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IMPACTS FROM AUTOMATION DIFFUSE LOCALLY – A NOVEL APPROACH TO ESTIMATE JOBS RISK IN US CITIES

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ABSTRACT

Workers that become automated may transfer productivity gains to their co-workers or make it easier to automate their jobs too. In this paper, I empirically investigate how automatable jobs have diffused impacts to neighbouring jobs in North American cities between 2007 and 2016. Results indicate that jobs that share similarities with neighbouring high-risk jobs grew less, even when controlling for their own technical risk of automation. Conversely, jobs that share complementarities with neighbouring high-risk jobs grew faster, possibly indicating productivity gains from working with recently automated jobs. In addition to the analysis in this paper, I provide an adjusted index of job automation risk that accounts for local diffusion of impacts (negative and positive) in US cities: tfarinha.wixsite.com/tfarinha.

Keywords: automation, diffusion, jobs, cities, similarity, complementarity.

JEL: J21, O20, O33, R10.

1 INTRODUCTION

The first quantitative study on *"How Susceptible Are Jobs to Computerisation"* (Frey & Osborne, 2013) put the world in jitters by estimating that 47% of US jobs were at risk of automation in the next few decades. It also sparked strong critics and, since then, many more studies have been added to the Future of Work literature, for different countries, levels of analysis, in less and more conservative approaches, including extensive regional comparative studies (Arntz et al., 2017; Bechichi, Grundke et al., 2018; Brynjolfsson et al., 2018; Lund et al., 2019; Manyika et al., 2017; Nedelkoska & Quintini, 2018; Roux, 2018). And yet, rather than converging, their estimations vary profoundly in numbers and forms of disruption (Winick, 2018).

A common caveat in these studies is that they only consider the technical feasibility of automating a task against the share of non-automatable tasks within a job (or within the portfolio of jobs in a city or country). But two workers with the same type of jobs (job-class) in different cities might have a different risk of having their jobs automated, given the local specificities that shape the diffusion of technology (Bessen et al., 2019; Brynjolfsson et al., 2018). Two main effects occur. First, once it starts automating jobs in a city, a new technology can more easily adapt to automate similar neighbouring jobs (Bechichi et al., 2018; Manyika et al., 2017; Nedelkoska et al., 2018). Second, besides substituting jobs, new technologies may also complement jobs, raising their productivity and labour demand (Autor, 2015). For instance, AI procedures may more efficiently assist health professionals with medical records and diagnosis. Here too, impacts seem to diffuse locally, this time positive, to where more complementary jobs can collaborate with new robots.

This, how local capabilities are related to each other, and how it affects their evolution, has been robustly investigated in the Evolutionary Economic Geography (EEG) literature (Boschma & Frenken, 2006; Hidalgo et al., 2018). For instance, relatedness between jobs seems to favour employment growth and job diversification in a city, preventing the exit and facilitating the entry of new job specializations (Alabdulkareem et al., 2018; Muneepeerakul et al., 2013; Neffke et al., 2018). This "magnet" effect seems particularly strong for the relatedness dimension of local synergies (specialized amenities and knowledge spillovers), but also for complementarities (input-output relationships) and similarities between jobs (Farinha et al., 2019). However, no study has shown how relatedness might, in particular, support the spread of automation impacts from one job to another, i.e., the "diffusion" effects of relatedness (Jun et al., 2019; Morrison et al., 2013).

This paper aims to address this gap in both literatures, the Future of Work and the EEG. It goes beyond the technical risk of automation to investigate the relatedness links through which impacts diffuse from automatable jobs to neighbouring jobs in a city, putting them in higher jeopardy or safety. Two pathways were found, similarity to high-risk jobs and complementarity to high-risk jobs. I test their impact on employment growth within job classes in US cities, from 2007 to 2016.

The structure of the paper is as follows. Section 2 presents the determinants of technology adoption and the role of local network dynamics. Section 3 describes the data, and Section 4 presents the results. Finally, Section 5 discusses the findings in this paper and implications for policy.

2 WHAT DETERMINES A JOB'S RISK OF AUTOMATION?

2.1 TECHNICAL FEASIBILITY

The execution of each task requires a certain set of skills, some of which offering better applications of technology than others (Autor et al., 2003; Brynjolfsson et al., 2018). This shapes the technical feasibility of automating tasks within a job. The ones that rely the most on automatable tasks are at higher technical risk of becoming automated (Frey & Osborne, 2013).

From Robotics to Artificial Intelligence (AI) and beyond, the new technologies evolve rapidly, and so its bottlenecks (Autor, 2014; Perrault et al., 2019). Initially confined to codified knowledge, computer algorithms could only automate routine and manual tasks, usually associated with low skills (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor et al., 2003). Later on, it could also take over cognitive and non-standardized tasks, collaborate with other robots (M2M), even "learn" through experience and surpass humans in image and speech recognition (Brynjolfsson & Mitchell, 2017; Klinger et al., 2018; McAfee & Brynjolfsson, 2016). Now, complex cognitive tasks are easy for robots, which can transform all sorts of problems into prediction ones, drastically reshaping labour in both manufacturing and services (Agrawal et al., 2018; Decker et al., 2017). Conversely, tasks such as gardening, caring for others, negotiating, usually require tacit skills of creativity, social and emotional intelligence, and cognitive flexibility[1], which are very difficult to codify in whatever form of language or require greater amounts of computation (Bradberry, 2017; J. Davies, 2019; Decker et al., 2017; WEF, 2016; World Bank, 2019). In sum, what the new technologies can and cannot automate at each point in time[2] shapes the future demand for labour.

However, although a necessary condition, technical feasibility is not sufficient to generate adoption of a new technology. Firms, institutions, and society at general, take time to adopt technology (Brynjolfsson, Rock, & Syverson, 2017), in some places more than others (Bresnahan & Greenstein, 1996). That is why, for instance, cashiers in the busy city of New York can be expected to get automated sooner than cashiers in the winery region of Napa Valley. In other words, geography conditions the diffusion of technology and, therefore, the impacts of automation.

2.2 LOCAL FEASIBILITY

A myriad of local idiosyncrasies condition the reach of AI, its relative costs to labour, and ultimately firms' choice for AI adoption (Craglia et al., 2018; Nedelkoska & Quintini, 2018). When a new technology has the potential to increase total factors productivity and profits, firms evaluate the relative costs of AI versus labour, considering all the reorganization necessary to accommodate the new technology (Brynjolfsson et al., 2018). For instance, in implementation,

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[1] Certain skills have low demand if isolated, yet high if combined with other skills (e.g., offer surplus of STEM skills in academia versus shortage in policy, where they require social skills too (Benzell et al., 2019; Xue & Larson, 2015).
[2] Initially bounded by Polanyi's paradox i.e., the fact that "we know more than we can tell" (Polanyi, 1966), now the most natural to humans seems to be the most difficult for robots (Moravec, 1988)

maintenance, training, and displacement, which highly depend on the bargaining power of labour unions and regulations on dismissal and working conditions (Harris & Krueger, 2015; Kochan, 2016; Nedelkoska & Quintini, 2018; Wisskirchen et al., 2017). Also, AI is "fed" by big data, and data access is heavily conditioned by technical and legal issues (ownership, cybersecurity, etc.).

In sum, from technical feasibility to actual automation of tasks, the firm must also assure the local feasibility (economic, legal, etc.) of a new technology (Manyika et al., 2017). Depending on the specific local context, some firms and institutions (governments, universities, etc.) are more prepared to adjust than others. In result, new technologies diffuse quicker in some cities and slower in others, as each place has its own portfolio of capabilities (workers, firms, institutions, etc.) and intricate web of interactions and connectivity between them (relatedness).

We can only account for this by analysing the local structure of capabilities, which has been extensively investigated in the Evolutionary Economic Geography (EEG) literature. For cities, regions, and countries, at several levels of analysis, being industries, products, jobs, or knowledge (Boschma & Frenken, 2006; Hidalgo et al., 2018), relatedness has robustly shown to affect both individual performance and the evolution of the local structure. Particularly, relatedness between jobs seems to favour employment growth and job diversification in a city (Alabdulkareem et al., 2018; Farinha et al., 2019; Muneepeerakul et al., 2013; Neffke et al., 2018; Shutters et al., 2018).

