Carbonero, Francesco; Scicchitano, Sergio

Working Paper

Labour and technology at the time of Covid-19. Can artificial intelligence mitigate the need for proximity?

GLO Discussion Paper, No. 765

Provided in Cooperation with:
Global Labor Organization (GLO)

Labour and technology at the time of Covid-19. Can artificial intelligence mitigate the need for proximity?*

Francesco Carbonero[a], Sergio Scicchitano[bc]

[a]University of Turin, Turin, Italy
[b]National Institute for Public Policies Analysis (INAPP), Rome, Italy
[c]Global Labour Organisation (GLO), Essen, Germany

January 4, 2021

Abstract

Social distancing has become worldwide the key public policy to be implemented during the COVID-19 epidemic and reducing the degree of proximity among workers turned out to be an important dimension. An emerging literature looks at the role of automation in supporting the work of humans but the potential of Artificial Intelligence (AI) to influence the need for physical proximity on the workplace has been left largely unexplored. By using a unique and innovative dataset that combines data on advancements of AI at the occupational level with information on the required proximity in the job-place and administrative employer-employee data on job flows, our results show that AI and proximity stand in an inverse U-shape relationship at the sectoral level, with high advancements in AI that are negatively associated with proximity. We detect this pattern among sectors that were closed due to the lockdown measures as well as among sectors that remained open. We argue that, apart from the expected gains in productivity and competitiveness, preserving jobs and economic activities in a situation of high contagion may be the additional benefits of a policy favouring digitization.

Keyword: artificial intelligence, automation, covid19, proximity

*Francesco Carbonero: francesco.carbonero@unito.it. Sergio Scicchitano: s.scicchitano@inapp.com.
We would like to thank Salvatore Marsiglia for his valuable research assistance. Moreover, we are grateful to Mauro Caselli, Andrea Fracasso, Aldo Geuna, Davide Vannoni as well as to the participants of the Covid Workshop organized by Collegio Carlo Alberto for useful comments. Francesco Carbonero thanks Collegio Carlo Alberto for its support. The views expressed in this paper are those of the authors and do not necessarily reflect those of INAPP.

1 Introduction

The emergency due to the Covid-19 epidemic has now spread throughout the world and has already caused important effects on the labour market in many countries, some of which are expected to be lasting (Adams-Prassl et al., 2020; Baert et al., 2020; Cho et al., 2020; Bennedsen et al., 2020). To limit the spread of the virus, many countries have had to suspend their production activities with severe lockdown measures that have caused obvious negative consequences on the GDP (Brodeur et al., 2020; Qiu et al., 2020). At the same time, most countries have significantly increased the share of workers that can work from home to allow businesses to continue while limiting public health risks and recessive consequences, but it is clear that this share has limits imposed by existing technology and the tasks of the workers themselves: not all workers can work remotely (see Palomino et al., 2020, for a cross-country comparison of teleworking capacity and of lockdown-related poverty risk). As a consequence, the "social distancing" has become worldwide the key public policy to be implemented during the Sars-Cov-2, and reducing the risk of proximity between workers is an important dimension (Toxvaerd, 2020; Toxvaerd and Makris, 2020).

Previous evidence shows that some workers are more at risk of contagion than others because they work in proximity with other people Barbieri et al. (2020). Thus, the spread of COVID-19 and the possibility that it may last over time, even leading to new lockdown in the absence of the vaccine, raise a relevant question about the future of the economy: can modern technologies and the adoption of Artificial Intelligence (AI) influence the degree of work proximity? It is clear that more intense use of digital tools and algorithms, especially when remotely controlled, can ease "social distancing" measures, leading to a reduction in the degree of proximity in the labour market. This is even more relevant in times of pandemics where digitization may let economic sectors active while limiting the risk to public health and the recessive effects. In particular, AI was found to have great potential to counter the spread of the COVID-19 virus (Bullock et al., 2020; Naudé, 2020).

In this paper, we investigate if and to what extent digitization may mitigate the risk of contagion during the COVID-19 pandemic across sectors in Italy. In doing this we use a unique and innovative dataset that combines data on advancements of AI at the occupational level with information on the required proximity in the job-place and administrative employer-employee data on job flows in the time span 2010-2015 for the Italian labour market. Using an econometric setting with instrumental variables we demonstrate that the relationship between AI and proximity follows an inverted U-shape pattern at sectoral level, with high advancements in AI that are negatively related to proximity. We found that this pattern holds among sectors that were closed due to the lockdown measure as well as among sectors that remained open.

The rest of the article is structured as follows. The next section presents a review of recent and contemporaneous literature on the topic. Section 3 describes the datasets, discusses the definition of our variables of interest and provides some descriptive statistics. Section 4 present the results of the econometric models. Section 5 concludes with some policy implications.

2 Current debate

This paper is related to different strands of economic literature. As a consequence of the spread of Covid-19, an expanding strand of related contemporaneous economic literature aims at investigating the degree of proximity in the workplace. For example, Koren and Pető (2020) and Leibovici et al. (2020) use the O*NET survey to classify occupations according to the degree of required face-to-face interactions and physical proximity. Mongey et al. (2020) explore characteristics of workers in low work-from-home (WFH) or high-physical proximity: it is shown that such workers tend to exhibit low levels of education, lower incomes, fewer liquid assets relative to income, and they are more likely renters. Béland et al. (2020) rank workers in the U.S according to the degree of proximity and exposure to disease (such as an infection) and find that the two measures stand in a positive relationship. Barbieri et al. (2020) use INAPP-ICP data to rank sectors and occupations in Italy according to the degree of proximity, the risk of disease exposure and the possibility to WFH, and they reach similar conclusions. They also demonstrate that the sectoral lockdown put in place by the Italian Government in March 2020 targeted sectors with a significantly higher degree of physical proximity and lower share of workers who can work remotely.

Moreover, in order to evaluate the economic impact of "social distancing" measures, it is necessary to measure the share of jobs that can be done at home. Dingel and Neiman (2020) show that 37% of jobs in the United States can be performed entirely remotely and that these jobs exhibit a wage premium with respect to jobs that cannot be done at home of about 46%. Baker (2020), conversely, use O*NET data to measure which occupation would find difficult the implementation of the WFH arrangement and count 28.2 million workers, mainly concentrated in service and transportation occupations. Regarding Italy, Boeri et al. (2020), using O*NET data measure for some European countries including Italy, estimate that the jobs doable from home amount to 46% (by relaxing the mobility constraint and/or the personal face-to-face contact). Cetrulo et al. (2020), using INAPP-ICP data for Italy, find that only 30% of the workforce, or 6.7 million workers, have an occupation that can be done remotely. Bonacini et al. (2020) show that a stable increase in the opportunity to WFH would favour high skilled workers thus risking to exacerbate the existing inequalities in the labour market.

