IMT School for Advanced Studies, Lucca
Lucca, Italy

Universidad de Alicante
Alicante, Spain

Public Policy in Italy: an empirical analysis on local governments and occupation

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Sara Landi

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Introduction

Research on public policy has been a fast developing fields among social sciences over many decades. In this rapid development, policy analysis reached levels of higher understanding of the policy making process together with the capability of supplying decision makers with reliable and relevant knowledge about urgent economic and social problems. Following Dunn (1981) policy analysis is *"an applied social science discipline which uses multiple methods of inquiry and arguments to produce and transform policy-relevant information that may be utilized in political settings to resolve policy problems."* And although policy advice is as old as government, modern society faces an increasing complexity that seriously reinforce the decision makers' need for information.

The institutional setting in Italy is ideal for studying public policy, as both the political environment and the labour market undergone dramatic changes over the last 30 years. After almost fifty years of proportional electoral system, in 1991 Italy enter into a period of electoral law reformation. Nevertheless, the debate is ongoing and intense in the attempt to answer the question on how to design an electoral system that is able to express the desired political outcomes in contrast with the rigid structure of the Constitution. Similarly, Italian labour market went through a process of liberalisation since the end of last century when a series of reforms were promoted aiming at fixed-term employment relationships, in the beginning and then moving to targeting open-ended contracts. Alongside, the latest production technologies are characterised by an increased digitalization (Brynjolfsson and McAfee, 2014) that is often included in the political debate with the name of 'Industry 4.0' and has been related to a significant shift towards the so-called 'smart factory' of the future.

The difficult health crisis, with all its economic and social consequences, has impacted on the country with a wide range of pre-existing structural problems, which it is crucial to maintain the focus on, aside the new paths drawn by the effects of the pandemic. The aim of this thesis is to analyse empirically the Italian institutional setting both in a political competition context and in the occupational structure. In the following chapters, we propose new methods to tackle disputed questions in the literature of political and labour economics: we make use of the traditional Regression Discontinuity Design, as framed by D. S. Lee (2008) with a new randomization tool to address endogeneity; we expand the application of Matrix Completion, a recently developed machine learning techniques to assess deficit in soft skills in the labor market; lastly, we adapt this new Matrix Completion formulation to make predictions on the future trends in the job market and job conditions after the Covid-19 pandemic.

The first paper explores the relationship between transfers from central state to political aligned municipalities and the effect of these transfers on local electoral consensus. This study contributes to the empirical literature of the political determinants of spikes in central transfers in pre-electoral periods and of the electoral benefits of pork barrel measures for incumbent politicians. Despite several findings of strong evidence that intergovernmental fiscal transfers rise during election years, in the Italian case researchers investigated little the political incentives that lay behind these increases or the success of these transfers in attracting votes. We focus on the so called swing municipalities, defined as those in which the probability of winning is close to one-half, analysing data of Italian comuni with more than 15 000 inhabitants, in the period 2007-2014.

From an empirical perspective, every attempt to estimate the causal impact of political alignment on the amount of federal transfers is clearly complicated by endogeneity issues. Without a credible source of exogenous variation in political alignment, the empirical correlation between alignment and transfers (if any) can be completely driven by socio-economic factors influencing both dimensions. We propose a new model specification to account for the endogeneity issue arising when estimating the causal impact of political alignment on transfers: the unpredicted change in the government occurred in 2011 after the resignation of Silvio Berlusconi and the following appointment of Mario Monti as prime minister. We perform our empirical estimation in two steps: first, we apply the close-race RDD setup (Lee 2008) to assess the impact of political alignment on transfers. Results from the close-race RDD show that aligned municipalities receive more grants, with this effect being stronger before elections. At a second empirical stage, we perform a local linear regression of the reelection probability of the local incumbent on transfers, including the first stage error term to have our coefficient of interest measuring only the effect of politically-driven transfers on electoral outcomes, and we conclude that this probability increases as grants increase.

The second paper stems from the observation of the most recent phenomena in the domestic and foreign labour market: technological progress has been associated to a crowding-out of cognitive-skill intensive jobs in favour of jobs requiring soft skills, such as social intelligence, flexibility and creativity. Soft skills can be defined as interpersonal, human, people or behavioural skills necessary for applying technical skills and knowledge in the workplace. The nature of the soft skills make them hardly replaceable by machine work, and Among soft skills, creativity is one of the hardest to define and to codify, therefore, creativity-intensive occupations have been shielded from automation.