Moreover, these "magnet effects" of relatedness – also referred as forces of agglomeration (Marshall, 1920) – may operate in three distinct ways. Local capabilities may co-locate because they share similar skills (forming labour market pools), complementary skills (input-output chains), or local synergies (specialized amenities and knowledge spillovers). Each of these three dimensions of relatedness has its own way of pulling capabilities together, with local synergy showing a particularly strong "magnet effect" in US cities (Farinha et al., 2019). And, although orthogonal to each other, they may occur in simultaneous. For instance, both similarity and complementarity make the relationship between lawyers and paralegals.

But relatedness might have an additional role, still poorly investigated, yet particularly relevant under technological transitions or any serious threat to labour systems. Relatedness seems to channel the spread of impacts between local capabilities – "diffusion effects". For instance, the Great Recession of 2008 was much caused by cascading impacts beyond the initial real estate bubble. Negative impacts diffused mainly through complementarities to products and services for which the final demand was contracting the most (Dolfmanm et al., 2018; Goodman & Mance, 2011). For instance, through input-output linkages in the car industry, from manufacturing to insurance. While jobs of low recessionary risk (e.g., doctors and nurses) could anchor the labour demand of their complementary jobs (e.g., medical equipment technicians)[3].

Also, the relatedness links through which impacts diffuse in a city differ from one type of event to another. In the case of disruptive technologies, rather than massively contracting the labour

[3] See Appendix 2 for how relatedness to jobs of high recessionary risk may have affected all other jobs in US cities.

demand, they reshuffle the allocation of production factors (Acemoglu & Restrepo, 2019). Two main effects weight against each other in firm's choices between capital and labour (Acemoglu & Restrepo, 2019; Lordan & Neumark, 2018) – displacement costs and productivity gains.

Displacement costs

Firms choose to automate tasks where the alternative choice of labour would be more expensive (Feng & Graetz, 2015). As low skill jobs usually display low labour cost-benefit ratio (especially in the initial development states of the technology), they might have less probability of being substituted by modern service robots than its technical feasibility would tell (Decker et al., 2017).

But technology gets cheaper the more it gets implemented by firms and diffuses in the local economy, as later adopters benefit and learn from the pioneers' adoption process (Manyika et al., 2017). And it diffuses quicker (shorter period from technical feasibility to actual implementation) the more similar tasks are available to the technology, within and across firms in the city. In other words, the more similarities exist between the jobs being automated and their neighbouring jobs, the easier to adapt the new technology to automate the latter too.

In result, automation tends to concentrate among jobs that share a similar set of automatable skills, despite having routine or non-routine, standard or cognitive tasks (Nedelkoska et al., 2018). Workers at the core of such labour pools face longer adaptation paths towards non-automatable jobs and higher probability of unemployment (Alabdulkareem et al., 2018). Conversely, similarities to low-risk jobs might facilitate labour flows to less automatable jobs.

Productivity gains

Automation has the power not only to substitute human labour, but also to augment it, wherever human-computer collaboration can be exploited (Brynjolfsson et al., 2018; Licklider, 1960; Sankar, 2012). In many jobs, only particular tasks can be rendered by robots in higher quality, in which human-computer collaboration may by far overcome the results of AI alone. For instance, certain delicate medical operations might be better performed by robots than humans, assisting the surgeon in its overall job, but hardly substituting all her/his tasks.

Technology also transforms and creates tasks within jobs. AI models and algorithms are not always interpretable or explainable, which creates new possibilities for their coordination with humans (Autor, 2014; Lin, 2011). Also, AI may create new tasks meant exclusively for robots, thus, definitely not substituting labour, possibly expanding it. For instance, the human capacity to land on Mars, or to dive towards the bottom of the Mariana Trench, is limited compared to a robot (Decker et al., 2017) and considerably eases the work of scientists. Finally, AI gradually leaves well-defined environments (like factories) and enables workers with no skills in information technology to control new robots and AI systems (Decker et al., 2017). A recent study (Merritt, 2018) found that AI have not only substituted but also changed traditional office jobs in Mexico.

In result, new technologies tend to bring higher productivity, earnings, and labour demand for the jobs that are complementary to recently automated ones (Autor, 2015; Decker et al., 2017; Griliches, 1969; Kremer, 1993). Accordingly, studies (Bessen et al., 2020; Dahlin, 2019; Graetz & Michaels, 2018) have found a positive impact of modern robots in labour productivity growth[4].

In sum, the demand for labour tends to increase in jobs complemented, and not substituted, by the new technologies, initiating adjustments in the labour supply and adaptation of the workforce (Bessen et al., 2019). Moreover, each city has its own portfolio of jobs and structure of similarities and complementarities between them, making technology to spread unevenly, like water choosing the best path to penetrate the soil. In each city, as a result of those two opposite effects, displacement costs and productivity gains, automation impacts diffuse through the existing structure of relatedness, "selecting" which workers lose their jobs to automation and which workers benefit from it in terms of productivity gains and labour demand.

For each worker in each city, this means that, besides the technical risk of automating her/his job, the overall risk also depends on how similar or complementary she/he is to co-workers in that city, given their risk to automation. At the end, the stronger complementarities, and weaker similarities, a job has with neighbouring high-risk jobs, the better it is expected to perform in terms of productivity and labour demand[5]. The opposite would rather increase chances of unemployment.

Therefore, in this paper, I test the following two hypotheses. Employment growth is (*H1*) higher for job-classes that are more complementary to neighbouring high-risk jobs (high technical risk of automation), and (*H2*) lower for job-classes that are more similar to neighbouring high-risk jobs.

3 EMPLOYMENT DATA

In order to test *H1* and *H2*, first, I need to identify which jobs have high technical risk of automation. Second, the similarities and complementarities between jobs in each city. Third, an employment performance indicator, and relevant control variables. This requires a considerable amount of data from distinct sources that is uniquely available for the USA, as follows.

The Bureau of Labour Statistics (BLS) provides yearly employment statistics for around 800 detailed job-classes (7digit OCC), within 22 job families (2digit OCC), 400 industries (NAICS), and 400 Metropolitan Statistical Areas (MSA), which represent unified labour systems (US Census

[4] Also, a stronger positive impact for high skill jobs. This is expected in certain industries like manufacturing, where capital tends to be more complementary to high skills (Acemoglu et al., 2020; Griliches, 1969). While in personal care, for instance, low skill jobs tend to have low automation risk (Atkinson, 2017; Nedelkoska & Quintini, 2018).

[5] Or conversely, being similar, and not complementary, to low-risk jobs would also have a positive impact.

Bureau, 2020). Also, the Industry Sectoring Plan (ISP) cluster classification, which unifies product value chains based on inter-industry linkages. This paper uses employment data at the OCC-MSA and OCC-NAICS levels of analysis, the latter which I aggregate into an OCC-ISP dataset.

The Occupational Information Network (O*NET) provides extensively detailed data on the work scope of each job-class. This paper uses two variables. The Intermediate Work Activities (IWA) describes how much each task is required in each job-class (% of importance), in an optimal level of analysis that allows network computation while providing enough detail to reveal the underlying skills in each task. The Job Zone captures the level of required skills for each job-class (low=1, high=5). It covers academic degree, experience, on-the-job training, and certifications.

Finally, I use Atkinson (2017)'s index of automation risk (high=1, low=5)[6], provided by the Information Technology and Innovation Foundation (ITIF). It estimates the technical risk of automation in each job-class by combining BLS employment data[7] with experts evaluation on the possibility of a job being radically altered by new technologies given its work scope (Atkinson, 2017). It directly covers all job-classes, aligns well with BLS employment projections (which also accounts for technological change) and, as expected, is weakly correlated with educational background (=-0.4), since recent developments of AI can substitute high-skill jobs too.

Since OCC and MSA classification schemes had major revisions before 2005 and after 2016, I restrict the period of analysis within those years. Also, I drop the OCCs and MSAs created/ceased during that period, and the "All Other" type of classes without match in O*NET data. The final data includes 733 OCC, 389 MSA, 179 ISP, 332 IWA, 5 Job Zones, 5 ITIF Automation Risk categories, and 12 years. For ease of interpretation, from here on, I will refer to those as "job", "city", "cluster", "task", "JobSkills", and "JobAutRisk", respectively. And the three datasets of OCC-MSA, OCC-ISP, and OCC- IWA, as "job-city", "job-cluster", and "job-task" datasets. Next, I transform the data to build the variables of interest, as presented in the next subsections.

3.1 THE JOB SPACE UNDER AUTOMATION

In order to capture the structure of jobs in cities, scholars have built network representations of the workforce (Alabdulkareem et al., 2018; Farinha et al., 2019; Muneepeerakul et al., 2013; Neffke et al., 2018; Shutters et al., 2018)[8]. In this paper, such network should also show which jobs are similar or complementary to other existing jobs of high (or low) technical risk of automation.