The impact of technology and digitization on the labour market is a widely investigated topic in the economic literature (Nicoletti et al., 2020; Grigoli et al., 2020). Within this branch, an increasing number of studies looks at the effect of AI on the labour market (Acemoglu et al., 2020; Webb, 2019; Felten et al., 2019; Frank et al., 2019; Furman and Seamans, 2019). In particular, Felten et al. (2018) have linked the improvements of AI in carrying out specific types of tasks to a set of abilities listed in the US O*NET database. The result is an index of AI exposure that captures the degree of structural transformation of an occupation. This is illustrated by the substantial correlation between the index and the probability that an occupation undergoes a major conceptual redefinition. The index has been used in a number of studies looking at at the impact of technology on the labour market. For instance, Fossen and Sorgner (2019a) have compared the AI scores of Felten et al. (2018) with the computerization score of Frey and Osborne (2017), which quantifies the disruptive effect of digitization, and find that the two measures do capture two distinct occupational perspectives (i.e. few occupations have both high or low AI and computerization scores). In another study, these AI scores have been used to assess the evolution of occupational demand brought by technology in a developing country (Carbonero and Bertulfo, 2020). However, the potential of AI in limiting the risk of contagion in times of COVID-19 has been largely unexplored. To our knowledge, the closest study is by Caselli et al. (2020) who investigate the possible effect of robots on the risk of contagion: using data from INAIL (National Institute for Insurance against Accidents at Work) on the risk of contagion due to COVID-19, they find that industries employing more robots per worker in production seem to show a lower risk of contagion.

However, robotization is only one component of the automation wave: digitization and artificial intelligence (AI) is the other important ingredient in the transformation taking place in the economy. In this paper, we investigate the potential of AI in reducing the risk of contagion, finding an inverse U-shape relationship between the adoption of AI and the degree of proximity across the sectors: this relationship remains confirmed both among the sectors closed due to the lockdown and among the sectors that remained open.

3 Data and descriptive statistics

Assessing the relationship between the IA adoption and the degree of proximity in the labour market requires to build a composite dataset spanning a number of individuals' characteristics and tasks of the local workforce. Thus, the novel approach consists of merging three sources of data, by putting together information on advancements of AI at the occupational level with information of the required proximity in the job-place and with administrative employer-employee data on job flows.

First, we take data from the Campione Integrato delle Comunicazioni Obbligatorie (CICO), a random sample of employees and quasi-employees from the administrative dataset Sistema delle Comunicazioni Obbligatorie, provided by the Italian Ministry of

Labour and Social Policies (Ministero del Lavoro e delle Politiche Sociali).[1] The random sample consists of the population of individuals born on 48 different days of the year, whose employment contracts received some modification (hiring, termination, extension, transformation) between 1 January 2009 and 30 June 2019. The database is made of matched employer-employee data on job flows for a total of around 19 million observations. Each record corresponds to a different contract and reports information on the employee (identification code, year of birth, gender, citizenship, education level, region of birth, residence and work), the contract (start date, termination date, contract type, full/part-time, professional qualification, reason for termination, collective labour agreement), the employer (identification code) and the sector of affiliation (Ateco 2007 classification, i.e. the Italian version of NACE Rev. 2). For our purpose, we consider the hirings between 2010 and 2015, the same period of the observed advancements in AI.

Second, regarding the degree of proximity, the index is built exploiting detailed information on the task-content of jobs at the 4-digit occupation-level from the last 2013 wave of the Survey of Professions (ICP). The ICP survey has been realized twice (2007 and 2012) by Italian National Institute for Public Policies Analysis (INAPP): it uses the whole occupational spectrum according to the 5-digit CP2011 classification (the Italian equivalent of the ISCO-08 ILO's classification) and involves about 16,000 workers. The ICP is a rather unique source of information on the work content and evaluates the characteristics of the occupations through a well-structured questionnaire articulated in seven sections (knowledge, skills, attitudes, generalized work activities, values, work styles and working conditions). The ICP is the only survey replicating the US O*NET structure. The latter is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, organizational features of workplaces at a very detailed level. Both the US O*NET and the Italian ICP focus on occupations (i.e. occupation-level variables are built relying on both survey-based worker-level information as well as on post-survey validation by experts' focus groups). The survey reports more than 400 variables on skills, attitudes and tasks and on average 20 workers per each Italian occupation are included providing representative information at the 5th digit. A fundamental aspect of our data is that our task and skill variables are specific to the Italian economy. Thus, the ICP may be used to define the structure of the labour market, the level of technology and the industrial relations, which characterize the Italian economy. More specifically, the use of ICP variables avoids potential methodological problems which may arise when information related to the US occupational structure (i.e. contained in the US O*NET repertoire) are matched with labour market data referring to different economies, like the European ones (e.g. Boeri et al., 2020). To our purposes, the ICP survey directly asks about physical

[1] Since 2007 in Italy, employers must communicate to the Ministry of Labour and Social Policy the hiring, extension, transformation and termination of each employment relationship. In doing so, they are obliged to submitting an online report on a dedicated web portal. The obligation concerns all types of payroll employment, some forms of self-employment, and other contractual typologies. The goal of these compulsory communications is that they have unified a series of procedures that previously followed different administrative paths.

proximity for every occupation, based on the following question: "Are you close to other people during your work?". The score, first introduced by Barbieri et al. (2020), goes from a 0 to 100 (from less to more intense) and is calculated for each of the 697 4-digit occupations.