In our work, we focus on creativity, starting from its definition in order to get significant insights on which occupational profiles in Italy can be considered creative and to explore their dynamics in the labour market. A possible analytical definition of creativity comes from the seminal work of Edward De Bono. According to his pioneering research in the field, lateral thinking is strictly related to creativity and it can be described along four dimensions: 1) fluidity, as the ability of a subject to give the highest possible number of answers to a certain question; 2) flexibility, as the number of categories to which we can bring back these questions; 3) originality: ability of expressing new and innovative ideas; 4) processing: ability of realizing concretely one's ideas. We apply this definition to the Survey on Occupations (Indagine Campionaria sulle Professioni, ICP hereafter), run by ISTAT and INAPP in 2007 and 2013, the Italian twin of the US O*NET dataset. The Survey on Occupations, in fact, presents a list of skills and competences and workers are asked to identify those they make use of in performing their job. Inside this list, we identify 25 skills associated to creativity and we formulate a Matrix Completion (MC) optimization problem, as discussed theoretically in Mazumder (2010). Matrix Completion is the exercise of reconstructing the missing entries of a matrix, which we generate by obscuring randomly 10%, 25% and 50% of the entries in the columns associated with the creative skills, given a fixed row (occupation). In our analysis, we use a formulation of the problem known as Nuclear Norm Minimization and we solve it with the Soft Impute Algorithm.

We conclude our analysis on social skills in our third paper where we analyse the effects of Covid-19 pandemic on soft skills in the context of Italian occupations, operating in about 100 economic sectors. We make use of the information included in the ICP, the Italian O*Net, and we simulate the impact of Covid-19 on those workplace characteristics and working style that were more seriously hit by the lockdown measures and the new sanitary dispositions (physical proximity, face-to-face discussions, working remotely, ecc.). We simulate three possible scenarios based on the intensity of the effects of COVID-19 on some working conditions, such as working from home, keeping physical distance and so on. We then apply matrix completion, a machine learning technique used in recommendation systems, in order to predict the levels of soft skills required for each occupation when working conditions change, as these changes might be persistent in the near future. Professions showing a lower intensity in the use of soft skills, with respect to the predicted one, are exposed to a deficit in their soft-skill endowment, which might ultimately lead to lower productivity or higher unemployment, thus enhancing the negative effects of the pandemic.

Chapter 1

Central Government and Swing Municipalities
Do higher national transfers drive local political consensus?

"All politics is local in the last analysis,
and local considerations come first."
- Byron Prince

Introduction

The amount of transfers assigned from the central government to municipalities are critical in determining the supply of public goods at local level, as this the main source of municipal revenues. Theoretical and empirical research, however, have claimed that the allocation of intergovernmental transfers is a response to politicians' incentives: despite the adoption of rules that aim at preventing political distortions to occur in the distribution of resources, public servants have relevant discretion in disposing of transfers to attract swing voters, compensate core supporters or create political alliances.

From a theoretical point of view, political economy models are not unanimous in interpreting the underlying mechanisms that motivate politically driven transfers: the aim could be increasing the reelection probability of the incumbent by targeting swing voters (Lindbeck and Weibull, 1987) or similarly, the goal could be the rewarding of core supporters (Cox and McCubbins, 1986). Nevertheless, insofar as local administration can allege some political credit for the funds it has received, the allocation of transfers might prove beneficial for political affiliated or detrimental for political enemies. As a consequence, political alignment between national and local governments is expected to increase the amount of transfers.

These intuitions were formalized into a simple model by Brollo and Nannicini (Brollo and Nannicini, 2012), where the central state assigns transfers to municipalities with a double goal: to please voters directly and to augment the winning probability of aligned candidates who, once elected, can be important allies, either for rent seeking or vote seeking in the following national elections. If electors are partially unqualified to distinguish the origin of transfers and political credit spillovers support municipal governments, aligned districts turn out to receive more transfers, as the legislator tries to either help affiliated mayors to get re-elected or prevent unaligned mayors from being re-elected. Furthermore, those aligned municipalities in which the incumbent wins by a small margin tend to receive more, since greater municipal revenues could considerably affect future electoral outcomes. Likewise, unaligned municipalities in which incumbent wins by a small margin receive less, as the government party wants to disarm its political rivals in the next electoral race.

Our paper stems from these consideration and tries to answer some disputed questions: whether contestability (i.e. being a municipality where the electoral race is tight) is associated with an increase in central transfer when the local major and the national government belong to the same political party and, when this occurs, if the central government allocates politically driven funds equally among politically aligned municipalities or it rather targets swing municipalities? If Italian swing municipalities, where local and national government are politically aligned, do receive extra-transfers do higher transfers result in higher consensus in the following local elections?

