which we also incorporate information on wages at $t$.

# 7 Counterfactual analysis

Table A6 in the appendix presents the results obtained from the estimation of structural equations (23) and (24), applying the appropriate observation weighting. As expected, the results are consistent with those obtained in the empirical analysis (column (4) of Table 2).[29] We then used the coefficients obtained from the structural regressions to compute the

[29]The only differences between the structural results and those obtained in the empirical analysis is that in the latter we normalized all distance measures to have mean 0 and standard deviation of 1, we did not

following counterfactuals:

- Simulated mobility without digital distance change : we impose the change in digital skill distance between 2011 and 2019 to be equal to zero. As such, we recover what would have happened to mobility flows if technological change only affected the demand channel but not the digital distance channel.

- Simulated mobility without digital distance change & demand change : we impose both that the relative size of all occupations remained constant between 2011 and 2019 (without demand effect), and that the digital distance between occupations remained constant between 2011 and 2019.

Comparing these simulations to the observed mobility flows allows us to calculate how much of the observed mobility is generated by technological change. First, note that in the second counterfactual we only impose that the distribution of employment between occupations has remained constant between 2011 and 2019, while we let the total number of jobs evolve as observed.[30] Second, note that in all our counterfactuals we allow the overall skill distance to evolve as observed, since we consider these changes to be driven by a multitude of factors that may be orthogonal to technological change.[31] Finally, as detailed in Section 6.7, we can exploit information on wages across occupations to decompose the effect of changing the digital distance into two different channels: a productivity channel and an amenity channel. The intuition is that, while the productivity channel increases both the mobility of workers

weight observations differently and we presented coefficients in exponentiated form. These simplifications were meant to facilitate the interpretation of the coefficients.

[30]We make this choice because changes in the size of the labor force are affected by many other elements orthogonal to technological change (e.g. demographics). In the second counterfactual, we assume that all changes in the relative size of occupations are the result of technological change, but we are aware that this might be an upper bound. As such, the importance of changing digital distances in the total effect of technological change can be interpreted as a lower bound.

[31]For instance, changes in the overall style of writing job adds may be captured by this measure. However, we consider as digital distance all changes in overall distance that involve a pair of occupations where at least one of the two is a reference digital occupation $d$. This group represents approximately 6000 observations (4% of the sample).

and their wages, the preferences channel increases mobility but decreases wages.

The results obtained from this exercise are summarized in Table 4, Table 5, and appendix Table A7. Table 4 summarizes the number of occupation switchers obtained in the different scenarios and in the two time periods of interest: endline (2018-19) and long-run (2011-19). The exercise is performed on all workers (panel A), on workers with high levels of digital knowledge – "high-digi workers" – (panel B) and on workers with low levels of digital knowledge – "low-digi workers" – (panel C), as defined by their initial occupation. Table 5 shows the same counterfactuals for the number of movers to non-employment, and Table A7 shows the same for the number of stayers in the same occupation.

Table 4: Counterfactual results on occupation switchers

| | Mobility 2018-19 | | | Mobility 2011-19 | | |
|---|---|---|---|---|---|---|
| | N. of movers | Change rel. to observed | % change rel. to observed | N. of movers | Change rel. to observed | % change rel. to observed |
| **Panel A: all workers** | | | | | | |
| Observed mobility | 3449114 | | | 4923017 | | |
| Simulated mobility w/o digi dist change | 3417827 | -31287 | -0.9% | 4898772 | -24245 | -0.5% |
| Simulated mobility w/o digi dist change & demand change | 3303807 | -145307 | -4.2% | 4762935 | -160082 | -3.3% |
| Role of amenities as share of digi dist effect | | 21.6% | | | 29.3% | |
| **Panel B: high-digi workers** | | | | | | |
| Observed mobility | 1813681 | | | 2577250 | | |
| Simulated mobility w/o digi dist change | 1778548 | -35133 | -1.9% | 2542930 | -34320 | -1.3% |
| Simulated mobility w/o digi dist change & demand change | 1707241 | -106440 | -5.9% | 2449495 | -127755 | -5.0% |
| Role of amenities as share of digi dist effect | | 30.1% | | | 36.4% | |
| **Panel C: low-digi workers** | | | | | | |
| Observed mobility | 1635433 | | | 2345767 | | |
| Simulated mobility w/o digi dist change | 1639279 | 3846 | 0.2% | 2355842 | 10075 | 0.4% |
| Simulated mobility w/o digi dist change & demand change | 1596566 | -38867 | -2.4% | 2313440 | -32327 | -1.4% |
| Role of amenities as share of digi dist effect | | 99.6% | | | 53.5% | |

**Notes:** The table summarizes the results obtained from our counterfactual exercise. We present the total number of people changing occupation (as opposed to staying in the same occupation or moving to non-employment) under the different scenarios, and we compute absolute and percentage changes relative to the observed flows. The first three columns relate to endline mobility flows (2018-2019) while the last three columns relate to long run mobility flows (2011-19). The exercise is done on all workers (panel A), on workers with initially high levels of digital knowledge, as measured by their initial occupation (panel B), and on workers with initially low levels of digital knowledge, based on the same definition (panel C).

The results in Table 4 show that technological change generated 4.2% additional end-line mobility and 3.3% additional long-run mobility. 20% of the effect on endline mobility and

15% of the effect on long-run mobility are driven by changes in digital distances between occupations, while the rest are explained by the demand of their own occupation. The role of changes in digital distance is thus non-negligible, especially considering that the employment shares of occupations, governing the demand effect, changed quite drastically over the decade, as shown by appendix Figure A8.