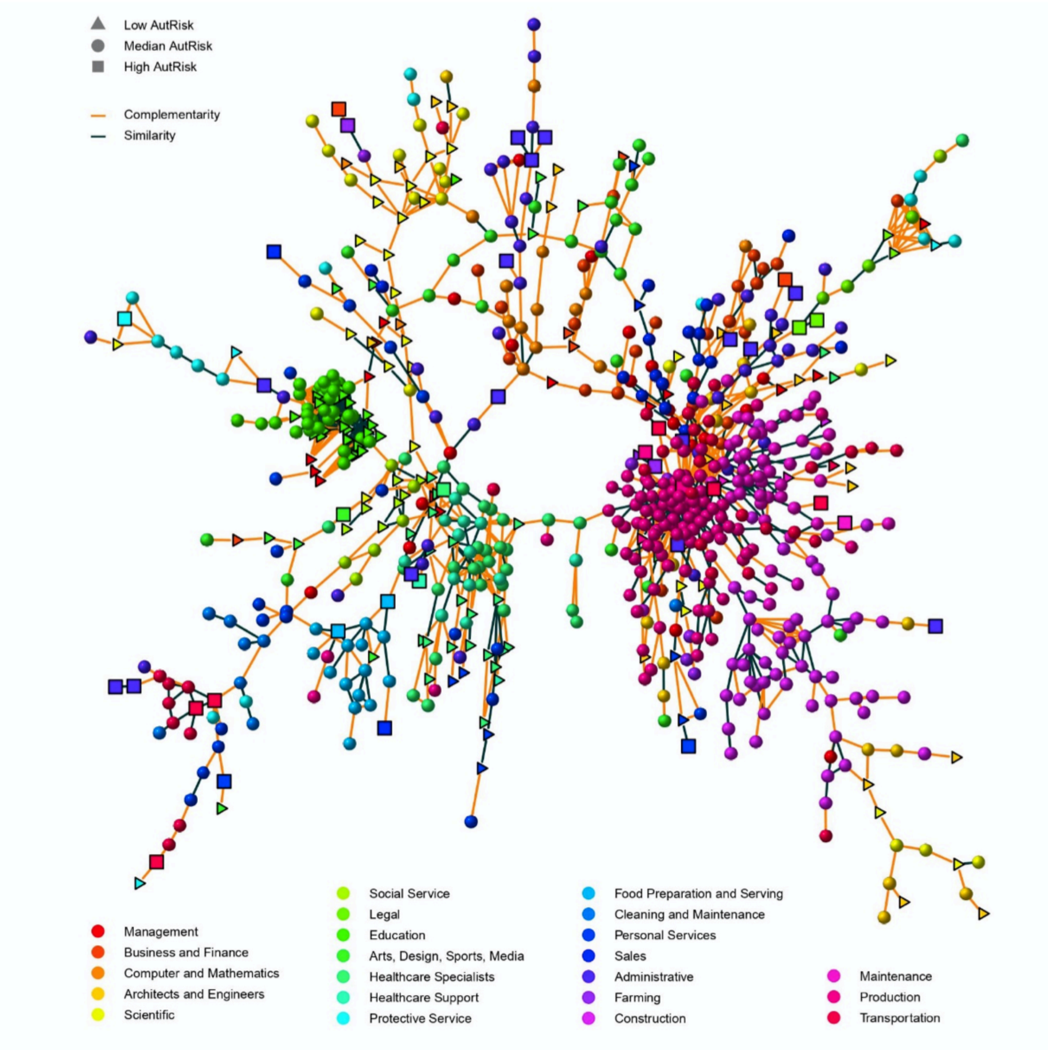
Therefore, I build a network representation of the USA workforce under automation, where nodes are job-classes, links are the level of relatedness between them, with two types of links for the

[6] E.g., cashiers and credit analysts have high risk, while actors, dentists, firefighters, hairdressers have low risk.
[7] Data series for 2014-2024, available in https://data.bls.gov/projections/occupationProj
[8] Recent applications of network visualization tools have resulted in remarkable online interactive platforms for exploring skills, professions, country and city profiles. To name a few, the Observatory of Economic Complexity (https://oec.world), the Data USA (https://datausa.io/), and the Skillscape (http://skillscape.mit.edu).

relevant dimensions of relatedness (complementarity and similarity), and three types of nodes for technical risk of automation (high, medium, or low). This way, although the network is not directed (relatedness matrices are symmetric), from the perspective of each node (source node), both its links and the destination of its links (target node)[9] are captured as having high, medium, or low technical risk of automation.

Figure 1 below allows the visualization of this network – *Job Space Under Automation*. The nodes' shapes represent the three levels of technical risk of automation. And their colours, their job families. Finally, links' colours are dimensions of relatedness (when two job-classes are simultaneously similar and complementary to each other, the stronger is displayed).

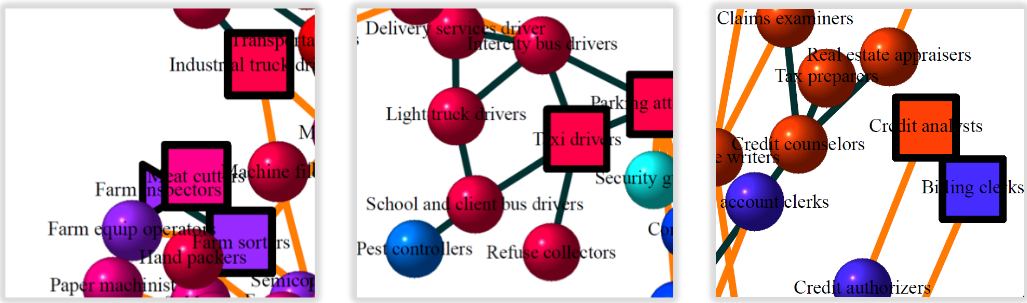
Figure 1. The Job Space Under Automation



[9] Each link, directed or undirected, connects two nodes, commonly referred as the source node and the target node.

For instance, farm inspectors (see examples in Figure 2 below) have low technical risk of becoming automated. Moreover, they are similar and also, although less, complementary to farm sorters, which have high automation risk. Thus, according to the literature discussed above, while farm inspectors can benefit with the automatization of colleagues sorters, the latter can use its similarities to the former to adapt skills and become agricultural inspectors, which is expected to be in high demand in the near future. A different example, taxi drivers and bus drivers are not particularly complementary, they rather share similar tasks (that require navigation skills, etc.). Although the former has high risk of automation, bus drivers require some other skills that are bottlenecks of AI (associated with social trust and safety), making them less susceptible to automation. Yet, in cities where automated cars are already well established, the technology can more easily expand to automate bus drivers too.

Figure 2. Examples (**"zoom in" sections of the Job Space Under Automaton**)



At the city level, the *Job Space Under Automation* assumes the same network structure of nodes and links, but only displaying the nodes that are job specializations of that city in a given year (nodes' colour turn grey if that job is not a specialization of the city). Moreover, for a comparison between cities, one can build a multi-layer network, choosing layers of the *Job Space Under Automation* for specific cities, years, or relatedness dimensions.

Figure 3 below allows a separate visualization of complementarities and similarities (which shows when two nodes are simultaneously similar and complementary), for both Boston and for Napa Valley, in 2016. Boston shows multiple job specializations in Education, Health Care, and Sciences (left side of the network), but also in Management, Finance, and Computer jobs (centre of the network). Whereas Napa Valley is much less diversified, with job specializations revolving around the wine industry (right side of the network), including food engineering, restaurants, and leisure. Such different job portfolios between Boston and Napa Valley must translate into different diffusion paths for the impacts of automation. For example, credit analysts (also in Figure 2 above) is a specialization of Boston but not of Napa Valley. Therefore, effects of automating credit analysts should reflect on credit analysts' employment levels, but also on jobs related to them, such as credit authorizers, which are more strongly represented in Boston than in Napa Valley.