As the empirical literature on the topic clearly states, every effort to assess the causal effect of political alignment on the amount of federal transfers is undermined by the issue of endogeneity (Migueis, 2013). Since there might be many different socio-economic factors influencing both political alignment and transfers, the empirical correlation between the two variables has to be estimated with an exogenous shock on political alignment. In order to overcome this problem, we reformulate our research questions focusing on unexpected changes in the national institutions as our exogenous variation affecting local political outcomes. In order to do so, we would exploit the peculiar Italian political situation in the year 2011 where a new government led by Monti was appointed, thus functioning as an exogenous shock. As it will be further explained, in fact, his advent was totally unexpected in the preceeding days as it was the result of an unbearable sovereign debt crisis which obliged PM Silvio Berlusconi to resign.

Using financial and census data from Italian municipalities in the period 2007-2015 we first adapt the regression discontinuity (RD) design in close electoral races pioneered by D. S. Lee (2008) to assess the impact of political alignment between the local mayor and the Italian government on the amount of central transfers allocated to each municipality by comparing places where the aligned candidate barely won with places where the aligned candidate barely lost. Then we test the hypothesis for which higher transfers, acting via several channels, can help increasing the reelection probability of the incumbent in the following local elections.

1.1 Literature

According to the theoretical model of Lindbeck and Weibull (1987) and Dixit and Londregan (1996) politicians target swing individuals, because, when groups of voters have similar consumption preferences, but different preferences over the parties, then the contending parties will tend to attract swing voters with the distribution of resources. Therefore, regions with many swing voters would collect grants.

Conversely, Cox and McCubbins' 1986 model explains the preferential allocation of resources toward loyal groups. Parties or politicians maximize their expected share of votes while individuals choose the party such that they reach a higher utility level, thus groups can be classified with respect to the responsiveness to transfers promised: "opposition" groups being the least responsive, "swing" groups being slightly more responsive and "loyal supporters" as the most responsive group. Consistently, politicians are more certain about the electoral responsiveness of their core supporters and more uncertain about the response of the other groups: thus the more risk averse the politician is, the more resources the core supporters receive.

Our study integrates the vast body of empirical literature that has undertaken the estimation of the effect of political alignment on the allocation of central transfers: Grossman (1994) shows that in the US the affinity of parties between federal and state politicians increases grants to that state; Levitt and Snyder Jr (1995) finds that the share of district votes to the democratic party can predict the amount federal transfers to that district, especially in periods of democratic majority in Congress. Recent studies developed the previous literature through panel estimation, controlling for time invariant confounding factors at the local level. Berry, Burden, and Howell (2010) analysis results in districts and counties receiveing more funds when their administrators are affiliated with the president's party. Solé-Ollé and Sorribas-Navarro (2008) find the same results for Spain employing a difference-in-differences strategy across both time and grantors. Consistent results are found for India by Arulampalam et al. (2009) and for Portugal by Veiga and Pinho (2007) and Migueis (2013) during the early years of democracy, but not afterwards. The presence of political motives underlying the allocation may generate welfare losses, excessive government spending, and inequities (Shah and Boadway, 2006).

Several studies foster the idea that politicians skew the allocation of resources towards their core groups of voters: Larcinese, Rizzo, and Testa (2006) analyse the impact of the president in the allocation of budget across states in the US and try to test if the resources were disproportionately allocated to swing or loyal states. The authors did not find any evidence supporting the swing voter view, whereas they found evidence supporting the loyal voter view. Ansolabehere and Snyder Jr (2006) argue that one of the problems with the swing voter models is the assumption of a fixed turnout, thus politicians' effort focus on bringing voters on their side rather than mobilizing new voters. Their results give no evidence of a favorable attitude toward swing electorate, yet counties where the national majority party has larger support receive additional funds, consistently with the loyal voters view. This conduct arises from the fact that spending impacts on turnout in the elections: it creates more jobs, therefore citizens feel personally affected by their votes and firms that rely on those transfers tend to push their workers to vote. Hence, it is more convenient for the ruling party to assign unduly more money to its loyal constituencies, in order to get more supportive voters in forthcoming elections.

Does this happen? Despite numerous studies investigate the relationship between political partnership and central transfers allocation, only a few focus on the Italian case and try to move the analysis further by asking whether these extra-transfers, aiming at pleasing voters in future electoral rounds, do have the awaited effect.