Furthermore, if we restrict our analysis to high-digi workers, we see that the total effect of technological change for them is 5.9% (5%) additional endline (long-run) mobility, and 33% (27%) of it is driven by changing distances. This reveals that the skill distance channel is sizable, especially for occupations most directly affected by new technologies, and should be considered when studying the effect of technological change on employment. Finally, we find that about 30% of the effect of the change in digital distance for high-digi workers is driven by amenities, thus signaling that productivity is the main driver of these additional moves. In contrast, the contribution of amenities is much higher in explaining the moves of low-digi workers, and for them mobility would have been higher in absence of changes in digital skill distances, highlighting the inequality generated by this channel.

Table 5 reveals that technological change also impacted mobility toward non-employment, and that the effect went in opposite directions for high-digi and low-digi workers. If we focus on the long-run mobility results, over the decade, 2.2% more high-digi workers and 1.5% less low-digi workers would have moved to non-employment in the absence of technological change. This result signals again that technological change helped the firsts and harmed the seconds, in line with the results obtained on occupation switching.

Table 5: Counterfactual results on mobility to non-employment

| | Mobility 2018-19 | | | Mobility 2011-19 | | |
|---|---|---|---|---|---|---|
| | N. of movers to non-empl | Change rel. to observed | % change rel. to observed | N. of movers to non-empl | Change rel. to observed | % change rel. to observed |
| **Panel A: all workers** | | | | | | |
| Observed mob to non-employment | 2647859 | | | 10173103 | | |
| Simulated mob to NE w/o digi dist change | 2647859 | 0 | 0.0% | 10173103 | 0 | 0.0% |
| Simulated mob to NE w/o digi dist change & demand change | 2647861 | 2 | 0.0% | 10173104 | 1 | 0.0% |
| **Panel B: high-digi workers** | | | | | | |
| Observed mob to non-employment | 1157370 | | | 4150933 | | |
| Simulated mob to NE w/o digi dist change | 1167115 | 9745 | 0.8% | 4170822 | 19889 | 0.5% |
| Simulated mob to NE w/o digi dist change & demand change | 1172488 | 15118 | 1.3% | 4261592 | 110659 | 2.2% |
| **Panel C: low-digi workers** | | | | | | |
| Observed mob to non-employment | 1490489 | | | 6022170 | | |
| Simulated mob to NE w/o digi dist change | 1480744 | -9745 | -0.7% | 6002281 | -19889 | -0.3% |
| Simulated mob to NE w/o digi dist change & demand change | 1475372 | -15117 | -1.0% | 5911512 | -110658 | -1.5% |

**Notes:** The table summarizes the results obtained from our counterfactual exercise. We present the total number of people moving to non-employment under the different scenarios, and we compute percentage changes relative to the observed flows.

# 8 Conclusion

In this paper, we propose a novel conceptual framework for thinking about the effect of technological change on the labor market, distinguishing between the effect of changes in occupation demand and the effect of changing distances between occupations, as defined by differences in skill requirements.

We take the framework to the data using a gravity model approach, and we document that the shrinking distances between occupations generated by the digitalization wave that took place during the 2010s significantly affected mobility patterns. In particular, these changes opened new occupational opportunities for digital workers.

Our estimations are micro-founded by a discrete two-sided matching model which enables us to quantify the respective role of changes in occupation demand and changes in distances between occupations. We find that this wave of technological change increased by 5% the long-run occupational mobility of digital workers, with one third of this effect driven by changes in the digital skill distance. In contrast, it increased the flows of non-digital workers toward non-employment by 1.5% over the decade.

These results highlight that taking into account the effect of changes in skill distances between jobs is crucial to obtain a complete picture of the effect of technological change on labor markets. In particular, they address the challenges businesses face in recruiting for STEM occupations (Elding and Morris, 2018, Grobon, Ramajo and Roucher, 2021). Our results reveal that not only the labor demand for STEM occupations increased over the last decades, but also that STEM workers are increasingly being demanded in other types of occupations.

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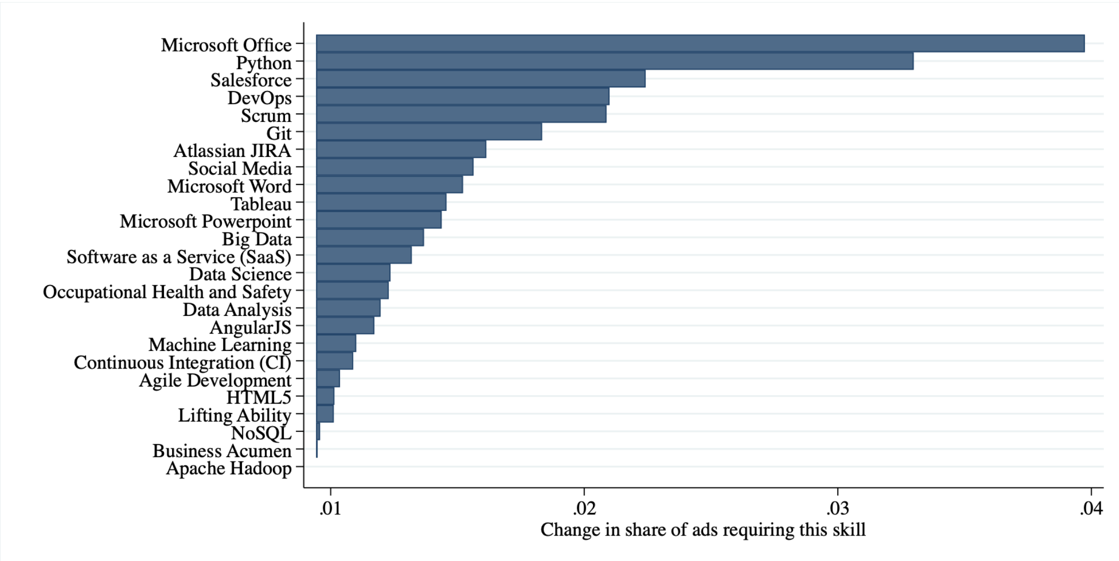
# Appendix