Figure 3. Network layers – complementarities and similarities in Boston, 2016

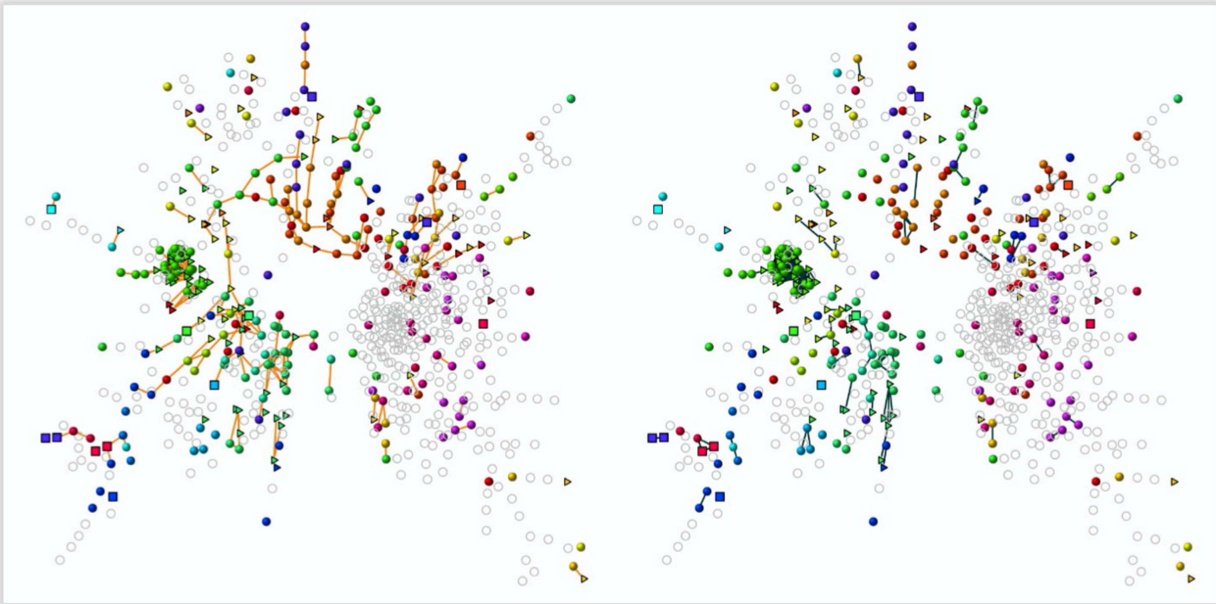
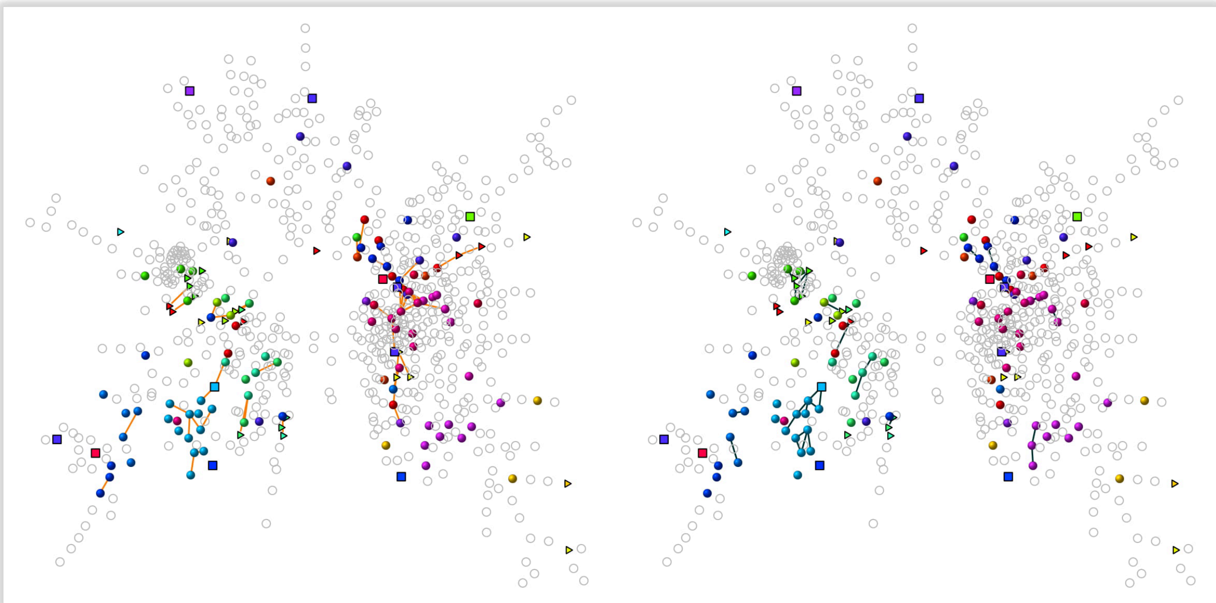


Figure 4. Network layers – complementarities and similarities in Napa Valley, 2016



3.2 RELATEDNESS TO HIGH-RISK-JOBS

From the *Job Space under Automation* of US cities, I "extract" the variables of interest for testing hypothesis *H1* and *H2*, as the level of relatedness of each job (source node) in each city to other existing jobs (target nodes) that have high technical risk of automation. It is computed for both similarities and complementarities, as they are expected to have opposite effects on employment growth. It follows a sequence of computation phases, described below.

Phase 1 computes each city's portfolio of job specializations that have high risk of automation, based on ITIF's index of jobs' automation risk (Atkinson, 2017). First, I transform the BLS data on the number of workers at the job-city level, into a C×P matrix, where C is the number of cities, and P is the number of job-classes. Second, I compute the commonly used location quotient (*LQ*) for each cell (*c,i*) of the matrix, as follows:

$$LQ_{c,i} = \frac{\left(\frac{x_{c,i}}{\sum_j x_{c,i}}\right)}{\frac{\sum_c x_{c,i}}{\sum_c \sum_j x_{c,i}}}$$

$LQ_{c,i}$ describes how much specialized a city c is in job i, in relation to the national employment levels of that job i. If higher than one, the job i is "over-represented" in city c (otherwise "sub-represented"). Third, I transform the above into a binary matrix, where =1 means the job i is "overrepresented" in city c and has *JobAutRisk*=1 (=0 otherwise).

Phase 2 computes the matrices for similarity and complementarity dimensions of relatedness (as in Farinha et al., 2019). First, I use O*NET data on tasks to build a 1×W vector for each job i, where W is the number of task classes (as in Hasan et al., 2015). Second, I join them to form a job-task matrix, W×P. Third, I compute a location quotient for tasks in jobs, $LQ_{w,i}$, in each cell (*w,i*), and transform it into binary, where =1 means the task w is of crucial importance for job i (=0 otherwise). Forth, I build a symmetric P×P matrix, in which each cell (*i, j*) contains similarity between jobs i and j, measured as the probability that a specific task is crucial for job i given that is also crucial for job j (co-occurrences measure, as in Eck & Waltman, 2009). Finally, I repeat Phase 2 steps for *Complementarity*, this time departing from the job-cluster data, to measure how often two jobs are jointly required in the same value chain. *Similarity* and *Complementarity* are lower bounded by zero (no task/cluster is relevant for job i and j) and upper bounded by one (all tasks/clusters that are relevant in job i are also relevant in job j, and vice versa).

Phase 3 computes the final variables for relatedness density of each job in each city considering only the target nodes that have high risk of automation. For this, I combine the two P×P relatedness matrices from Phase 1 and 2 (*Similarity* and *Complementarity*) into two P×C relatedness density matrices (as in Balland et al., 2019) as follows:

$$RelatednessToHighRisk_{i,c} = \frac{\sum_{i \neq j, j \in c, JobAutRisk_j = 1} Relatedness_{i,j}}{\sum_{i \neq j} Relatedness_{i,j}} * 100$$

In result, the *Similarity* density matrix contains, in each cell (*i,j*), similarity density of job i to all other jobs j that exist in the city <u>and</u> have high technical risk of automation (note how a job in a city can have a low relatedness density to high-risk-jobs even having an overall high relatedness density, in which case, its relatedness to existing jobs would concern mostly medium and low risk jobs). The *Complementarity* density matrix contains complementarity values instead. Finally, I transform these matrices into the following two relatedness variables:

(i) Similarity of a job to neighbouring high-risk jobs (*SimilarToHighRisk*)

(ii) Complementarity of a job to neighbouring high-risk jobs (*ComplementaryToHighRisk*)

4 IMPACT OF AUTOMATION ON EMPLOYMENT GROWTH IN US CITIES

4.1 VARIABLES AND DESCRIPTIVES

Although impossible to pin-point its start, the first wave of automation under the current technological transition has obviously arrived and has been affecting jobs at speeding rates in the last few years (Brynjolfsson & McAfee, 2014; Rao & Verweij, 2018). Therefore, the local net impacts from automation (replacement needs and job losses, higher productivity and labour demand, transformations within the job) must reflect on employment growth at the job-city level. This is, of course, controling for other factors that affect this performance indicator under the same period. Such as the past Great Recession, which heavily affected employment from 2008 to 2014, when it finally reached pre-crisis levels (Dolfmanm et al., 2018; NBER, 2010).