As far as the effects of reelection incentives are concerned, two main types of models apply in the political economy literature, as summarized by (Dalle Nogare and Kauder, 2017). In the first class, elections lead the incumbent to deviate from standard fiscal policy as this increases, through several channels, the probability of being reelected (Nordhaus, 1975; Rogoff and Sibert, 1988). More recent contributions along this stream relate to the literature on the conditional rational budget cycle and analyze the role of political institutions when observing the phenomenon (Tabellini and Persson, 2003; Brender and Drazen, 2005; Shi and Svensson, 2006). Empirical studies in this sense reveal that the cycle is mostly evident when considering public spending. Aidt and Shvets (2012) examine the consequences of electoral motivations on redistribution policies and conclude that the common-pool problem (Weingast, Shepsle, and Johnsen, 1981) is intensified when candidates differ in their ability to do pork barrel spending and citizens cannot directly observe this ability. According to this view, in case a legislator might be reelected, constituencies experience larger spending while, on the contrary, politicians with a term-limited position does not undertake any effort in bringing home more pork.

In the second class of models elections are considered as a signal for political accountability and consequently, they regulate the incumbent's behavior (Barro, 1973; Ferejohn, 1986). The work of Besley and Case (1995) demonstrate that there is a concern for reputation during the first mandate, but once reelected the officeholder, not depending on political constraints, only maximizes her own return. Deriving from the two theoretical frameworks, empirical predictions are the opposite for the two classes of models: the former expects public servants to deviate from the optimal policy before the first term elections; the latter claims it is during the second term that the incumbent deviates. Recent studies on term limits, like Smart and Sturm (2013), underline the relevance of the selection effect elections give rise to, asserting that in equilibrium, electors support only those contestants with a stronger sense of civic responsibility or higher competences. Recollecting the two perspectives, Smart and Sturm predict that fiscal policy in second terms would be more in accordance with voters' tastes and believe that this occur because second-term politicians are a portion of public-spirited first-term incumbents, being this category more likely to be reelected. Conversely, Alt, Bueno de Mesquita, and Rose (2011) propose a model in which the presence of both a political accountability effect and a selection effect makes it hard to foresee how first-term policies will differ from second-term policies.

Lastly, our work owes much to Carozzi and Repetto (2016), who investigate central government current transfers to "connected" municipalities, birthplace of one or more MPs which do not coincide with their electoral district, and show that these municipalities receive more funds because of the aspiration of parlamentarians to run for mayor office in their hometown after their career in parliament. From the methodological point of view, we follow Bracco et al. (2015) studying the impact of alignment on current transfers to municipalities by including in the model the fact that grants are signals in the local electoral competition, though more emphasis is given to the role of central government than to that of mayors in the determination of grant size.

This study contributes to the empirical literature of the political determinants of spikes in central transfers in pre-electoral periods and of the electoral benefits of pork barrel measures for incumbent politicians. Despite several findings of strong evidence that intergovernmental fiscal transfers rise during election years, in the Italian case researchers investigated little the political incentives that lay behind these increases or the success of these transfers in attracting votes. The focus of this work goes even deeper into the analysis of central State behaviour towards swing municipalities, those where the government party is more willing to win the following local elections. From an empirical point of view, this work proposes an alternative way to address the endogeneity issue arising when estimating the causal effects of political alignment on central transfers. To the best of our knowledge, the exogenous shock provoked by the resignation of Silvio Berlusconi and the appointment of Mario Monti in November 2011 has not yet been exploited to assess the impact of change in political alignment on intergovernmental grants.

1.2 Endogeneity Issue

In developing our empirical methodology, the issue of endogeneity plays a key role as it entangles the estimation of the causal relationship between political alignment and federal transfers. In order to have a source of exogenous variation in the observational data, we reverse and reformulate our research question and we exploit the peculiar instability of the italian political institutions. The republican history of Italy (1946-present), in fact, counts 17 completed legislatures, of which only half lasted for the 5 years provided for in the Constitution and none had had the same prime minister and the same government composition for the entire period. On the contrary, at the local level it is highly unlikely that a mayor resigns before the end of his term, or that cases of criminal infiltrations emerge for which it is required that special commissioners are sent to the municipality before new elections are called. Moreover, while national electoral outcomes might affect local elections, especially in larger cities, as the citizens could prefer to be ruled by someone who is politically aligned with the government, so to have a sponsorship in the allocation of the state budget, the opposite happens rarely. When voting for the mayor, voters take considerably into account the individual characteristics of the candidates (e.g. marital status, education, job as well as attitude, determination and personal acquaintance), while political affiliation, especially in small villages, has minor importance. When voting for the parliament, instead, it is harder to know personally the candidates, whereas citizens take more into account the political party they belong to and how this party acted in the previous legislature, regardless being part of the government or not.