## A Additional Tables and Figures

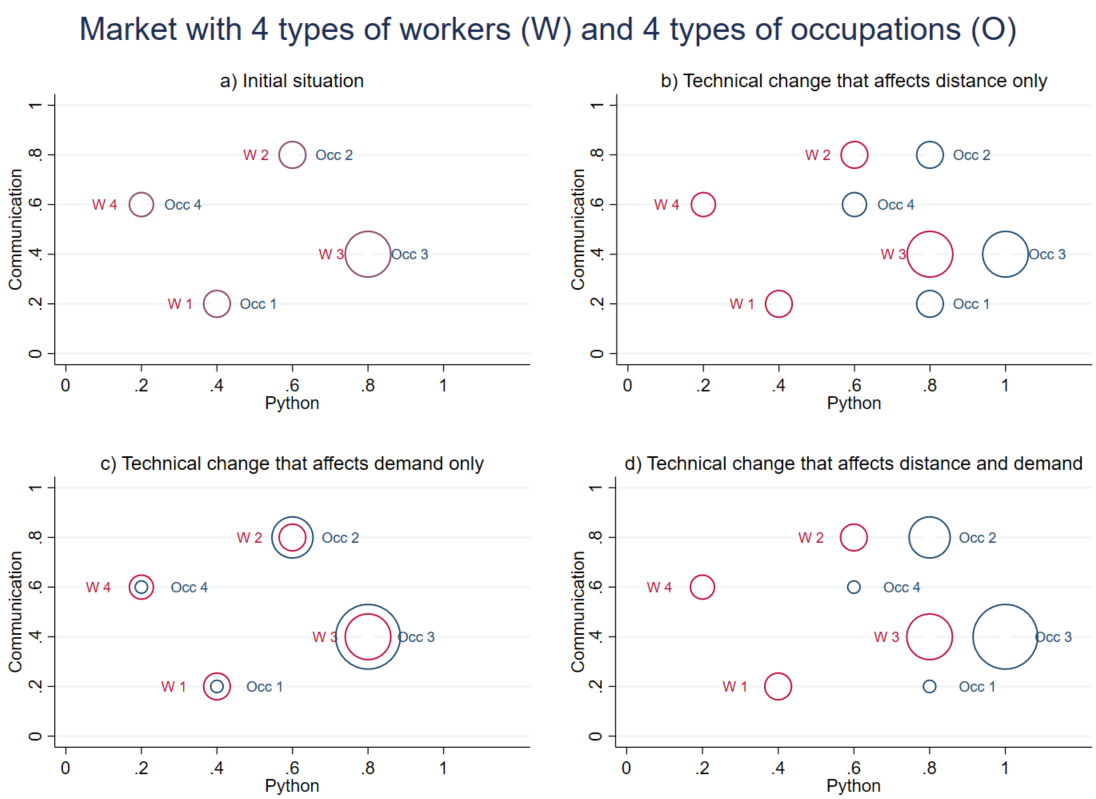
### A.1 figures

Figure A1: The 25 skills with the highest growth in demand over 2011 - 2019



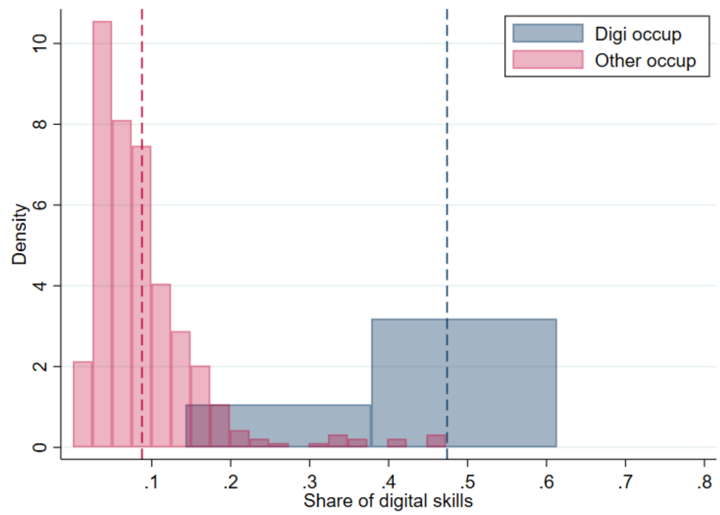

**Notes:** The figure summarizes the 25 skills with the higher growth in demand between 2011 and 2019, as measured by the change in share of ads recording that skill among all occupations pooled together.

Figure A2: Visualization of the conceptual framework




**Notes:** Circle's size reflects mass of jobs/workers. The figure sketches the two distinct effects of technological change in the context of our conceptual framework.