With the information included in ICP we are also able to build a Routine Task Index (RTI) which measures the degree of task routineness. In line with Autor et al. (2003), we qualify jobs according to their relative degree of routineness using six occupational categories (see Table A1 in Appendix B). For each 4-digit occupation i, the RTI is calculated as follows:

$$RTI_i = RM_i + RC_i - (NRCA_i + NRCI_i + NRM_i + NRMCA_i) \tag{1}$$

where each category on the right-hand side is built as the mean of a set of characterizing dimensions (see Autor and Dorn, 2013; Autor et al., 2003, for previous seminal elaboration of the RTI).[2] We use the RTI as a control to account for a possible effect of the Routine Bias Technological Change in the Italian labour market (Basso, 2020; Naticchioni et al., 2014). Again, compared to the data used in parallel studies (Goos et al., 2014), a key point of our data is that our task and skill variables directly refer to the Italian economy. Similar to the proximity index, the RTI is standardized over the interval 0-1 and aggregated at the ISCO 4-digits level to merge it with CICO data.[3]

Third, our index on AI adoption builds upon the work of Felten et al. (2018), who have linked the technical improvements of AI to the set of abilities listed in the US O*NET database[4]. Examples of abilities are image recognition or speech recognition. The result is a score of AI advancement at the occupational level weighted by the prevalence of the specific abilities in each occupation. The key feature of this score is that it captures a certain degree of transformation of the occupation. Indeed, the authors show that there is a positive link between their AI impact score and the probability that the occupation receive a definition upgrade between 2010 and 2018.

The occupational classification used by Felten et al. (2018) follows the US Standard Occupational Classification (SOC) with the definitions given by O*NET 2009. Italy is the only country in the world with a description of the importance of abilities in each occupation equivalent to that in the O*NET dataset, which is provided by the survey ICP. The 52 abilities which serve as a key to match the category of AI advancements are the same listed in the O*NET. This allows us to build a score of AI which suits the Italian context of occupations using the same approach as Felten et al. (2018). Given

[2]The dimensions are collected by the ICP survey described in the Appendix B and take value from 1 to 5. Then, they are transformed into a continuous interval between 0 and 100 through the formula $X = \frac{Y-min}{max-min} \times 100$, where X is the dimension and Y is the original answer (from 1 to 5) and min and max are the minimum and maximum value reported for that occupation.

[3]Additional information on building the RTI index using ICP is in Cirillo et al. (2020).

[4]See the seminal work of Graetz and Michaels (2018) for a similar exercise using the tasks of robots.

that the characteristics of a profession are strongly linked to both the level proximity and the exposure to AI of that profession, in a second step, we build an instrument of the AI advancements using the US score of Felten et al. (2018). The logic behind this instrument is similar to the one used in the most recent local labour market approaches (see Acemoglu and Restrepo, 2020; Dauth et al., 2017) and assumes that the advancement in AI is an exogenous shock, while the abilities and the level of proximity may be affected by common demand or supply shocks. For this reason, we match the SOC with the Italian *Classificazione delle Professioni* (CP2011) by using the correspondence between SOC and the International Standard Classification of Occupations (ISCO) 2008 and, then, we match the ISCO08 with CP2011 classification. The match with ISCO08 is available at 3-digit level, therefore we end up having 494 occupations in CP2011.

Table 1: Top and bottom five AI score occupations.

Code	Description	AI score
Top five		
34433	Graphologist	47.304
34432	Numismatist	45.718
31372	Textile Designer	45.708
25513	Garment Designer	45.702
31240	Computer database assistant	45.513
Bottom five		
61262	Floor layer	23.281
34270	Athletes	22.793
83220	Livestock farm labourer	22.677
74240	Driver of animal-drawn vehicles	22.421
84210	Civil Engineering Labourers	21.531

In the 90s and early 2000s, we observed a polarization of employment along the routine-intensity task dimension. In Italy, such evidence is largely consistent with the country's specialization in routine, low-tech, and low-skill sectors (Basso, 2020; Cirillo et al., 2020; Brunetti et al., 2020; Marcolin et al., 2019). The literature points to the adoption of computers that transformed the labour demand for routine occupations (as shown in Goos et al., 2014; Autor and Dorn, 2013). Behind the mechanism was an overlap between routine tasks and the abilities of computers. With the score of AI advancements, we assess whether the AI wave has different characteristics from the computer wave. Table 1 and 2 display some descriptive statistics at the occupational level (see Jaimovich and Siu, 2020; Autor and Dorn, 2013, for the classification of the occupations according to their degree of routininess). In terms of new hires between 2010 and 2015, we count 6.2 million workers at the aggregate level, the majority of them employed in manual occupations (services and elementary occupations). A large fraction of workers has been hired also in routine occupations (clericals, plant and craft workers), while only 15% in cognitive occupations. The largest AI score is found in this last class of occupations. A higher AI score for cognitive occupations means stronger advancements in the abilities of AI in cognitive occupations. This fact enriches the evidence on the occupational consequences of the technological change of the last decades. Our evidence suggests that AI adoption has two different characteristics from computer adoption: first, the overlap now is between AI abilities and cognitive tasks; second, this overlap enhances the complementarity between machine and human.

Table 2: Descriptive statistics across occupations between 2010 and 2015.

Occupations	N	New hires (thousand)	AI score	Physical proximity	Mean Age	Share of women
All	697	6267	38	53	37	0.36
Non-routine cognitive	342	929	41	52	37	0.43
Routine	277	1567	35	52	37	0.25
Non-routine manual	78	3181	33	61	35	0.41

Concerning the probability of contagion, Table 2 shows that manual occupations own the largest values of physical proximity while cognitive occupations the smallest. We also display two structural characteristics at the occupational level, the age of workers and the share of women hired. Hirings in manual occupations on average are younger compared to those in routine and cognitive occupations. Moreover, in non-routine occupations (cognitive and manual) the presence of women turns to be much higher than in routine occupations. The relationship between AI score and proximity at the occupational level is negative, the correlation is $\rho = -0.20$ (Figure 1). This is driven mainly by cognitive occupations, while manual occupations, not surprisingly, show a positive correlation (Figure 2). Manual occupations, per definition, have little to do with AI, which is illustrated by an average AI score of 33.

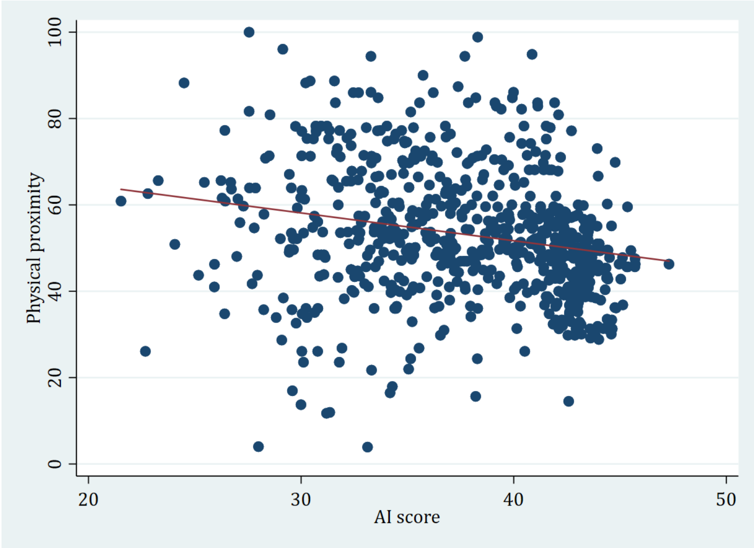

Figure 1: Scatterplot of AI impact score and physical proximity for 697 occupations. Source: Author's calculations.