To the extent of our knowledge, the relationship between national and local electoral outcomes has not been so widely investigated in the literature. Latest studies on the attribution of accountability hypothesis, such as Geys and Vermeir (2014), prove that, in institutional frameworks with several layers of government, citizens find it difficult to account for the individual responsibility of every politician and so they make use of proxies (for instance, the partisan affiliation) in order to solve the problem. Garry (2014) as well tackle the issue and demonstrates that *"voters' ability in differentiating the accountability of parties is higher in less ideological contexts"*. The literary debate so far has only focused on how to strengthen economic voting in a system of multilevel governance and has always concluded that the political affiliation provides a powerful mechanism to smooth this accountability problem. Therefore, we take advantage of the fact that party affiliation provides an important cues about politicians' individual characteristics and behavior after the election.

Political economy theory defines party cues as *"the process through which party labels of candidates increase the information available to voters"* (Geys and Vermeir, 2014). When local and national politicians belong to the same party (i.e., political power is "aligned" across levels of government), local political outputs give insights to citizens for the evaluation of the national incumbent mandate, although they have no influence on this output. The underlying mechanisms is that, even if the policy outcome is positive for the local politician, it is transferred onto the national politician through partisan connection. Moreover, when the national and regional politician are from different parties (i.e., political power is "unaligned"), regional public output has a smaller positive effect, that could turn out to be negative, on the national incumbent.

Therefore, if an unforeseen change in the government occurs or the two houses are dissolved unexpectedly, these events can be considered as an exogenous variation during the mayoral term that is not correlated with the political party the mayor is associated with, but that could potentially affect subsequent local elections. Hence, we would consider the "artificial end" of the legislature as our random shock, when it is unanticipated.

Using the designation of Monti as the random device on our treatment variable (political alignment) we get to four categories of municipalities:

- AA - aligned to the majority party before and after a change in the parliament

- UU - unaligned to the majority party before and after a change in the parliament
- AU - aligned to the majority party before and unaligned after a change in the parliament
- UA - unaligned to the majority party before and aligned after a change in the parliament

where *political alignment* is defined as having a major who belongs to the government party or coalition. Following this definition, we would generate two subsamples of municipalities based on whether they changed their political alignment as a consequence of the appointment of Monti's government. Therefore, we would consider AU/UA municipalities as our treatment group and AA/UU ones as our control group and we would compare pairwise their outcome, to assess the magnitude of the expected positive effect of alignment on transfers for UA municipalities and/or the negative impact of losing the alignment with the central government.

1.2.1 Monti Government

It was mostly the sovereign debt crisis of 2011 coupled with the strong international pressure after the dismal performance at the G8 summit in Nice that forced the resignation of Berlusconi and the creation of the present Monti government, whose overarching goal was the need to reestablish the trust of the markets and of the international partners towards Italy's prospects (and its immense public debt) (Marangoni, 2012).

Only four days after the resignation of Silvio Berlusconi as Prime Minister, a new government run by the economist Mario Monti took office (Marangoni, 2012). Its life span from the beginning was defined in no more than 18 months and consequently all the decisions had to be almost self-implementing as there was no time for fine tuning or institution building. The Monti cabinet was supported by a vast parliamentary majority including the two main Italian parties (the Berlusconi's Popolo delle Liberta' and the centre-left Partito Democratico) as well as a minor centrist party (the UDC). It has opposition both in the right (the Lega Nord the traditional ally of the Popolo delle Liberta') and in the left (the IDV party, normally an ally of the Partito Democratico).

Monti government was appointed in order to deal with a dramatic situation of economic and political emergency: *"a technocratic government, staffed by people from outside the world of politics. In this sense the executive headed by Monti can be defined as an 'interim government'"* (Verzichelli and Cotta, 2018). In that period, political parties were incapable to agree on a majority that could govern the country, thus delegating some of their power. Its composition closely approximates the model of a pure technocratic government, where almost all members had not had any political experience before.

For the purpose of our analysis, it is important to highlight not only the technocratic composition of the new executive but also, and mainly, the change in the political parties forming the government coalition. The last Berlusconi Government (Berlusconi IV, 2008–2011) was supported by a coalition between *Il Popolo delle libertá* (PdL), a federation of political parties including *Forza Italia* and *Alleanza Nazionale*, which participated as a joint election list in the 2008 general election, the *Lega Nord*, a right-wing, federalist, populist party led by Umberto Bossi, together with the Sicilian *Movimento per le Autonomie*, a regionalist, Christian-democratic political party that demands economic development, greater autonomy and legislative powers for Sicily and the other regions of southern Italy.