Figure A3: Digital intensity of occupations in 2011

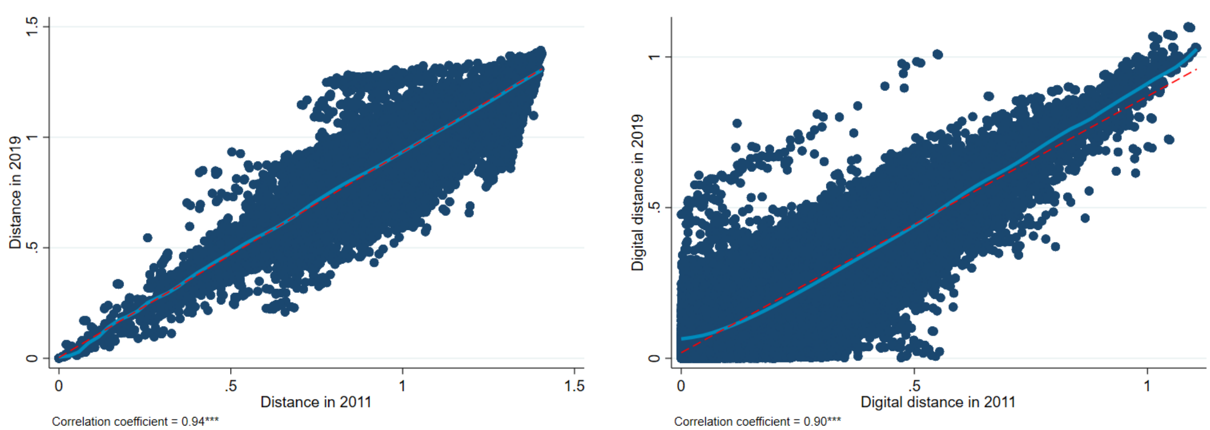



**Notes:** The figure summarizes the distribution of the share of digital skills, defined as any skill related to IT software or hardware, in the occupations that we define as fully digital and the others.

Figure A4: Correlation between distance in 2011 and in 2019 by occupation pairs

(a) Overall distance

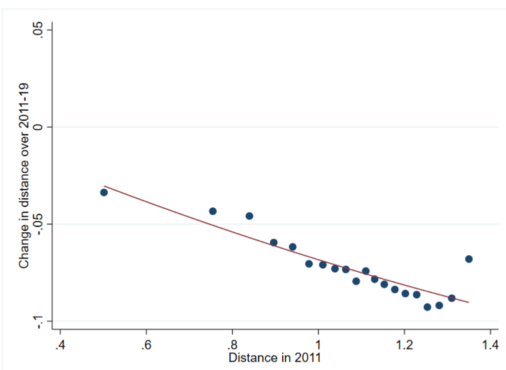
(b) Digital distance



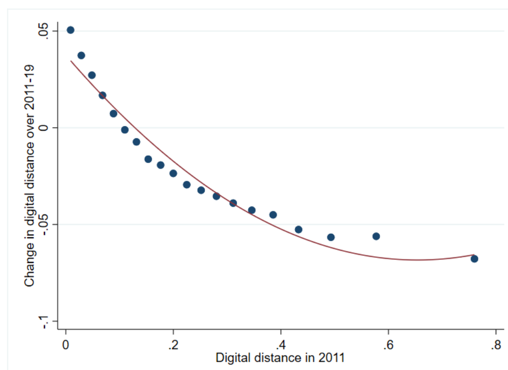

**Notes:** The figure shows the correlation between the level of distance in a given occupation pair in 2011 and the level of distance observed in 2019 for the same pair. The red dashed line depicts the 45 degree line, while the light blue bold line depicts the fitted line obtained from a local polynomial.

Figure A5: Correlation between distance in 2011 and change in distance between 2011 and 2019 by occupation pairs

(a) Overall distance




(b) Digital distance



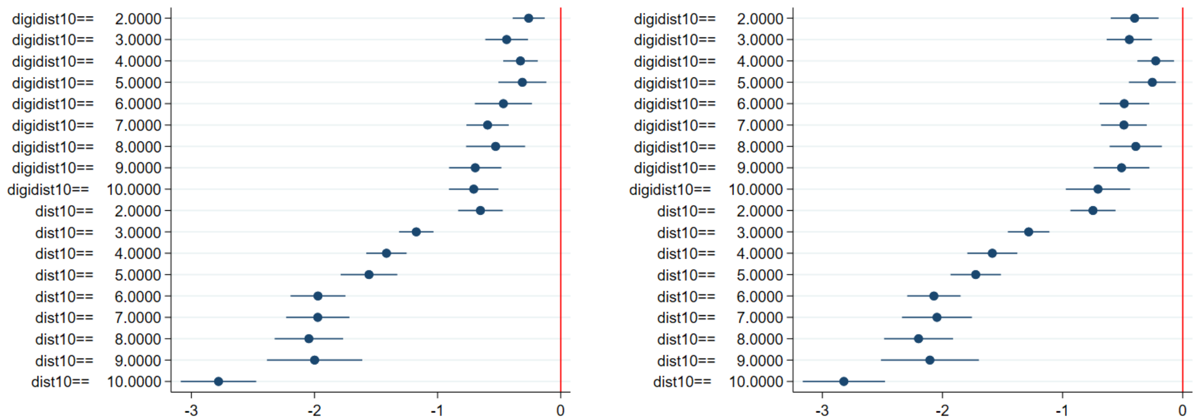

**Notes:** The figure shows the correlation between the level of distance in a given occupation pair in 2011 and the change in distance observed between 2011 and 2019 for the same pair. To ease the reading of the figure observations are binned together.

Figure A6: Matrix of bilateral flows from 2011 to 2012


**Notes:** The figure shows the matrix of mobility flows in 2011, where darker areas indicate higher flows. To increase readability the stayers have been dropped (flows within the same occupation along the diagonal) as well as flows to and out of non-employment. Occupations are ranked following the French PCS 3-digits classification, which goes from executives and engineers, to technicians and intermediate professionals, to clerical workers, to skilled and finally unskilled blue collar workers. The ordering thus corresponds coarsely to socio-economic status.