Therefore, in order to test how relatedness to high-risk-jobs have recently affected local employment performance, while "jumping" the past recessionary shock, the dependent variable in this analysis is employment growth of a job in a city from 2007 to 2016 ($Growth_{i,c}$). The independent variables of interest (*SimilarToHighRisk* and *ComplementaryToHighRisk*) are in levels of 2007. And the control variables include factors and trends since 2005, as follows below.

As previously discussed, relatedness between jobs seems to promote employment growth and diversification in cities (Farinha et al., 2019; Muneepeerakul et al., 2013; Shutters et al., 2018). Therefore, although this paper focus on the "diffusion" effects of relatedness, the "magnet" effects should still be controlled for. Accordingly, I compute the geographical relatedness of a job to all job specializations of a city in 2007 (*GeoRelated*). As an overall measure of relatedness, it combines all dimensions of relatedness that bring jobs together in a city (Farinha et al., 2019).

City size (*CitySize*) and job size (*JobSize*) in terms of employment levels are also included, in log levels of 2007, as both are expected to affect employment growth (Chen et al., 2019; Frank et al., 2018). Moreover, I control for the local dominance of a job in a city, with a dummy variable =1 if job i was a job specialization of city c in 2007, and 0 otherwise (*RCA*). I also account for major labour demand trends prior to 2007 that might have conditioned the effects from both the Great Recession and automation in subsequent years. More concretely, I add employment growth from 2005 to 2007 at the city level (*CityEmpTrend*), at the job level (*JobEmpTrend*), and, for local trends, at the job-city level (*EmpTrend*). Also, the Great Recession had its own diffusion dynamics, particularly strong between 2008 and 2010, with some jobs in certain cities recovering quicker than others, thus affecting the geography of jobs in the US (Beyers, 2013) beyond the impacts of automation. Therefore, I control for a job's local resilience capacity during the worse years of the crisis, i.e., between 2007 and 2010, using two variables. Employment growth (*EmpResilienceGR*) accounts for the capacity to maintain employment levels regardless of ongoing adaptation and structural changes. And geographical relatedness growth (*StructuralResilienceGR*), as the Great Recession may also have affected a job's level of relatedness in a city, which has been shown to strenghten its future capacity grow in terms of employment (Muneepeerakul et al., 2013).

Finally, I control for specific characteristics of jobs that are associated with current labour demand trends (in 2007 levels). First, automation impacts are, of course, and to a certain extent, conditioned by the technical risk of automating tasks within a job (*JobAutRisk*). Second, there seems to be a non-linear (U-shaped) relationship between level of skills within a job (*JobSkills*) and automation impacts, commonly referred as skills polarization (Autor & Dorn, 2013; Goos et al., 2014; Jaimovich and Siu, 2012). Third, jobs that reply the most on complex skills currently show an increasing demand for labour (B. Davies & Maré, 2019; Moretti, 2012). Therefore, I add jobs' complexity (*JobComplexity*), computed with the method of reflexions (Hidalgo & Hausmann, 2009) adapted to jobs in cities (Farinha et al., 2019), where a highly complex job tends to be found in few cities (low Job ubiquity) that are very diverse (high City diversity). The final data includes 733 job-classes in 389 cities. Table 1 below presents variable's descriptive statistics.

Table 1. Descriptive statistics

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
SimilarToHighAR	125,183	1.9	1.2	0.0	1.1	2.3	18.4
ComplementaryToHighAR	125,183	2.0	1.4	0.0	1.1	2.7	17.0
GeoRelated	125,183	35.7	8.8	4.7	29.6	42.0	100.0
RCA	125,183	0.5	0.5	0	0	1	1
EmpTrend	125,161	0.1	0.5	-1.0	-0.2	0.2	9.8
EmpResilienceGR	122,451	-0.02	0.6	-1.0	-0.3	0.2	9.8
StructuralResilienceGR	125,183	0.01	0.1	-0.6	-0.04	0.1	1.3
CitySize	125,183	426,125.1	661,648.0	7,915	66,250	507,790	4,814,970
CityEmpTrend	125,183	0.02	0.04	-0.2	-0.005	0.04	0.2
JobSize	125,183	287,570.5	467,646.2	90	50,500	294,660	3,843,040
JobEmpTrend	125,183	0.03	0.1	-0.6	-0.02	0.1	0.9
JobComplexity	125,183	19.2	13.6	0.0	7.8	27.7	100.0
JobAutRisk	125,183	3.2	1.2	1	2	4	5
JobZone	125,183	3.0	1.1	1	2	4	5

As expected, *JobAutRisk* is positively yet weakly correlated with employment growth at the job-class level, possibly due to local dynamics that also affect technology adoption and employment levels, as this paper aims to demonstrate (see correlation matrix in Appendix 1).

4.2 JOB-CITY EMPLOYMENT GROWTH UNDER AUTOMATION

In this section, I test the hypothesis *H1* and *H2* by regressing $Growth_{j,c}$ on *SimilarToHighRisk* and *ComplementaryToHighRisk*, plus controls, as follows:

$$Growth_{j,c} = \beta_1 SimilarToHighRisk_{j,c} + \beta_2 ComplementaryToHighRisk_{j,c} +$$

$$+ \beta_3 GeoRelDen_{j,c} + \beta_4 RCA_{j,c} + \beta_5 EmpTrend_{j,c} +$$

$$+ \beta_6 EmpResilienceGR_{j,c} + \beta_7 StructuralResilienceGR_{j,c} +$$

$$+ \beta_8 \ln(JobSize)_j + \beta_9 JobEmpTrend_j + \beta_{10} JobComplexity_j +$$

$$+ \beta_{11} dyJobSkills2_j + \beta_{12} dyJobSkills3_j + \beta_{13} dyJobSkills4_j + \beta_{14} dyJobSkills5_j +$$

$$+ \beta_{15} dyJobAutRisk2_j + \beta_{16} dyJobAutRisk3_j + \beta_{17} dyJobAutRisk4_j + \beta_{18} dyJobAutRisk5_j +$$

$$+ \delta_c + \varepsilon_{j,c}$$

where ε is the error term, and δ fixed effects for cities, which comprises all invariant factors that characterise each city economic context. In such model specification, observable variables at the city level, such as cities' 2007 employment levels (*CitySize*) and growth trends (*CityGrowth*), are controlled for as fixed effects, rather than as independent variables. Whereas observable variables at the job level (*JobAutRisk*, *JobSkills*, *JobComplexity*, etc) are independent variables, so to allow its isolated analysis. Alternative model specifications are presented in Appendix 3. Finally, the categorical variables *JobAutRisk* and *JobSkills* are included as dummies (from 2 to 5), in reference to *JobAutRisk*=1 (high-risk) and *JobSkills*=1 (low-skills), respectively.

Table 2 below presents the results for the econometric analysis in four model specifications. Model (1) contains only control variables, all of them statistically significant, except the dummies *dyJobSkills5* and *JobAutRisk2*. Together with the other dummies, they seem to confirm the current trend of skills polarization referred above (U-shaped relationship between skills level and employment under automation). More concretely, while the coefficients for the *JobAutRisk* dummies (in relation to high-risk-jobs) show somewhat linear effects on employment growth (starting from no significant differences between high and medium-high risk, to major differences between high and low risk), the coefficients for *JobSkills* (in relation to low-skills) are non-linear, with negative and stronger coefficients for medium-skills. Also, note how the national and local employment trends before the recession (*JobEmpTrend* and *EmpTrend*), and the local growth and structural change during recession (*EmpResilienceGR* and *GeoRelResilienceGR*) do not exclude each other in terms of statistical significance. Their strong coefficients seem to confirm distinct growth dynamics between national and local, before and during the Great Recession. Finally, geographical relatedness (*GeoRel*) is statistically significant in all five models. Independently of which variables of interest enter the model, "magnet" effects keep relevant along with "diffusion" effects of relatedness. Models (2) and (3) add the variables of interest, one at time. Model (4) adds them together. Model (5) has scaled variables of interest instead, for comparison of coefficients.