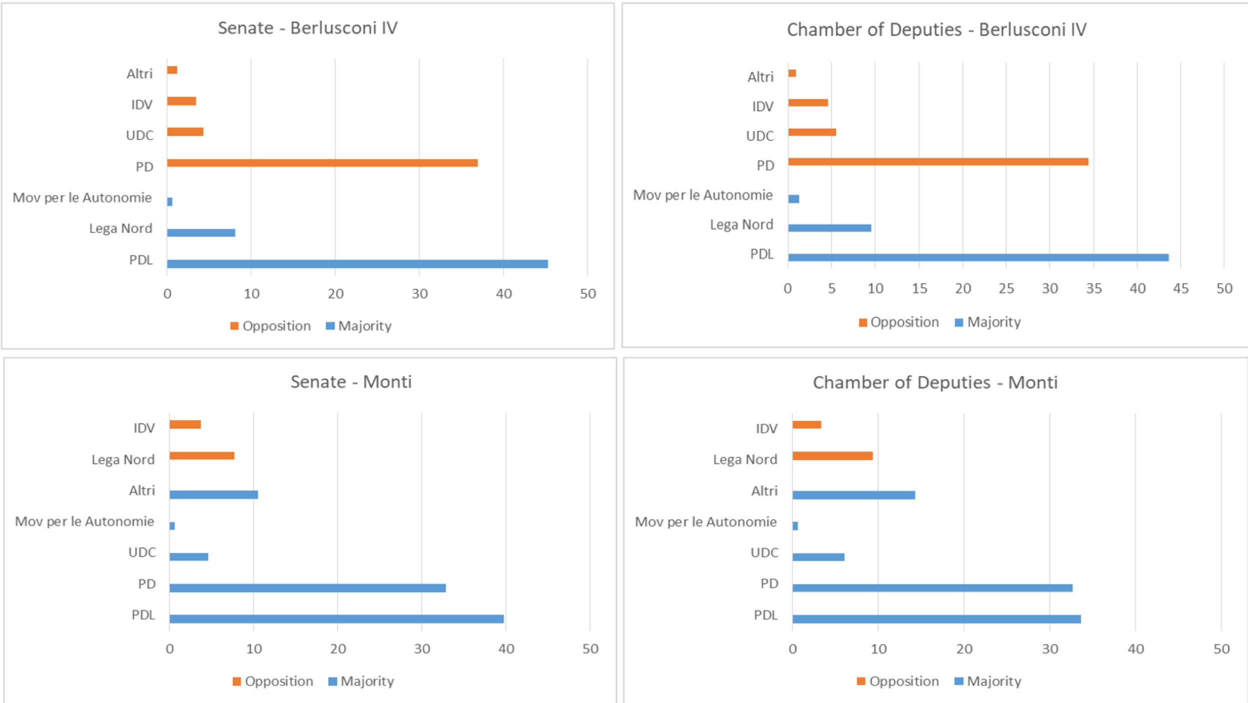


Figure 1: Changes in the majority coalition from Berlusconi IV to Monti government

At the designation of Mario Monti as new prime minister, it is Lega Nord abandoning the majority coalition while *Partito Democratico*, a centre-left party and *Unione di Centro*, the remains of the christian-democrats tradition, decide to give their support to the new leader. Thus, now the opposition is only formed by deputies and senators from Lega Nord as well as *Italia dei Valori*, a populist and anti-corruption party, as shown in the figure below. Overall, Berlusconi could count on 343 deputies (out of 630) and 174 senators (out of 322); Monti, instead, had the favour of 550 deputies and 285 senators.