Figure 2: Scatterplot of AI impact score and physical proximity by routine-intensity. Source: Author's calculations.

The political debate around the lockdown in Italy was focused on the industries which have been shut down and those that have been allowed to continue working. Therefore, our analysis will be at the industry level (4-digit). Table 3 shows our key indicators using the aggregation of the industry classification Ateco (equivalent to Nace) at ten categories. Wholesale, retail trade, transportation and accommodation have led the job creation between 2010 and 2015, followed by manufacturing and professional activities. Among these three classes of industries, we do not observe a large variation in both the AI score and proximity, which seem close to the averages of routine occupations. Financial and insurance activities display a relatively high AI score together with the second-lowest value of proximity. In this sector, it is common the use of algorithms and digital tools that support the work of, generally, high-skill workers (the sector absorbs more the one-third of this class of workers). Moreover, workers in this sector are usually well connected via internet and have higher chance of working from home (Dingel and Neiman, 2020) or in flexible time-space arrangements (which explains the low level of physical proximity). By disaggregating between open and closed sectors, we find that both groups reveal similar AI scores and a small difference in the degree of proximity, larger for closed sectors. The remaining characteristics are also similar, except for the share of high-skill workers which is two times as large in open sectors as in closed sectors. This suggests that the lockdown hides important inequality consequences (Bonacini et al., 2020).

Table 3: Descriptive statistics across industries between 2010 and 2015.

Industry	New hires (thousand)	AI score	Physical proximity	Mean Age	Share of women %	Share of high-skill workers %
Agriculture	153	34	48	38	34	1
Manufacturing and mining	1128	37	52	36	27	10
Construction	622	36	51	39	8	3
Wholesale, retail trade, transport, storage, accommodation	2432	37	53	35	43	8
Information and communication	288	39	53	35	44	23
Financial and insurance activities	45	40	49	34	55	39
Real estate activities	24	37	52	37	54	8
Professional, scientific, technical activities	910	38	53	35	44	16
Public administration	286	38	55	36	59	28
Other services	382	37	54	35	48	9
Active sectors	3470	37	52	36	38	15
Closed sectors	2799	37	53	35	38	8

In order to visualize the relationship between the two measures, we show in Figure 3 the scatter plot of physical proximity and AI score for 1222 industries classified at the 4-digit, both averaged over the period 2015-2010. Interestingly, the relationship appears to be non-linear and reveals a hump shape. For values of AI smaller than the sectoral mean, AI score and proximity stand in a positive relationship, while for values above the average there is a clear negative relationship. It is clear that the inverted U-shape pattern depends upon the relative weight of different types of professions within sectors. Figure 3 shows the share of workers in cognitive, manual and routine occupations, along with the score of AI. The increasing section of the curve above the scatter corresponds to a greater use of routine occupations and a large share of manual workers, for which AI score and proximity have a positive relationship. Instead, the decreasing section corresponds to a greater relative weight of cognitive professions for which AI and proximity show a negative correlation. In other words, we show that also the technological change brought by AI, as those of information and communication technologies, is biased and directed towards specific types of workers (Acemoglu, 2015, 2002). Such a pattern between AI abilities and proximity within sectors indicates that there is some minimum level of proximity which is necessary to run the activities. We call it an *organizational barrier*. Passing from a small to a medium level of digitization does not break this binding level of proximity, rather the opposite, it increases further the need for workers acting close to each other. When cognitive tasks and technology are employed on a large scale, sectors break the need for proximity and access to a different organizational structure, where digitization implies lower proximity. We test the statistical significance of this relationship in the next section.

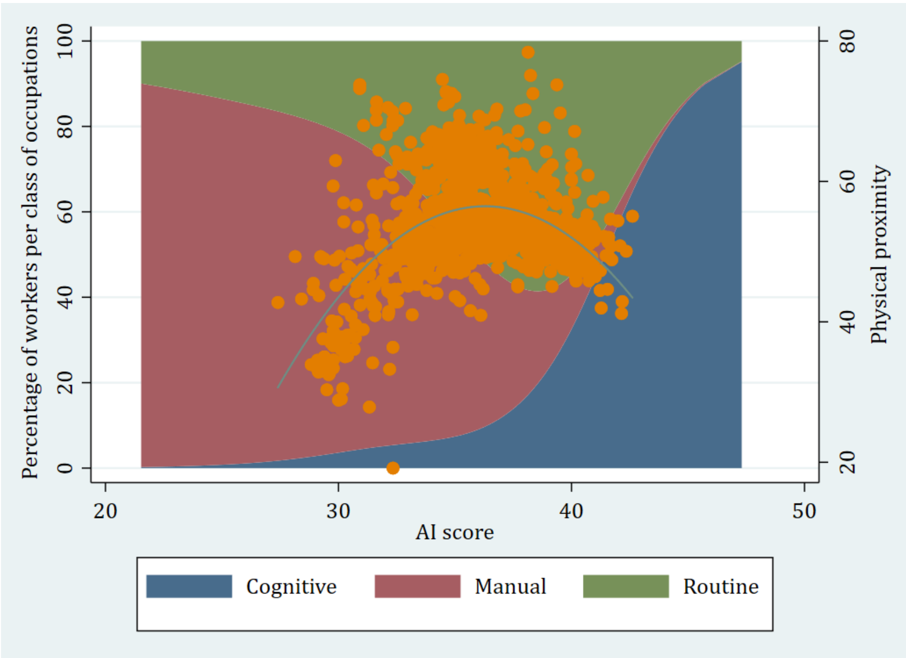

Figure 3: Share of workers across classes of occupations together with (mean) AI impact score and (mean) physical proximity for 1222 industries. Source: Author's calculations.