Table 2. The impact of automation in city-job employment growth

	Dependent variable:				
	EmpGrowth 2007-2016 (%)				
	(1)	(2)	(3)	(4)	(5)
SimilarToHighAR		0.0003		-0.013***	-0.014***
		(0.002)		(0.002)	(0.003)
ComplementaryToHighAR			0.031***	0.034***	0.043***
			(0.002)	(0.002)	(0.002)
GeoRelated	0.017***	0.017***	0.017***	0.017***	0.203***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)
RCA	-0.189***	-0.189***	-0.193***	-0.193***	-0.193***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
EmpTrend	-0.110***	-0.110***	-0.109***	-0.109***	-0.109***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
EmpResilienceGR	0.525***	0.525***	0.522***	0.523***	0.523***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
GeoRelResilienceGR	0.599***	0.599***	0.604***	0.598***	0.598***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
ln(JobSize)	0.036***	0.036***	0.028***	0.029***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
JobEmpTrend	0.931***	0.931***	0.925***	0.926***	0.926***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
JobComplexity	0.003***	0.003***	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
dyJobSkills2	-0.085***	-0.084***	-0.067***	-0.073***	-0.073***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
dyJobSkills3	-0.069***	-0.069***	-0.054***	-0.060***	-0.060***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
dyJobSkills4	-0.043***	-0.043***	-0.015	-0.025**	-0.025**
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)

dyJobSkills5	-0.012	-0.012	0.016	0.006	0.006
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
dyJobAutRisk2	0.013	0.013	0.020^{**}	0.017^{*}	0.017^{*}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
dyJobAutRisk3	0.072^{***}	0.072^{***}	0.088^{***}	0.080^{***}	0.080^{***}
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
dyJobAutRisk4	0.149^{***}	0.149^{***}	0.164^{***}	0.152^{***}	0.152^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
dyJobAutRisk5	0.171^{***}	0.171^{***}	0.191^{***}	0.179^{***}	0.179^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	122,356	122,356	122,356	122,356	122,356
R^2	0.267	0.267	0.269	0.269	0.269
Adjusted R^2	0.265	0.265	0.267	0.267	0.267
Residual Std. Error	0.721 (df = 121951)	0.721 (df = 121950)	0.720 (df = 121950)	0.720 (df = 121949)	0.720 (df = 121949)
Note:					*p<0.1; **p<0.05; ***p<0.01

In the main Model (4), *SimilarToHighRisk* shows a statistically significant and negative coefficient (-0.014), which seems to confirm that, when the similarity of a job to local high-risk jobs increases by, say, 10 percentage points, its local employment growth decreases (-14%). And the reverse for *ComplementaryToHighRisk*, which shows a statistically significant, positive, and even stronger coefficient (0.034), thus, increasing employment (34%). This is independent of having low or high technical risk of automation, as dummies for *JobAutRisk* are included. An illustrative example taken from the data, surgeons (*JobAutRisk*=5) were less *SimilarToHighRisk* and more *ComplementaryToHighRisk* in New York than in Portland in 2007. In line with the above results, surgeons had greater employment growth in New York (0.25) than in Portland, where it even decreased (-0.75), perhaps due to less replacement needs. In Model (5), we see that effects of productivity gains seem to be more than three times stronger than substitution effects.

Moreover, *SimilarToHighRisk* and *ComplementaryToHighRisk* show to be weaker or even loosing statistical significance when including one and not the other (Models 2 and 3). This is also expected, since these two diffusers of impacts have opposite effects on employment and yet may occur in simultaneous between two jobs for which the automation impacts are mixed. For instance, paralegals (number 7 of previous Figure 1) are complementary and similar to the high-risk job of law examiners (8). Therefore, when AI automates tasks within the latter job, the former may have its productivity increased while becoming easier to automate too. Finally, note how the variables of interest seem to affect employment at the job-city level even when controlling for *RCA* and city fixed effects (i.e., beyond cities specific portfolio of job specializations, commonly used in previous studies to extrapolate jobs' risk to cities' risk of automation). Which seems to confirm that, indeed, the "diffusion" effects of relatedness should be accounted for when estimating impacts from automation, both for jobs and for cities.

4.3 Robustness analysis

Some methodological considerations were taken when building the main model (4). For instance, regarding the chosen index of technical risk of automation (*JobAutRisk*). Although from Frey & Osborne (2013) to Atkinson and ITIF (2017) many indexes have been built, criticised, and improved, they keep somewhat redundant in its essence, i.e., based on experts' opinion on the bottlenecks and technical potential of AI. As this paper goes on step further to capture local diffusion of impacts, results should be robust to which index of technical risk it departs from. Accordingly, robustness checks using alternative indexes for *JobAutRisk* are strongly aligned with the main results. See Appendix 4 for robustness analysis with Frey & Osborne (2013)'s index.

I run additional robustness analysis for alternative model specifications regarding fixed effects (Appendix 3), period of analysis (Appendix 2, where I further add the particular "diffusion" effects of the Great Recession, i.e., relatedness to jobs of high-recession-risk), and stratified results for different skill levels and automation risk (Appendix 5). All these robustness exercises confirm the main analysis in this paper. In particular, the negative effects of *SimilarToHighRisk* become even stronger within low-skill and high-risk groups (as discussed before, skills of high risk tend to concentrate in labour pools of low-skills jobs, leaving them not only with longer adaptation paths towards low-risk skills, but also more susceptible to diffusion of technology through similarities). The positive effects of *ComplementaryToHighRisk* also become stronger, but for high-skills and low-risk instead (lower concentration of similarities to high-risk-jobs, thus negative effects spread less, and positive ones spread more given higher potential for human-computer-collaboration).

Still, as discussed before, labour pools with high concentration of low skills (or high skills) may contain some heterogeneity regarding automation risk. And jobs' levels of relatedness to high-risk jobs also differ among cities, as each city has its own structure of jobs. For instance, taxi drivers in Napa Valley and taxi drivers in Boston must have different adaptation paths towards less automatable skills (as for paralegals, or credit analysists, or any other job-class). This means that, based on the technical risk of automation and the local relatedness to high-risk jobs, opportunities can be found to prevent job losses and increase productivity of each job-class in each city.

5 Concluding remarks

In this paper, I empirically investigate how impacts from automation spread between jobs in US cities. The results show that job losses/gains can be exacerbated by the local employment structure, beyond what jobs' technical risk of automation alone would determine. More concretely, controlling for the latter, a job in a city seems to show (i) higher employment growth when having more complementarities to local high-risk jobs, and (ii) lower employment growth when having more similarities to local high-risk jobs.

The results agree with existing case studies and theory explaining how automation can benefit jobs that are complementary, and not similar, to neighbouring high-risk jobs (Autor, 2015). Moreover, it confirms that, under major economic events, impacts may spread unevenly between cities, as some existing relatedness links are more prone to transmit effects than others. Thus, beyond how much related to local capabilities, it matters to which type of local capabilities one is related to.

This paper also opens new research avenues that need further investigation. First, diffusion effects should be incorporated and tested in a new automation risk index that goes beyond technical risk. As each city has its own labour structure, such would result in place-based rankings. Second, to which extent the results hold for different economic contexts, such as developing countries, and for more granular levels of analysis. Other levels of analysis, such as job-industry-city, firm level, or case studies, can more directly capture technology adoption in firms and reveal specific industrial dynamics. A third avenue of research regards the interaction with other strong events that have distinct diffusion mechanisms, as they might either exacerbate or smooth the diffusion of impacts from automation. For instance, the current global health pandemic, Covid19, is pushing many jobs to adopt new digital technologies while destroying the ones that cannot go online (Lu, 2020), including jobs of low automation risk, such as hairdressers, dentists, etc. Forth, this paper asks for a new theoretical formulation of how labour systems evolve under technological change.

Finally, we might be able to prevent great damage from automation by redesigning jobs and reengineering business processes to meet symbiotic relationships between technology and labour (Brynjolfsson & McAfee, 2014; Brynjolfsson et al., 2018; Rio-Chanona et al., 2019; Nedelkoska & Quintini, 2018). As shown in this paper, such "right" linkages would be local complementarities to high-risk-jobs, whereas the "harmful" linkages would be local similarities to high-risk-jobs. Therefore, for cities with a large labour pool of high-risk skills, jobs outside that labour pool that collaborate with jobs within it will likely benefit from automation. But workers within are in greater jeopardy (than in cities where such labour pool is smaller) and urge to adapt skills and/or find a symbiotic relationship with the new technologies. Regional policies can use the linkages between local capabilities (Balland et al., 2019) to neutralise negative effects and promote the spread of positive ones. Especially needed where similarities to high-risk-jobs out rule complementarities to high-risk-jobs. As a demonstration, based on the results of this paper, I provide a novel (and very preliminary) index of automation that accounts for the local diffusion of impacts in each US city (available in tfarinha.wixsite.com/tfarinha).