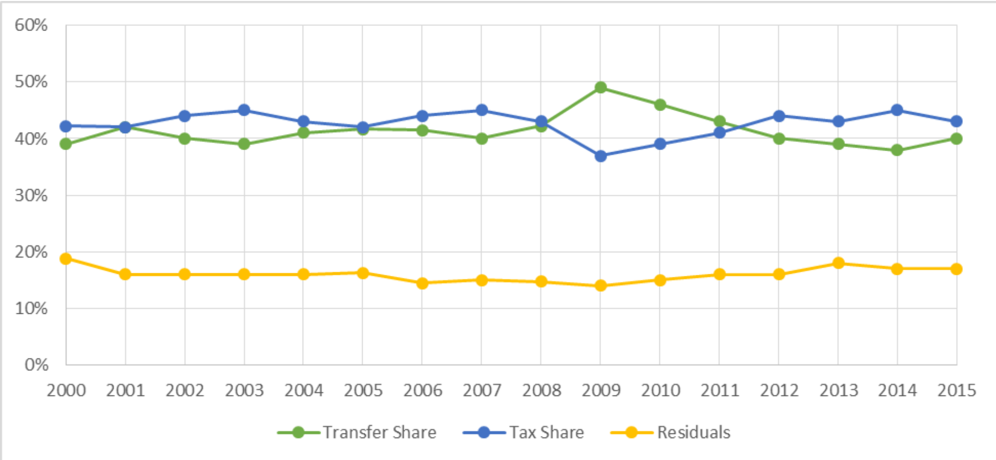
1.3 Institutional Setting

1.3.1 *Municipalities*

As of February 2017, Italy hosts 7,982 municipalities (*comuni*). Municipal governments' revenues come from taxes, transfers from the central or regional government or from the European Union (which accounts for more than 30% of the expenses), fees (e.g. building permits, provision of public services, museums) or fines, capital transfers and sales of public assets or, finally, by borrowing (around 3,7% Carozzi and Repetto, 2016). Municipalities are responsible for the provision of public goods and services (e.g. public transportation), welfare (e.g. nursery schools) and regulation of public utilities (Gagliarducci and Paserman, 2012, these expenses cover 27% of the total). They have restricted autonomy in setting the local real estate tax rate (called ICI until 2012, then IMU) and, although taxation is their most relevant resource, still they largely count on transfers, mostly from the central and regional governments (Carozzi and Repetto, 2016).

Figure 2 depicts the trend in transfer receipt and tax collection for all municipalities in the sample. Taxes revenues at the municipal level includes property tax (*IMU*), a surcharge on the personal income tax (*addizionale IRPEF*) and the waste collection and disposal tax (*TARI*). Moreover, there is a municipal tax on building licenses (OECD 2016) and, in certain municipalities, a tourist tax (Conti, Grassini, and Monicolini, 2020). Measured as share of general government revenue, local government tax revenue decreased before 2009 whereas it steadily increases in the years after. One reason for the increasing share after 2009 lies in the national cuts of transfers to regions and municipalities. A significant drop in tax revenues and peaking transfers mark dramatically the pattern 2009, right after the great recession crisis. This year saw the creation of an equalisation mechanism (*fondo di solidarietá comunale*) in order to foster the allocation of general-purpose non-capital transfers to municipal governments with a lower capacity to tax. Nevertheless, some earmarked grants do exist: these transfers are assigned from central level to smooth regional inequalities and for economic development, social cohesion, natural disasters, etc.

Figure 2: Local Government Aggregate Transfers and Taxes as a share of Total Revenues



Data Source: Eurostat Government Finance Statistics, OECD Fiscal Decentralisation Database

The share of state transfers to municipalities that suffices ordinary running costs is defined by law, based on population, surface and density, age composition, previous expenses and the presence of a military base (see Decreto Legislativo n.504/1992). The remaining part is questionably more arbitrary (which accounts for about 5% of the total transfers), as it is calculated to finance expenditure on public works of primary interest and to promote convergence of under-endowed areas. The effective volume of transfers is decided yearly in the budget law and ratified by the Parliament at the end of December. During the budgetary process, parliamentarians usually press for additional government transfers to finance personal projects at the local level.

Table 1 shows a series of sample descriptive statistics, grouped by legislature in the period 2007-2015. Municipalities are small (around 7000 inhabitants on average), with a mean surface of slightly more than 40 km^2. Population density slowly increased at the end of the century, reaching 248.2 inhabitants per square kilometre in the 2011 legislature.

1.3.2 *Electoral Law*

The mayor is the head of the municipal committee (*Giunta comunale*, the executive body), and is also part of the town council (*Consiglio comunale*), which has legislative powers.

Table 1: Descriptive Statistics for municipalities, 2007-2015

	2007-2011	**2011-2015**
Population	$6963,6$	$7058,3$
	(28855,8)	(28429,5)
Transfers p.c.	$248,2$	$226,8$
	(124,3)	(129,5)
Surface (km^2)	$43,6$	$44,3$
	(315,5)	(318,9)
Population density	$287,6$	294,8
	(641,3)	(646,9)
Total Revenues p.c.	$644,29$	$513,72$
	(231,29)	(234,5)
Total Taxes p.c.	$348,66$	$404,41$
	(158,41)	(150,13)
Current Expenditures p.c.	$676,68$	$651,94$
	(207,94)	(210,8)
Income p.c.	$35503,15$	$34019,47$
	(2221,06)	(3405,60)
Observations	7467	7463

Note: numbers in the table are the sample average of each variable, standard deviation is in brackets.