4 AI advancement and proximity

Our main aim is to establish if there is any link between the potential advances in AI and the level of proximity. In order to assess the statistical impact of AI, we estimate the following model at the industry level j:

$$prox_j = \gamma_0 + \gamma_1 AIscore_j + \gamma_2 AIscore_j^2 + \gamma_3 RTI_j + \gamma_4 W_j + \gamma_5 G_j + \epsilon_j \quad (2)$$

where AI score enters also with its squared term to account for the non-linearity, RTI is the routine-task index computed using ICP, W_j is a set of workers characteristics (age, share of female workers, share of high and medium skilled workers) and G_j are geographical characteristics (share of firms in the north, in the south and in the islands). Equation (1) is estimated with OLS. Given that the abilities required in the occupation could influence both the AI score and the level of proximity, we also run an instrumental variable regression where we use the impact of AI on US occupation. In this way, we are confident to isolate the role of advancements in AI.

Table 4 shows the results with the sequential inclusion of the control variables to assess the validity of each covariate in our OLS approach (columns 1 to 5). For small values of AI, we find a positive impact on proximity. However, for large values of AI, the proximity declines. For the purpose of testing an inverse U-shaped relationship between the level of proximity and advances in AI we need to examine whether the relationship is increasing at low values and decreasing at high values within the data range. Therefore, we check whether this relationship is monotonic within the data range and whether its first derivative is positive when evaluated at the minimum and negative when evaluated at the maximum of the AI score. Following Lind and Mehlum (2010), the appropriate null hypothesis is:

$$H_0 = \gamma_1 + 2\gamma_2 AIscore_{\min} \leq 0 \text{ and/or } H_0 = \gamma_1 + 2\gamma_2 AIscore_{\max} \geq 0 \quad (3)$$

against the alternative:

$$H_1 = \gamma_1 + 2\gamma_2 AIscore_{\min} > 0 \text{ and } H_0 = \gamma_1 + 2\gamma_2 AIscore_{\max} < 0 \quad (4)$$

where $AIscore_{\min}$ and $AIscore_{\max}$ are the minimum and the maximum levels of the AI score. The result of test rejects the null hypothesis and supports the existence of an inverse U-shape relationship (see Table A2 in Appendix A).[5] The size of the coefficient remains stable to the inclusion of all the covariates, which is a convincing signal of the robustness of the estimates. In column (6) we run an IV estimation, where the score of AI and its squared term are instrumented with the US score and its squared term.[6] The results are very close to the OLS estimation. With regard to the other coefficients, Table 4 indicates that the age is negatively associated with physical proximity, while sectors employing more female workers witness higher proximity, in line with Chernoff and Warman (2020) who find that females are about twice as likely as males to be in occupations that are at high

[5]We have also tested whether the estimates are driven by the presence of outliers (we excluded the 5 sectors with proximity below 42 that appears in the bottom left corner of figure 3), but we find no remarkable change. Results are available upon request.

[6]Table A3 in the Appendix reports the first stage regression. Moreover, we have tested the quality of the identification strategy using the Kleibergen-Paap test and we find an F-statistic much larger than the corresponding Stock-Yogo critical values.

Table 4: Regression of physical proximity on AI score for 1222 industries.

	(1)	(2)	(3)	(4)	(5)	(6)
AI advancements	0.109	18.990***	22.506***	22.790***	22.880***	25.249***
	(0.103)	(1.865)	(1.844)	(1.811)	(1.823)	(2.560)
AI advancements^2		-0.258***	-0.311***	-0.315***	-0.317***	-0.350***
		(0.025)	(0.025)	(0.024)	(0.025)	(0.036)
Age			-0.083**	-0.124***	-0.117***	-0.118***
			(0.038)	(0.038)	(0.039)	(0.039)
Share of women			3.772***	3.057***	3.067***	3.099***
			(0.360)	(0.380)	(0.407)	(0.406)
$Share\ of\ high-skill$			0.031***	0.001	0.001	0.009
			(0.010)	(0.010)	(0.010)	(0.014)
$Share\ of\ med-skill$			0.020***	0.005	0.005	0.007
			(0.007)	(0.008)	(0.008)	(0.008)
RTI				-12.443***	-12.405***	-12.491***
				(1.580)	(1.584)	(1.590)
North					-0.736	-0.756
					(0.793)	(0.787)
South					-1.900*	-2.007**
					(1.009)	(0.998)
Island					-0.559	-0.732
					(1.390)	(1.395)
N	1222	1222	1222	1222	1222	1222
R-sq	0.00	0.19	0.34	0.39	0.40	0.40
Kleibergen-Paap F statistics						30.58

Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. OLS regression in columns 1-5, IV regression in column 6.

risk of both COVID transmission and automation. The level of education does not seem to influence the level of proximity, while the routine intensity has a negative relationship with it.

At this stage, it is interesting to assess whether this relationship varies between the sectors that were shut down and the sectors that were allowed to be active. We use as a reference, the sector code mentioned in the lockdown act of the 22nd April 2020 (Ateco classification) and we run separate regression (equation 1) for active and closed sectors. In line with Barbieri et al. (2020), we expect the first to be characterized by lower proximity than the second, also (but not only) due to higher adoption of technology, such as robots and digital tools. Table 5 reveals that it is indeed the case: the non-linear relationship is sharper for active sectors, namely, high AI advancements are associated with much lower proximity. Conversely, the sectors that were closed own some sort of rigidity in working with low proximity, which dampens the role of technology and explains a smaller coefficient of the squared term. Nevertheless, high AI advancements reduce proximity also in the sectors that were closed. This means that AI has the potential to save jobs and economic activities also in sectors that are intended by the policymaker to be at high risk of contagion.

Table 5: Regression of physical proximity on AI score for active and closed sectors, according to the Government Act of the 22nd of April 2020.

	Active sectors	Closed sectors
AI advancements	28.401***	11.239***
	(2.927)	(3.120)
AI advancements^2	-0.394***	-0.159***
	(0.041)	(0.043)
Controls	Yes	Yes
N	646	576
R-sq	0.44	0.34

IV regression. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

By the same token, we establish the role of AI for the share of employment with high proximity. Following the generation of routine employment share of Autor and Dorn (RSH; see eq. 17, Autor and Dorn, 2013), we calculate the percentage of sectoral employment in the top tercile of the employment-weighted distribution of the physical proximity index. More specifically, such a percentage is calculated for each sector j as follows:

$$\%Top\,proximity_j = 100 \times (\sum_k L_j k \times 1[Proximity_k > Proximity^{P66}]) \times L_j^{-1}, \qquad (5)$$

where Ljk is the employment in occupation k in sector j and $1[\cdot]$ is the indicator function, which takes the value of one if the occupation's physical proximity is above the 66th percentile of the employment-weighted index.[7]

Table 6 shows that high AI advancements have a statistically significant negative impact on the share of workers employed in high proximity occupations. The shape of this relationship does not change much between active and closed sectors; rather, the downward pattern is more pronounced for closed sectors. In contrast with the belief that young workers are more abreast of digital tools and, therefore, more able to work remotely, sectors employing more elderly workers tend to have a lower share of employees working close to each other (not the case for active sectors). Conversely, sectors hiring more women tend to employ more workers in high-proximity occupations. The skill level reveals a negative correlation with proximity but the estimates are rather imprecise. Lastly, northern and southern Italy seem to be less characterized by high-proximity occupations, compared to center Italy (we visualize this using a Local Labour Market Areas approach, depicted in

[7] As a robustness check we modify the threshold by including only the share of workers in the top 25 percent of proximity (Table A4 the Appendix). Results remain confirmed.