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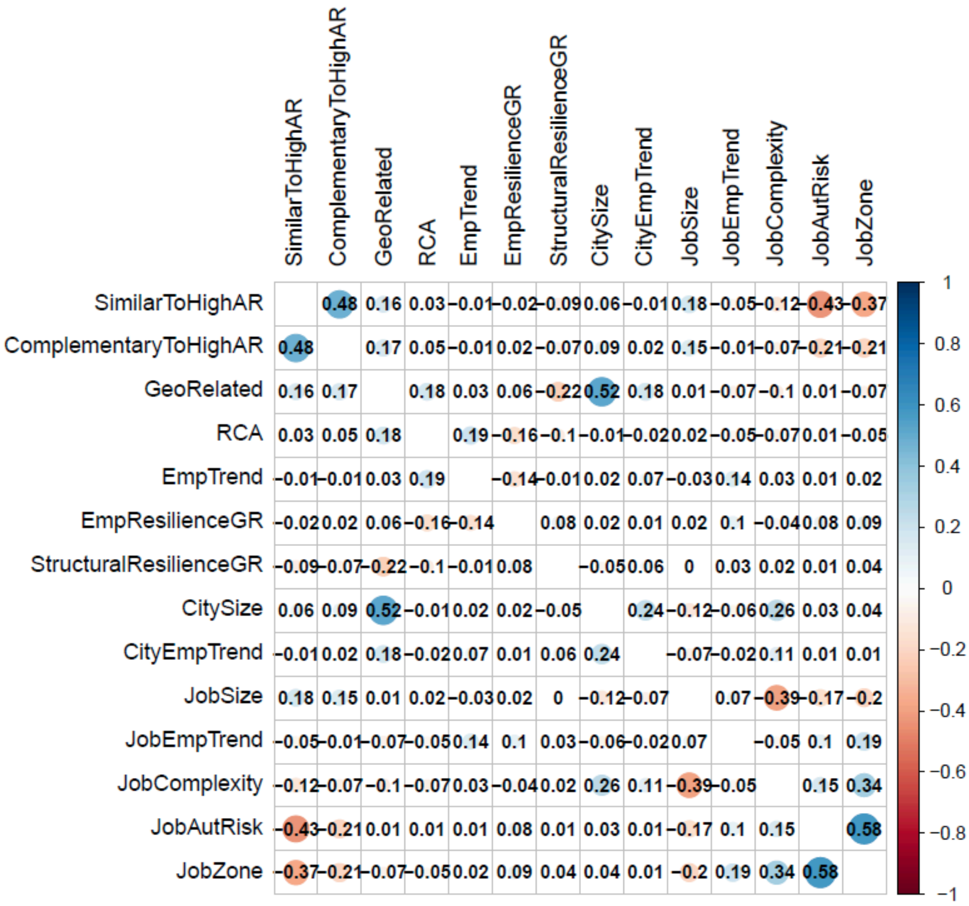
Appendix 1

Correlation Matrix



Appendix 2

Diffusion effects of the great recession

The current technological revolution has been operating at least since the 90s, i.e., substituting human tasks per robots before, during, and after the last recessionary shock (Acemoglu & Restrepo, 2017). More recently, the Great Recession started spreading in the economy and labour markets in 2008 (Xue & Larson, 2015), pushed by the American financial shock of 2007. It massively destroyed jobs until 2010 (the worse year of the crisis) and only in 2014 the economy seemed to have returned to pre-crisis employment levels. These two (totally different) events are contemporary to each other during the period 2008-2014, and their spreading effects might have overlapped each other[10]. For instance, between 2007-2010, cashiers and chief executives experienced similar employment decrease while having opposite technical risk, *JobAutRisk*=1 and *JobAutRisk*=5 respectively. Or, cashiers and court clerks have the same high automation risk (#1) and yet they performed opposite in terms of employment growth distribution (cashiers grew at -6%, court clerks at 16%). Accordingly, the correlation between national employment growth during the past recession (2007 to 2010) and the Automation Risk is rather low (0.11).

Model (1) in Table 8 below repeats the analysis in main model except that employment growth between 2007 and 2010 (*EmpResilienceGR*) is now the dependent variable (Cappelli et al., 2018). Results show that, under the Great Recession, the recessionary employment dynamics seem to have outperformed the effects of automation. Not only the "diffusion" effects of automation loose strenght, *SimilarToHighRisk* coefficient even becomes positive. Moreover, while jobs of low *JobAutRisk* seem to have been less harmed, in medium-risk employment growth was worse than in high-risk. This is expected as some jobs of high automation risk have rigid labour demand, which seems to rule employment growth during a major recession. Model (2), in same table, repeats the analysis, while adding the particular "diffusion" effects of the Great Recession, i.e., similarity and complementarity to jobs most harmed, in terms of employment, under the recession (*SimilarToHighRiskGR* and *ComplementaryToHighRiskGR*). Again, results seem to confirm how the "diffusion" effects identified in the main model seem to be specific of the current wave of automation, and less effective under the past Great Recession, when the recession's "diffusion" effects must have outcome the automation ones (being similar or complementary to jobs more severely affected by the recession had negative impacts on employment under the past recession).

Table 4. Models for city-job employment growth under the Great Recession

	Dependent variable:

[10] The past recession might have intensified a change of skills in the workforce (Schumpeterian creative destruction process), with automation selectively helping the recovery of industries better aligned with the skills of the future and labour saving through substitution per automated solutions (Autor, 2015). Or it might have delayed the technological transition (Charles et al., 2016) where, for instance, the automation negative effects on manufacturing would have appeared earlier without the large and temporary increases in housing demand pre-crisis.

	EmpGrowth 2007-2010 (%)	
	(1)	(2)
SimilarToHighRisk	0.005^{**}	-0.002
	(0.002)	(0.002)
ComplementaryToHighRisk	0.016^{***}	0.012^{***}
	(0.001)	(0.001)
SimilarToHighRiskGR		-0.013^{***}
		(0.001)
ComplementaryToHighRiskGR		-0.009^{***}
		(0.001)
GeoRelated	0.019^{***}	0.019^{***}
	(0.001)	(0.001)
RCA	-0.219^{***}	-0.214^{***}
	(0.004)	(0.004)
EmpTrend	-0.149^{***}	-0.149^{***}
	(0.003)	(0.003)
GeoRelatedTrend	0.302^{***}	0.296^{***}
	(0.033)	(0.033)
ln(JobSize)	0.015^{***}	0.011^{***}
	(0.002)	(0.002)
JobEmpTrend	0.601^{***}	0.596^{***}
	(0.020)	(0.020)
JobComplexity	0.002^{***}	0.002^{***}
	(0.0002)	(0.0002)
dyJobSkills2	-0.032^{***}	-0.029^{***}
	(0.007)	(0.007)
dyJobSkills3	0.019^{**}	-0.001
	(0.008)	(0.008)
dyJobSkills4	0.065^{***}	0.031^{***}
	(0.009)	(0.009)
dyJobSkills5	0.117^{***}	0.068^{***}
	(0.010)	(0.010)
dyJobAutRisk2	-0.029^{***}	-0.011
	(0.007)	(0.007)
dyJobAutRisk3	-0.021^{***}	-0.006
	(0.008)	(0.008)
dyJobAutRisk4	0.046^{***}	0.044^{***}
	(0.008)	(0.008)
dyJobAutRisk5	0.058^{***}	0.054^{***}
	(0.009)	(0.009)

Observations	122,429	122,429
R^2	0.091	0.094
Adjusted R^2	0.088	0.091
Residual Std. Error	0.582 (df = 122023)	0.581 (df = 122021)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix 3

Alternative model specifications regarding fixed effects

For robustness analysis, I test alternative model specifications regarding fixed effects. In model (1) of Table 9 below, I run a one-way fixed effects for jobs. Since local economy dynamics affecting employment are vast, observable variables at the city level must be added. But they are also usually highly correlated, which can compromise the analysis if joinlty added to the model. Therefore, I include only *CitySize* (ln) and *CitySizeGrowth* as regressors, as these are not highly correlated to each other, and are highly correlated to other city characteristics left out (such as city complexity, etc.). In model (2) of the same table, I run the a two-way-fixed effects version, for cities and for jobs. In result, all invariant specific variables for cities and for jobs become *NA* in the model ("the matrix is either rank-deficient or indefinite" compromising the analysis), and we loose further varibility (and statistical significance of *SimilarToHighRisk*) yet an increase in the R^2. Finally, in model (3), I test the model specification of no fixed effects, adding all previous variables together in the regression. Results seem to indicate the importance of city fixed effects, which are mostly unobservable, while keeping the variables of interest at the job-city and job level.