Figure A7: Linearity of the effect of skill distance and digital skill distance

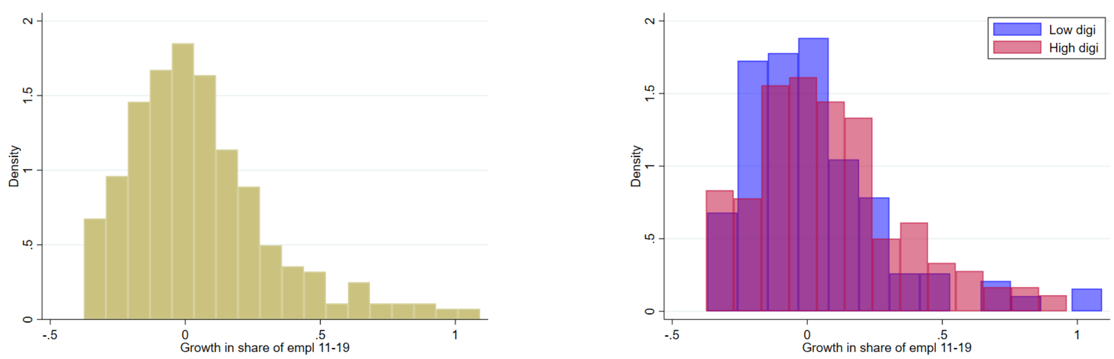
(a) Mobility 2018 - 19 (b) Mobility 2011 - 19




**Notes:** The figure shows the coefficients obtained from estimating equation 4 on 10 deciles of skill distance and digital skill distance, where the first decile is omitted. Both distances are measured in 2011. All the other controls are included in the regressions.

Figure A8: Distribution of growth rates in employment shares across occupations

(a) Overall (b) By high-digi and low-digi status




**Notes:** The figure shows the distribution of the growth in employment shares across occupations between 2011 and 2019. We dropped the bottom and top 5% from the data because outliers (very small occupations subject to very large changes plausibly due to noise). Panel A) shows the overall distribution, while Panel B) distinguishes between high-digi and low-digi occupations defined in 2011.

## A.2 tables

Table A1: List of occupations classified as fully digital

| PCS code | Occupation |
|---|---|
| 388a | IT engineers in R&D |
| 388b | IT engineers in charge of maintenance, support and user services |
| 388c | IT project managers, IT managers |
| 388d | Engineers and technical sales executives in IT and telecommunications |
| 478a | IT design and development technicians |
| 478b | IT production and operations technicians |
| 478c | IT installation, maintenance, support and user services technicians |
| 478d | Telecommunications and network computing technicians |

**Notes:** The table includes the list of occupations classified as fully digital, which serve as comparison group to define digital distance between any two pairs of occupations. In practice, they represent all the occupation codes reported for the job of IT engineers and IT technicians.

Table A2: Effect of distance and digital distance on mobility flows using distance measures assuming skill obsolescence

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | Mobility 2018 - 19 | | | | Mobility 2011 - 19 | | | |
| | Distance in '19 | Distance in '11 | | | Distance in '19 | Distance in '11 | | |
| Distance | 0.524*** | 0.535*** | 0.512*** | 0.496*** | 0.507*** | 0.504*** | 0.487*** | 0.487*** |
| | (0.0280) | (0.0153) | (0.0223) | (0.0206) | (0.0253) | (0.0153) | (0.0184) | (0.0189) |
| Digital distance | 0.913** | 0.834*** | 0.815*** | 0.854*** | 0.932* | 0.947 | 0.909** | 0.915** |
| | (0.0375) | (0.0338) | (0.0321) | (0.0339) | (0.0366) | (0.0351) | (0.0339) | (0.0341) |
| Change in distance (obso) | | | 0.909* | 0.889** | | | 0.925** | 0.926** |
| | | | (0.0482) | (0.0445) | | | (0.0344) | (0.0345) |
| Change in digital distance (obso) | | | 0.940 | 1.003 | | | 0.892*** | 0.954 |
| | | | (0.0629) | (0.0567) | | | (0.0354) | (0.0411) |
| Change in digitak distance (obso) for digital intensive occupations | | | | 0.874** | | | | 0.862** |
| | | | | (0.0557) | | | | (0.0541) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The table summarizes the results obtained from estimating equations 4 and 5 using the skill distance measures that assume that workers do not learn on the job (skill obsolescence hypothesis). Results are obtained with pseudo-poisson maximum likelihood (PPML). All regressions include origin and destination occupation fixed effects and and control for a dummy for stayers and a dummy for occupational switches involving a change in socio-economic status. With the obsolescence measures, distance and digital distance change also for stayers. We thus also control for the interaction between stayers and all changes in distances. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form (larger than 1 signals a positive effect and smaller than 1 signals a negative effect). Columns (1) to (4) show results using endline mobility as outcome, while columns (5) to (8) use long-term mobility as outcome.