Figure A1 in the Appendix[8]).

Table 6: Regression of the share of workers in the top tercile of physical proximity on AI score across sectors.

	All sectors		Active	Closed
	OLS	IV	IV	IV
AI advancements	63.514***	82.531***	74.188***	103.880***
	(7.618)	(13.222)	(14.918)	(18.915)
AI advancements^2	-0.893***	-1.160***	-1.040***	-1.453***
	(0.106)	(0.185)	(0.210)	(0.258)
Age	-0.437**	-0.444**	0.198	-1.123***
	(0.209)	(0.209)	(0.299)	(0.275)
Share of women	9.044***	9.299***	13.599***	4.725
	(2.336)	(2.326)	(3.449)	(3.157)
$Share\ of\ high-skill$	-0.185***	-0.120	-0.164	-0.227***
	(0.067)	(0.081)	(0.109)	(0.080)
$Share\ of\ med-skill$	-0.051	-0.036	0.035	-0.065
	(0.041)	(0.043)	(0.063)	(0.053)
RTI	-115.270***	-115.953***	-123.724***	-92.450***
	(12.445)	(12.255)	(16.814)	(15.620)
North	-6.808*	-6.968*	-7.022	-9.286**
	(3.678)	(3.686)	(5.467)	(4.527)
South	-8.029	-8.833*	-10.561	-8.614
	(5.216)	(5.207)	(7.492)	(6.497)
Island	0.779	-0.573	6.394	-11.034
	(9.157)	(9.311)	(13.579)	(8.382)
N	1222	1222	646	576
R-sq	0.26	0.25	0.31	0.23

Dependent variable: share of workers (by sector) employed in occupations with proximity within the top 33rd percentile. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

All in all, our estimates point to a negative relationship between AI advancements and physical proximity at the occupational level. At the sectoral level, the constellation of different occupations suggests that it is necessary a ”critical mass” of AI advancement in order to observe a decline in physical proximity. One limitation of our analysis is that we do not observe the actual implementation of AI in the workplace, which would allow a

[8]Local Labour Market Areas are functional geographic areas that go beyond administrative boundaries and represent economically integrated spatial units that has been shown being the most suitable geographical unit to discuss geographical heterogeneity (see Acemoglu and Restrepo, 2020; De Blasio and Poy, 2017).

quantification of reduction in proximity due to AI adoption. However, our results remain precious because they show the overlap between AI and human abilities and the connection of this overlap with the degree of proximity in the labour market.

5 Conclusions

The COVID-19 pandemic is determining shocking health and economic effects around the world (Giannitsarou et al., 2020). In particular, it has accelerated the use of innovative technologies at an unprecedented pace (see Hantrais et al., 2020). Some scholars see the COVID-19 as an automation-forcing event, whose effects on technology and work are destined to last over time (see Autor and Reynolds, 2020). In this paper, we contribute to the debate by exploring the potential of AI to influence the organization of the workforce at the sectoral level. Inspired by the lockdown measures implemented during the pandemic of Covid-19, this paper investigates the relationship between the advancements in AI and physical proximity in the labour market, with the glance at the ongoing technological change and future epidemics. The aim of the lockdown is to enforce social distancing and reduce the degree of contagion of COVID-19. However, this enforcement has dramatic economic consequences on the sectors which have been shut down. Therefore, it is important to investigate, firstly, which are the sectors that require a high level of physical proximity, and, secondly, if technology may help keep the sectors open and, ultimately, save jobs. In this context, the potential impact of AI in fighting the COVID-19 pandemic is enormous, but it has not yet been exploited, also due to a lack of data (Naudé, 2020).

We find that high advancements in AI are negatively associated with proximity at the occupational level. At the sectoral level, the relationship between proximity and AI follows an inverted U-shaped pattern, signaling the existence of possible organizational barriers for limited use of AI. Results show that the relationship holds significant both among sectors considered as essential, and therefore remained open during the lockdown, and among closed sectors, although at a lower extent for the latter (in line with the expectations on the lockdown target). Moreover, we find that proximity is lower for sectors employing more elderly male workers, engaged in routinary tasks, and for firms located in the north and the south of Italy.

Italy was the first Western country to implement lockdown measures to limit the risk of contagion from COVID-19. Many other countries have adopted similar measures and are currently struggling, on the one hand, with the recovery of the economy, and, on the other hand, with further waves of the virus and the risk to face again a lockdown. In view of new unexpected and inauspicious pandemics, the evidence we provide shows how much AI can be useful for every economy in limiting the risk of contagion. Our results inform policymakers of the still unexplored potential of AI available to fight the spread of the virus. We argue that the progress in digitization, apart from the expected benefits for productivity and competitiveness (see Fossen and Sorgner, 2019b), may save jobs and preserve economic activities in a situation of high contagion.

References

Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies 69*(4), 781–809.

Acemoglu, D. (2015). Localised and Biased Technologies: Atkinson and Stiglitz's New View, Induced Innovations, and Directed Technological Change. *The Economic Journal 125*(583), 443–463.

Acemoglu, D., D. Autor, J. Hazell, P. Restrepo, et al. (2020). Ai and jobs: Evidence from online vacancies. Technical report, NBER Working Paper N° 28257.

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics 189*, 104245.

Autor, D. and E. Reynolds (2020). The nature of work after the covid crisis: Too few low-wage jobs. *The Hamilton Project, Brookings*.

Autor, D. H. and D. Dorn (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review 103*(5), 1553–97.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Baert, S., L. Lippens, E. Moens, P. Sterkens, and J. Weytjens (2020). How do we think the covid-19 crisis will affect our careers (if any remain)? *IZA Discussion Paper No. 13164*.