Table 5. Models with alternative model specification regarding fixed effects

	Dependent variable:		
	EmpGrowth 2007-2016 (%)		
	(1)	(2)	(3)
SimilarToHighAR	-0.013***	0.003	-0.021***
	(0.003)	(0.004)	(0.002)
ComplementaryToHighAR	0.015***	0.019***	0.040***
	(0.003)	(0.003)	(0.002)
GeoRelated	0.077***	0.242***	0.074***
	(0.005)	(0.008)	(0.005)
RCA	-0.175***	-0.204***	-0.169***
	(0.004)	(0.004)	(0.005)
EmpTrend	-0.125***	-0.127***	-0.108***
	(0.004)	(0.004)	(0.004)
EmpResilienceGR	0.485***	0.473***	0.535***
	(0.004)	(0.003)	(0.004)
GeoRelResilienceGR	0.084***	0.136***	0.252***
	(0.027)	(0.052)	(0.027)
ln(CitySize)	-0.002		-0.004
	(0.003)		(0.003)
CitySizeGrowth	1.025***		0.981***

	(0.052)		(0.055)
ln(JobSize)			0.032***
			(0.002)
JobEmpTrend			0.916***
			(0.025)
JobComplexity			-0.0001
			(0.0003)
dyJobSkills2			-0.075***
			(0.009)
dyJobSkills3			-0.062***
			(0.010)
dyJobSkills4			-0.039***
			(0.011)
dyJobSkills5			0.003
			(0.012)
dyJobAutRisk2			0.015*
			(0.009)
dyJobAutRisk3			0.071***
			(0.010)
dyJobAutRisk4			0.149***
			(0.010)
dyJobAutRisk5			0.172***
			(0.011)
Constant			-0.310***
			(0.047)
Observations	122,356	122,356	122,356
R^2	0.329	0.360	0.239
Adjusted R^2	0.325	0.354	0.238
Residual Std. Error	0.691 (df = 121614)	0.676 (df = 121228)	0.734 (df = 122335)
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix 4

Alternative index for technical risk of automation – Frey and Osborne (2013)

Table 4 below shows the results for the alternative analysis using the Frey & Osborne (2013) index for professions' technical risk of automation (*JobAutRiskF&O*), transformed into five dummies (equivalent to *JobAutRisk* categories from high to low risk, i.e. from 1 to 5). The results are strongly aligned with the main results in this paper. Both indexes capture the technical feasibility to automate tasks within jobs and arrive at similar rankings for professions' automation risk. More importantly, as this paper aims to demonstrate, both indexes are insufficient to evaluate the overall impacts from automation, as it further depends on local spread of impacts, which can be captured by jobs' levels of relatedness to local high-risk-jobs.

Table 6. Models with F&O index (alternative index of jobs' technical risk of automation)

	Dependent variable: Job-City Employment Growth 2007-2016 (%)			
	(1)	(2)	(3)	(4)
SimilarToHighRisk		-0.014***		-0.019***
		(0.002)		(0.002)
ComplementaryToHighRisk			0.006***	0.011***
			(0.001)	(0.002)
GeoRelated	0.019***	0.019***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
RCA	-0.180***	-0.180***	-0.181***	-0.181***
	(0.005)	(0.005)	(0.005)	(0.005)
EmpTrend	-0.113***	-0.114***	-0.113***	-0.114***
	(0.004)	(0.004)	(0.004)	(0.004)
EmpResilienceGR	0.524***	0.524***	0.524***	0.524***
	(0.004)	(0.004)	(0.004)	(0.004)
StructuralResilienceGR	0.747***	0.737***	0.754***	0.746***
	(0.045)	(0.045)	(0.045)	(0.045)
ln(JobSize)	0.028***	0.031***	0.027***	0.029***
	(0.002)	(0.002)	(0.002)	(0.002)
JobEmpTrend	0.987***	0.983***	0.989***	0.987***
	(0.026)	(0.026)	(0.026)	(0.026)
JobComplexity	0.003***	0.003***	0.002***	0.003***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
dyJobSkills2	-0.077***	-0.080***	-0.078***	-0.085***
	(0.009)	(0.009)	(0.009)	(0.009)
dyJobSkills3	-0.031***	-0.030***	-0.033***	-0.035***
	(0.010)	(0.010)	(0.010)	(0.010)
dyJobSkills4	-0.023**	-0.022**	-0.026**	-0.028***

	(0.011)	(0.011)	(0.011)	(0.011)
dyJobSkills5	0.020	0.017	0.020	0.016
	(0.013)	(0.013)	(0.013)	(0.013)
dyJobAutRiskF&O2	0.063***	0.054***	0.069***	0.063***
	(0.009)	(0.010)	(0.010)	(0.010)
dyJobAutRiskF&O3	0.084***	0.067***	0.092***	0.076***
	(0.010)	(0.010)	(0.010)	(0.010)
dyJobAutRiskF&O4	0.120***	0.101***	0.129***	0.112***
	(0.010)	(0.010)	(0.010)	(0.010)
dyJobAutRiskF&O5	0.174***	0.151***	0.183***	0.161***
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	116,876	116,876	116,876	116,876
R^2	0.270	0.270	0.270	0.271
Adjusted R^2	0.267	0.268	0.268	0.268
Residual Std. Error	0.708 (df = 116471)	0.708 (df = 116470)	0.708 (df = 116470)	0.708 (df = 116469)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix 5

Results for stratified dependent variable

I repeat the analysis of the main model (relatedness variables are scaled to allow comparison), for alternative dependent variables. More specifically, the dependant variable is *EmpGrowth* 2007-2016 (%) for the specific groups: high-skills, low-skills, high-risk, and low-risk jobs (*JobAutRisk*)

Table 7. Results for stratified data

	Dependent variable:			
	EmpGrowth 2007-2016 (%)			
	HighSkillJobs (1)	LowSkillJobs (2)	HighRiskJobs (3)	LowRiskJobs (4)
SimilarToHighAR	-0.011	-0.025***	-0.012***	0.008
	(0.008)	(0.004)	(0.003)	(0.007)
ComplementaryToHighAR	0.087***	0.039***	0.028***	0.052***
	(0.006)	(0.003)	(0.003)	(0.004)
GeoRelated	0.190***	0.233***	0.210***	0.180***
	(0.014)	(0.012)	(0.013)	(0.011)
RCA	-0.226***	-0.166***	-0.164***	-0.224***
	(0.008)	(0.007)	(0.007)	(0.007)
EmpTrend	-0.106***	-0.115***	-0.103***	-0.113***
	(0.007)	(0.006)	(0.006)	(0.006)
EmpResilienceGR	0.574***	0.466***	0.468***	0.559***
	(0.006)	(0.006)	(0.006)	(0.005)
GeoRelResilienceGR	0.332***	0.587***	0.336***	0.908***
	(0.076)	(0.070)	(0.067)	(0.067)
log(JobSize)	0.050***	0.010***	0.027***	0.038***
	(0.004)	(0.004)	(0.003)	(0.004)
JobEmpTrend	1.161***	0.370***	1.234***	0.614***
	(0.040)	(0.041)	(0.046)	(0.036)
JobComplexity	0.005***	-0.003***	0.0005	0.004***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)
JobSkills2		-0.096***	-0.069***	-0.160***
		(0.009)	(0.010)	(0.031)
JobSkills3			-0.051***	-0.169***
			(0.012)	(0.030)
JobSkills4			-0.046***	-0.126***
			(0.016)	(0.031)

JobSkills5	0.075***		-0.177***	-0.096***
	(0.009)		(0.034)	(0.032)
JobAutRisk2	-0.063	0.059***	0.013	
	(0.045)	(0.010)	(0.008)	
JobAutRisk3	0.041	0.074***		
	(0.044)	(0.011)		
JobAutRisk4	0.179***	0.135***		
	(0.044)	(0.012)		
JobAutRisk5	0.161***	1.102***		0.034***
	(0.044)	(0.030)		(0.007)
Observations	41,103	47,339	41,899	57,954
R^2	0.293	0.265	0.260	0.268
Adjusted R^2	0.286	0.259	0.252	0.262
Residual Std. Error	0.745 (df = 40699)	0.698 (df = 46935)	0.670 (df = 41495)	0.752 (df = 57550)
Note:				*p<0.1; **p<0.05; ***p<0.01