Table A3: Robustness of the effect of changes in digital distance on long run mobility flows

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Mobility 2011 - 19 | | | | | |
| | top 50% digi-int | top 25% digi-int | Continuous digi-int | level switch FE | ctr for digipair | ctr for baseline mob |
| | PPML | PPML | PPML | PPML | PPML | PPML |
| Distance | 0.471*** | 0.471*** | 0.471*** | 0.482*** | 0.470*** | 0.471*** |
| | (0.0148) | (0.0147) | (0.0149) | (0.0150) | (0.0150) | (0.0143) |
| Digi distance | 0.950 | 0.951 | 0.948 | 0.954 | 0.964 | 0.955 |
| | (0.0373) | (0.0376) | (0.0377) | (0.0363) | (0.0395) | (0.0363) |
| D distance | 0.742*** | 0.743*** | 0.741*** | 0.749*** | 0.742*** | 0.738*** |
| | (0.0324) | (0.0322) | (0.0326) | (0.0334) | (0.0326) | (0.0335) |
| D digi distance | 1.054 | 1.150** | 1.035 | 1.072 | 1.047 | 1.055 |
| | (0.0579) | (0.0689) | (0.0461) | (0.0512) | (0.0588) | (0.0596) |
| D digi distance x high-digi | 0.896* | 0.831*** | 0.656** | 0.918 | 0.909 | 0.894* |
| | (0.0555) | (0.0505) | (0.136) | (0.0520) | (0.0579) | (0.0572) |
| **Controls:** | | | | | | |
| Level switch | 5.325*** | 5.337*** | 5.319*** | 6.022*** | 5.321*** | 0.638*** |
| | (0.553) | (0.557) | (0.555) | (0.606) | (0.545) | (0.0539) |
| Stayers | 0.634*** | 0.634*** | 0.634*** | | 0.631*** | 6.165*** |
| | (0.0522) | (0.0522) | (0.0523) | | (0.0519) | (1.307) |
| digipair | | | | | 0.863 | |
| | | | | | (0.294) | |
| D distance x digipair | | | | | 0.776 | |
| | | | | | (0.128) | |
| D digi distance x digipair | | | | | 2.346*** | |
| | | | | | (0.662) | |
| D digi distance x digipair x high-digi | | | | | 0.541*** | |
| | | | | | (0.114) | |
| Mobility 2011 - 12 | | | | | | 1.000 |
| | | | | | | (1.12e-06) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 |
| p-val interaction | 0.0782 | 0.00242 | 0.0419 | 0.130 | 0.134 | 0.081 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
The table summarizes the results obtained from estimating equation 5 with pseudo-poisson maximum likelihood (PPML), where the change in digital distance is interacted with initial digital intensity at origin. All regressions include origin and destination occupation fixed effects. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form.

Table A4: Effect of distance and digital distance on mobility flows using distance measures that exclude generic skills and using a more aggregate classification of occupations

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent varaible: | Mobility 2018 - 19 | | | | | | | | | |
| | Dropping "generic skills" from distance measures | | | | | Aggregating occupations at the 3-digit level | | | | |
| | Distance in '19 | Distance in '11 | | | | Distance in '19 | Distance in '11 | | | |
| Distance | 0.630*** | 0.641*** | 0.640*** | 0.640*** | 0.640*** | 0.442*** | 0.468*** | 0.427*** | 0.429*** | 0.431*** |
| | (0.0138) | (0.0140) | (0.0137) | (0.0137) | (0.0136) | (0.0336) | (0.0359) | (0.0345) | (0.0346) | (0.0350) |
| Digital distance | 0.862*** | 0.884*** | 0.867*** | 0.866*** | 0.855*** | 0.658*** | 0.627*** | 0.655*** | 0.651*** | 0.646*** |
| | (0.0412) | (0.0384) | (0.0394) | (0.0392) | (0.0356) | (0.0493) | (0.0527) | (0.0571) | (0.0573) | (0.0570) |
| Change in distance | | | 0.886*** | 0.886*** | 0.886*** | | | 1.032 | 1.080 | 1.122 |
| | | | (0.0209) | (0.0209) | (0.0210) | | | (0.0754) | (0.0767) | (0.0928) |
| Change in digital distance | | | 0.904*** | 0.920 | 0.966 | | | 0.679*** | 0.682*** | 0.681*** |
| | | | (0.0330) | (0.0474) | (0.0503) | | | (0.0544) | (0.0548) | (0.0544) |
| Change in digital distance for digital intensive occupations (discrete measure) | | | | 0.971 | | | | | 0.906 | |
| | | | | (0.0590) | | | | | (0.0798) | |
| Change in digital distance for digital intensive occupations (continuous measure) | | | | | 0.544** | | | | | 0.349*** |
| | | | | | (0.142) | | | | | (0.139) |
| **Controls :** | | | | | | | | | | |
| Level switch | 0.389*** | 0.375*** | 0.391*** | 0.391*** | 0.392*** | 16.52*** | 15.77*** | 19.19*** | 19.29*** | 19.48*** |
| | (0.0329) | (0.0324) | (0.0327) | (0.0326) | (0.0326) | (3.441) | (3.451) | (3.872) | (3.881) | (3.957) |
| Stayers | 23.45*** | 23.74*** | 24.11*** | 24.11*** | 24.22*** | 0.662*** | 0.584*** | 0.671*** | 0.671*** | 0.672*** |
| | (3.400) | (3.708) | (3.694) | (3.696) | (3.694) | (0.0751) | (0.0711) | (0.0718) | (0.0718) | (0.0718) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 | 148,995 | 15,949 | 15,949 | 15,949 | 15,949 | 15,949 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The left portion of the table summarizes the results obtained from estimating equations 4 and 5 using the skill distance measures that exclude skills that are considered generic (are required in more than 90% of occupations). Results are obtained with pseudo-poisson maximum likelihood (PPML). The right portion of the table summarizes the same results obtained when using a more aggregated classfication of occupations (PCS 3 digits rather than 4 digits). All regressions include origin and destination occupation fixed effects and and control for a dummy for stayers and a dummy for occupational switches involving a change in socio-economic status. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form (larger than 1 signals a positive effect and smaller than 1 signals a negative effect).