Baker, M. G. (2020). Characterizing occupations that cannot work from home: a means to identify susceptible worker groups during the covid-19 pandemic. *medRxiv*.

Barbieri, T., G. Basso, and S. Scicchitano (2020). Italian workers at risk during the covid-19 epidemic. *Available at SSRN 3572065*.

Basso, G. (2020). The evolution of the occupational structure in italy, 2007-2017. *Social Indicators Research 152*(2), 673–704.

Béland, L.-P., A. Brodeur, and T. Wright (2020). The short-term economic consequences of covid-19: exposure to disease, remote work and government response. *IZA Discussion Paper No. 13159*.

Bennedsen, M., B. Larsen, I. Schmutte, and D. Scur (2020). Preserving job matches during the covid-19 pandemic: firm-level evidence on the role of government aid.

Boeri, T., A. Caiumi, and M. Paccagnella (2020). Mitigating the work-safety trade-off. *Covid Economics: Vetted and real-time papers 1*(2), 60–66.

Bonacini, L., G. Gallo, and S. Scicchitano (2020). Working from home and income inequality: risks of a 'new normal' with COVID-19. *Journal of Population Economics*, 1–58.

Brodeur, A., I. Grigoryeva, and L. Kattan (2020). Stay-at-home orders, social distancing and trust. *IZA Discussion Paper No. 13234*.

Brunetti, I., V. Intraligi, A. Ricci, and V. Cirillo (2020). Low-skill jobs and routine tasks specialization: New insights from italian provinces. *Papers in Regional Science 99*(6), 1561–1581.

Bullock, J., K. H. Pham, C. S. N. Lam, M. Luengo-Oroz, et al. (2020). Mapping the landscape of artificial intelligence applications against covid-19. *arXiv preprint arXiv:2003.11336*.

Carbonero, F. and D. J. Bertulfo (2020). The Future of Work in the Philippines. Assessing the impact of technological changes on occupations and sectors. *ILO report*.

Caselli, M., A. Fracasso, and S. Traverso (2020). Mitigation of risks of covid-19 contagion and robotisation: Evidence from italy1. *Covid Economics*, 174.

Cetrulo, A., D. Guarascio, and M. E. Virgillito (2020). The privilege of working from home at the time of social distancing. *Intereconomics 55*, 142–147.

Chernoff, A. W. and C. Warman (2020). Covid-19 and implications for automation.

Cho, S. J., J. Y. Lee, and J. V. Winters (2020). COVID-19 Employment Status Impacts on Food Sector Workers. *IZA Discussion Papers No 13334*.

Cirillo, V., R. Evangelista, D. Guarascio, and M. Sostero (2020). Digitalization, routineness and employment: an exploration on italian task-based data. *Research Policy*, 104079.

Dauth, W., S. Findeisen, J. Südekum, and N. Woessner (2017). German Robots - The Impact of Industrial Robots on Workers. *CEPR Discussion Paper No. DP12306 (new version 2019)*.

De Blasio, G. and S. Poy (2017). The impact of local wage regulation on employment: A border analysis from italy in the 1950s. *Journal of Regional Science 57*(1), 48–74.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *Journal of Public Economics Volume 189*, 104235.

Felten, E. W., M. Raj, and R. Seamans (2018). A Method to Link Advances in Artificial Intelligence to Occupational Abilities. *AEA Papers and Proceedings 108*, 54–57.

Felten, E. W., M. Raj, and R. Seamans (2019). The occupational impact of artificial intelligence: Labor, skills, and polarization. *Available at SSRN 3368605*.

Fossen, F. and A. Sorgner (2019a). Mapping the Future of Occupations: Transformative and Destructive Effects of New Digital Technologies on Jobs. *Foresight and STI Governance 13*(2), 10.

Fossen, F. M. and A. Sorgner (2019b). Digitalization of work and entry into entrepreneurship. *Journal of Business Research*, doi: https://doi.org/10.1016/j.jbusres.2019.09.019.

Frank, M. R., D. Autor, J. E. Bessen, E. Brynjolfsson, M. Cebrian, D. J. Deming, M. Feldman, M. Groh, J. Lobo, E. Moro, et al. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences 116*(14), 6531–6539.

Frey, C. B. and M. A. Osborne (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change 114*, 254–280.

Furman, J. and R. Seamans (2019). AI and the Economy. *Innovation Policy and the Economy 19*(1), 161–191.

Giannitsarou, C., S. Kissler, and F. Toxvaerd (2020). Waning Immunity and the Second Wave: Some Projections for SARS-CoV-2. *London, Centre for Economic Policy Research*.

Goos, M., A. Manning, and A. Salomons (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review 104*(8), 2509–26.

Graetz, G. and G. Michaels (2018). Robots at work. *Review of Economics and Statistics 100*(5), 753–768.

Grigoli, F., Z. Koczan, and P. Topalova (2020). Automation and labor force participation in advanced economies: Macro and micro evidence. *European Economic Review*, 103443.

Hantrais, L., P. Allin, M. Kritikos, M. Sogomonjan, P. B. Anand, S. Livingstone, M. Williams, and M. Innes (2020). Covid-19 and the digital revolution. *Contemporary Social Science*, 1–15.

Jaimovich, N. and H. E. Siu (2020). Job polarization and jobless recoveries. *Review of Economics and Statistics 102*(1), 129–147.

Koren, M. and R. Pető (2020). Business disruptions from social distancing. *arXiv preprint arXiv:2003.13983*.

Leibovici, F., A. M. Santacreu, and M. Famiglietti (2020). Social distancing and contact-intensive occupations. *On the economy, St. Louis FED*.

Lind, J. T. and H. Mehlum (2010). With or without u? the appropriate test for a u-shaped relationship. *Oxford bulletin of economics and statistics 72*(1), 109–118.

Marcolin, L., S. Miroudot, and M. Squicciarini (2019). To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. *Industrial and Corporate Change 28*(3), 477–501.

Mongey, S., L. Pilossoph, and A. Weinberg (2020). Which workers bear the burden of social distancing policies? *NBER Working Paper N°27085*.

Naticchioni, P., G. Ragusa, and R. Massari (2014). Unconditional and Conditional Wage Polarization in Europe. *IZA Discussion Paper No. 8465*.

Naudé, W. (2020). Artificial intelligence against covid-19: An early review. *IZA Discussion Paper No. 13110*.