Table A5: Robustness of the effect on long run mobility flows to following age cohorts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Mobility 2011 - 19 | | | |
| | Distance in '19 | Distance in '11 | | |
| Variables | PPML | PPML | PPML | PPML |
| Distance | 0.473*** | 0.499*** | 0.467*** | 0.468*** |
| | (0.0132) | (0.0139) | (0.0135) | (0.0136) |
| Digi distance | 0.946* | 0.942* | 0.946 | 0.940* |
| | (0.0303) | (0.0314) | (0.0331) | (0.0334) |
| D distance | | | 0.745*** | 0.749*** |
| | | | (0.0329) | (0.0330) |
| D digi distance | | | 0.997 | 1.080* |
| | | | (0.0389) | (0.0468) |
| D digi distance x high-digi | | | | 0.854*** |
| | | | | (0.0458) |
| **Controls :** | | | | |
| Stayers | 5.284*** | 5.243*** | 5.400*** | 5.410*** |
| | (0.615) | (0.573) | (0.601) | (0.601) |
| Level switch | 0.618*** | 0.571*** | 0.619*** | 0.620*** |
| | (0.0473) | (0.0465) | (0.0476) | (0.0474) |
| Observations | 148,995 | 148,995 | 148,995 | 148,995 |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
The table summarizes the results obtained from estimating equation 5 with pseudo-poisson maximum likelihood (PPML), where the change in digital distance is interacted with initial digital intensity at origin. All regressions include origin and destination occupation fixed effects. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model and thus coefficients are reported in their exponentiated form.

Table A6: Structural estimation of mobility and wage equations

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Mobility 2018 - 19 | Log relative wages 2018-19 | Mobility 2011 - 19 | Log relative wages 2011-19 |
| Variables | PPML | PPML | PPML | PPML |
| Distance | -6.256*** | -4.087*** | -6.757*** | -4.307*** |
| | (0.113) | (0.0231) | (0.138) | (0.0258) |
| Digi distance | -1.886*** | -1.218*** | -0.712*** | -0.460*** |
| | (0.144) | (0.0320) | (0.157) | (0.0331) |
| D distance | -6.734*** | -3.662*** | -6.861*** | -3.860*** |
| | (0.386) | (0.0803) | (0.445) | (0.0899) |
| D digi distance | 0.889** | 0.269*** | 0.489 | 0.133 |
| | (0.431) | (0.104) | (0.609) | (0.113) |
| D digi distance x high-digi | -2.754*** | -1.596*** | -1.874*** | -1.030*** |
| | (0.655) | (0.138) | (0.698) | (0.149) |

**Notes:** Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The table summarizes the results obtained from estimating the structural equations 23 and 24 for mobility and wages respectively, which are presented at the end of the model section. All regressions include origin and destination occupation fixed effects and fixed effects for changes in socioeconomic status. Standard errors are double-clustered at the origin and destination occupation level. Regressions are estimated using the PPML model.

Table A7: Counterfactual results on stayers

| | Mobility 2018-19 | | | Mobility 2011-19 | | |
|---|---|---|---|---|---|---|
| | Number of stayers | Change rel. to observed | % change rel. to observed | Number of stayers | Change rel. to observed | % change rel. to observed |
| **Panel A: all workers** | | | | | | |
| Observed stayers | 16581745 | | | 4920883 | | |
| Simulated stayers w/o digi dist change | 16613031 | 31286 | 0.2% | 4945128 | 24245 | 0.5% |
| Simulated stayers w/o digi dist change & demand change | 16727051 | 145306 | 0.9% | 5080964 | 160081 | 3.3% |
| **Panel B: high-digi workers** | | | | | | |
| Observed stayers | 6977404 | | | 1902177 | | |
| Simulated stayers w/o digi dist change | 7002792 | 25388 | 0.4% | 1916608 | 14431 | 0.8% |
| Simulated stayers w/o digi dist change & demand change | 6898234 | -79170 | -1.1% | 1919273 | 17096 | 0.9% |
| **Panel C: low-digi workers** | | | | | | |
| Observed stayers | 9604341 | | | 3018706 | | |
| Simulated stayers w/o digi dist change | 9610240 | 5899 | 0.1% | 3028520 | 9814 | 0.3% |
| Simulated stayers w/o digi dist change & demand change | 9828817 | 224476 | 2.3% | 3161691 | 142985 | 4.7% |

**Notes:** The table summarizes the results obtained from our counterfactual exercise. We present the total number of people staying in the same occupation (as opposed to changing occupation or moving to non-employment) under the different scenarios, and we compute absolute and percentage changes relative to the baseline one. The first three columns relate to endline mobility flows (2018-2019) while the last three columns relate to long run mobility flows (2011-19). The exercise is done on all workers (panel A), on workers with initially high levels of digital knowledge, as measured by their initial occupation (panel B), and on workers with initially low levels of digital knowledge, based on the same definition (panel C).

# B Model extensions

## B.1 Model Extension 1: including non-filled jobs by types of occupation

We still consider a highly differentiated labor market where workers and jobs are grouped into types.

The supply side is unchancged.

On the demand side, jobs are differentiated by their type denoted $j \in O$. There is a mass $X_j$ of jobs of type $j$. However, we append the set of potential types of workers from which employers can choose from with $\{\emptyset\}$ which indicate the job is not filled. Hence employers can choose among $O_0^{\emptyset} = O_0 \cup \{\emptyset\}$.

It follows that $Y_i$ is the mass of workers that were employed in occupation $i \in O$ at $t$ whereas $X_i$ is the mass of jobs available in occupation $i \in O$.

The worker's problem is unchanged but now the employer's problem reads as

$$\max_{i \in O_0^{\emptyset}} \gamma_{ij} - w_{ij} + \eta_i$$

where $\eta_i$ is an idiosyncratic taste for workers of type $i$, $\gamma_{ij}$ is the systematic productivity for a worker of type $i$ in occupation $j$ and $w_{ij}$ is the wage paid by employers in occupation $j$ to workers of type $i$. Note that $w_{0j}$ needs not be 0 as it corresponds to the wage employers in occupation $j$ have to pay to workers that were not employed previously, i.e. of type 0. In contrast, since $X_{\emptyset j}$ is the mass of vacant (unfilled) jobs in occupation $j$, one has $w_{\emptyset j} = 0$.

The problems on the two sides solve to yield

$$
\begin{aligned}
\log X_{ij} &= \alpha_{ij} + w_{ij} - s_i \forall i \in O_0, j \in O_0, \\
\log X_{ij} &= \gamma_{ij} - w_{ij} - m_j \forall i \in O_0^{\emptyset}, j \in O.
\end{aligned}
$$

Equilibrium is then characterized by

$$
\begin{aligned}
X_{ij} &= \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right), \forall i \in O_0, j \in O \\
X_{i0} &= \exp\left(\alpha_{i0} - s_i\right), \forall i \in O_0 \\
X_{\emptyset j} &= \exp\left(\gamma_{\emptyset j} - m_j\right), \forall j \in O
\end{aligned}
$$

where $\varphi_{ij} = \alpha_{ij} + \gamma_{ij}$ and with

$$
\begin{aligned}
\sum_{j \in O_0} X_{ij} &= Y_i, \ \forall i \in O_0 \\
\text{and} \sum_{i \in O_0^{\emptyset}} X_{ij} &= X_j, \forall j \in O.
\end{aligned}
$$

More specifically the accounting constraints are

$$
\begin{aligned}
\underbrace{X_{i0}}_{\text{Employed in } i \text{ at } t, \text{ not employed at } t+1} + \underbrace{\sum_{j \in O} X_{ij}}_{\text{Employed in } i \text{ at } t, \text{ employed at } t+1} &= \underbrace{Y_i}_{\text{Workers in } i \text{ at } t, \text{ from } i \text{ at } t+1} \\
, \forall i &\in O_0 \\
&\text{and} \\
\underbrace{X_{\emptyset j}}_{\text{Vacant jobs in } j \text{ at } t+1} + \underbrace{\sum_{i \in O_0} X_{ij}}_{\text{Filled jobs in } j \text{ at } t+1} &= \underbrace{X_j}_{\text{Total number of jobs in } j \text{ at } t+1} \\
, \forall j &\in O.
\end{aligned}
$$

## B.2 Model Extension 2: How to incorporate wages at $t$

Remember that the transfer $w_{ij}$ was defined as the (log) wage at $t+1$ received by workers from $i$ in $j$. These workers were in $i$ at $t$ and are in $j$ at $t+1$.

Let us slightly change the notation in order to introduce the time dimension more explicitely.

Let $w_{ij}^{t+1}$ be the (log) wage at $t+1$ recevied by workers having moved from $i$ to $j$ between $t$ and $t+1$.

Similarily, let $w_{ij}^{t}$ be the (log) wage at $t$ received by workers having moved from $i$ to $j$ between $t$ and $t+1$.

Let assume that the transfer $w_{ij}$ is in fact the (log) wage differential

$$w_{ij} = w_{ij}^{t+1} - w_{ij}^{t}$$

it is therefore defined as the log wage differential necessary to attract a worker previously employed in occupation $i$ at $t$ to work in occupation $j$ at $t+1$.

Note that we still have that

$$\begin{aligned} \log X_{ij} &= \frac{\alpha_{ij} + w_{ij} - s_i}{\sigma_1} \forall i \in O_0, j \in O_0, \\ \log X_{ij} &= \frac{\gamma_{ij} - w_{ij} - m_j}{\sigma_2} \forall i \in O_0, j \in O. \end{aligned}$$

It follows that in equilibrium

$$\begin{aligned} X_{ij} &= \exp\left(\frac{\varphi_{ij} - s_i - m_j}{2}\right), \forall i \in O_0, j \in O \\ X_{i0} &= \exp\left(\alpha_{i0} - s_i\right), \forall i \in O_0 \end{aligned}$$

so the equilibrium flows are not affected by our choice of definition for the transfer and they can still be estimated using the same technique (Poisson regression) and will yield the exact same results.

However, even though equilibrium transfers are still given as

$$w_{ij} = \frac{1}{2}\left((\gamma_{ij} - m_j) - (\alpha_{ij} - s_i)\right), \forall i \in O_0, j \in O$$

the interpretation of the transfer as changed and is $w_{ij} = w_{ij}^{t+1} - w_{ij}^{t}$ instead of $w_{ij}^{t+1}$. It follows that the estimation of the transfer regression becomes a regression of the (log) difference in earnings instead of a (log) earnings regression. One indeed now has

$$\begin{aligned} \hat{w}_{ij} &\equiv w_{ij}^{t+1} - w_{ij}^{t} \\ &= \gamma_{ij} - \log X_{ij} - m_j + e_{ij} \end{aligned}$$

So this rewrites as

$$w_{ij}^{t+1} = \gamma_{ij} - \log X_{ij} - m_j + w_{ij}^{t} + e_{ij}$$

and we note that this is a (log) earnings regression as before except that we now additionally control for $w_{ij}^{t}$ forcing a coefficient of 1.