Nicoletti, G., C. von Rueden, and D. Andrews (2020). Digital technology diffusion: A matter of capabilities, incentives or both? *European Economic Review 128*, 103513.

Palomino, J. C., J. G. Rodriguez, and R. Sebastian (2020). Wage inequality and poverty effects of lockdown and social distancing in europe. *European Economic Review 129*.

Qiu, Y., X. Chen, and W. Shi (2020). Impacts of social and economic factors on the transmission of coronavirus disease (covid-19) in china. *medRxiv*.

Toxvaerd, F. (2020). Equilibrium Social Distancing.

Toxvaerd, F. and M. Makris (2020). Great Expectations: Social Distancing in Anticipation of Pharmaceutical Innovations.

Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.

Appendix A

Table A1: The dimensions of the Routine Task Index.

Routine cognitive (RC)
Importance of repeating the same tasks
Importance of being exact or accurate
Structured v. Unstructured work (reverse)
Routine manual (RM)
Pace determined by speed of equipment
Controlling machines and processes
Spend time making repetitive motions
Non-routine cognitive: Analytical (NRCA)
Analyzing data/information
Thinking creatively
Interpreting information for others
Non-routine cognitive: Interpersonal (NRCI)
Establishing and maintaining personal relationships
Guiding, directing and motivating subordinates
Coaching/developing others
Non-routine manual (NRM)
Operating vehicles, mechanized devices, or equipment
Spend time using hands to handle, control or feel objects, tools or controls
Manual dexterity
Spatial orientation
Non-routine manual: interpersonal adaptability (NRMIA)
Social Perceptiveness

Table A2: Test for non-monotonic U-shaped function between physical proximity and AI score

Slope at the lower bound	Slope at the upper bound	T-test of the presence of an inverse U relationship	P-value
4.62	-3.84	11.36	0.000

Table A3: First stage regression. Dependent variable AI advancements in Italy.

US AI advancements	1.341***
	(0.063)
Age	0.001
	(0.010)
Share of women	-0.382***
	(0.124)
Share of high−skill	0.013***
	(0.004)
Share of med−skill	0.008***
	(0.003)
RTI	1.089**
	(0.461)
North	0.251
	(0.207)
South	-0.486*
	(0.272)
Island	-0.723**
	(0.330)
N	1222
R-sq	0.84

Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

Table A4: Robustness check. Regression of the share of workers in the top 25th percentile of physical proximity on AI score across sectors.

	OLS	IV
AI advancements	47.666***	63.054***
	(5.402)	(10.011)
AI advancements^2	-0.675***	-0.896***
	(0.076)	(0.140)
Age	-0.596***	-0.600***
	(0.184)	(0.184)
Share of women	6.185***	6.437***
	(2.069)	(2.074)
$Share\ of\ high-skill$	-0.121**	-0.045
	(0.054)	(0.064)
$Share\ of\ med-skill$	-0.053	-0.027
	(0.034)	(0.036)
RTI	-79.224***	-79.808***
	(11.018)	(10.840)
$North$	-3.257	-3.371
	(3.107)	(3.133)
$South$	-10.444**	-11.694***
	(4.239)	(4.230)
$Island$	-11.422**	-12.895**
	(5.212)	(5.261)
N	1222	1222
R-sq	0.19	0.18

Dependent variable: share of workers (by sector) employed in occupations with proximity within the top 25th percentile. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

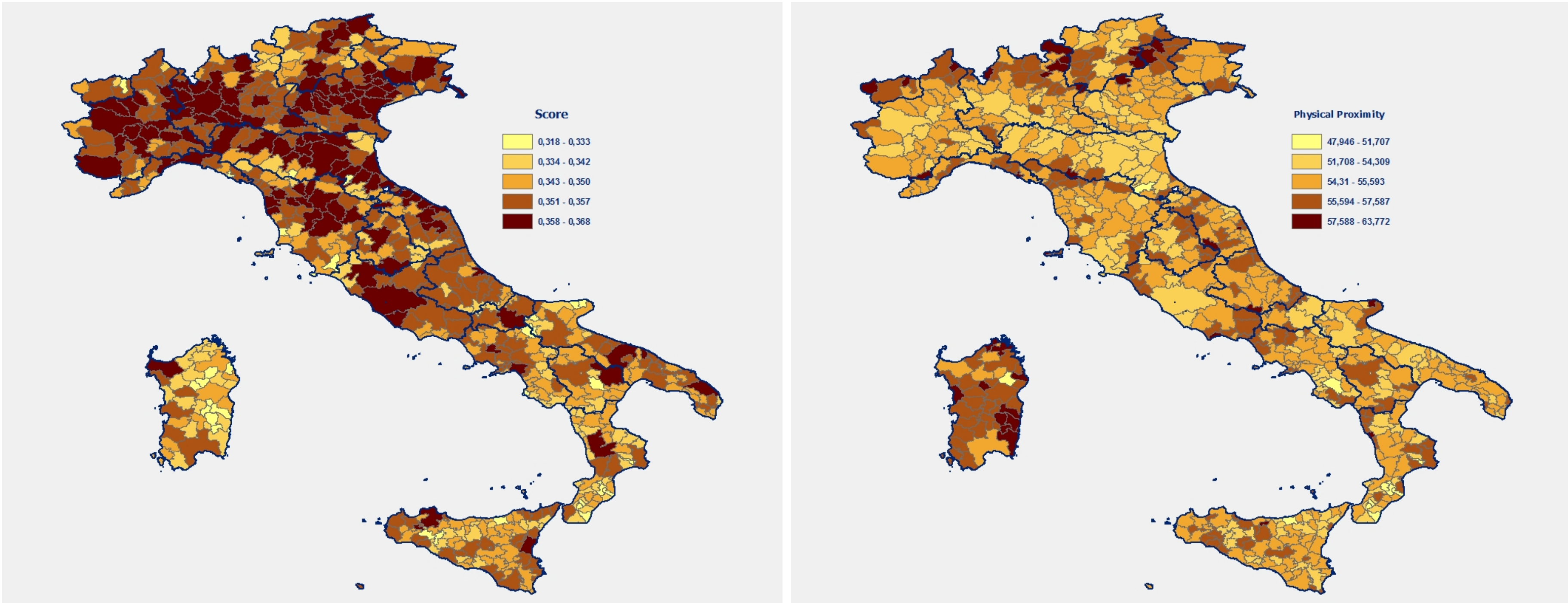

Figure A1: Geographical distribution of AI score (left panel) and proximity (right panel) at commuting zone level. Source: Author's calculations.