Until 1993, Italian municipalities followed a system of proportional representation with single ballot - a majoritarian system municipalities with less than 5,000 inhabitants - which resembled the electoral rules at the national level. People voted for local parties or lists and expressed a preference for councillors: both the mayor and the members of the cabinet were selected after the election by the council from its own ranks. The winning party obtained the four fifths of the seats, so to favour the development of a two-party system at local level (CARETTI, 1996).
This system was believed to be detrimental to good governance of municipalities, because in any moment a vote from the municipal council could bring the mayor's resignation and this happened rather frequently, as local interests were combined with national political tensions, generating a state of great discontentment. To overcome these impediments, on 25 March 1993 the Italian Parliament approved the electoral reform as Law 81, the *Law for the direct election of the mayors*.
Independently of the size of the municipality, the new electoral process envisaged that citizens vote directly for a mayor and that the mayor himself can designate and discharge the municipal government members, who can also be recruited from outside the council. The electoral rules variate according to the population size. Below the limit of 15,000 inhabitants, a single ballot applies so the candidate who achieves the relative majority is elected mayor. This system entails the possibility of a unique list to back up each candidate for the seat of mayor and the assignment of a considerable victory premium: the incumbent list gets two-thirds of the seats in the council, while the rest of the seats are distributed to the remaining lists according to a proportionality criterion.

At the threshold of 15,000 inhabitants the dual ballot applies: candidates can be supported

by more than one list and voters can separate their vote by choosing one mayoral candidate and a list associated with a different contestant (disjoint vote). Electors express a direct preference for the mayor or implicitly by voting for a party within the candidate's coalition. If no aspirant obtains the majority of votes, the top two candidates face a second round two weeks later. The City Council is elected concurrently: voters decide from a list of candidates and can express up to two preferences from the same list, provided they are selecting candidates of both genders. Seats are attributed proportionally to parties, and the candidates with the highest number of preferences are elected. The winning coalition is guaranteed a majority in the council with the attribution of extra seats.
For the purpose of our study, a municipality is defined as swing when, in the second electoral round, the margin of victory/loss is at most 5%.

1.4 Data

The final dataset is a combination of several sources: the open source data from the Ministry of Internal Affairs reports municipal budgets; the local and national electoral results, as well as personal informations on the mayor; socio-demographic variables from the Italian Statistical Institute (ISTAT). The sample includes yearly data on revenues and expenditures items, votes obtained and vote share, supporting party, birth town and some individual characteristics, for each elections and candidate, municipalities characteristics. The final sample consists of 6,705 *comuni* (out of the 8,109 existing in 2010) for the years 2007-2015. The special autonomous regions of Trentino-Alto Adige, Friuli-Venezia Giulia, Valle d'Aosta, Sicily and Sardinia are ruled out from the analysis, as they follow different accounting and electoral rules, and their municipalities are financed via different channels.

Our analysis take into account the so-called 'central government current transfers': entirely non discretionary, partially but not exclusively formula-based transfers; they constitute the amount of revenues coming from top layers of government. Transfers are divided into current and capital, the former reserved to cover basic running costs and the latter devoted to investments.

Table 2: Political alignment of mayors in all elections, 2007-2015

	All sample		**pop<15 000**		**pop>15 000**	
	N	%	N	%	N	%
CSX	5161	23.70	4147	20.695	1014	57.19
CDX	3357	15.41	2731	13.63	626	36.12
Lista Civica	13253	60.87	13160	65.67	93	5.36
Total	21 771		20 038		1 733	

The table above indicates that for large municipalities, only a small fraction of the winners, about 5%, could not be classified as left or right. However, in the case of small municipalities, the reverse is true, and most of the winners, around 66%, could not be classified. Our study of alignment effects requires accurate identification of the party type (left or right). For this reason,we do not include the small municipalities in our data-set.

Table 2 and 3 show the distributions of observations between aligned and non-aligned local governments and breaks down the figures by the margin of alignment, respectively

Table 3: Number of observations for which we can identify the political alignment before 2011, according to the winning margin

	Full Sample		**Wmg < 5%**		**Wmg < 2%**	
	pre	*post*	*pre*	*post*	*pre*	*post*
ALIGNED	2 597	2024	298	232	130	101
UNALIGNED	3 275	1567	362	174	141	67
TOTAL	5 872	3 591	660	406	271	168

before and after the exogenous shock. Overall we have almost 6000 observations, but, if we consider only elections close to treatment thresholds, namely with a value of Wmg less than either 5% and 2%, the number of observations reduces drastically; however the proportion of aligned and non-aligned municipalities remains virtually unchanged.

Looking at the average per capita data for the full sample we can see that comuni's current public expenditures amount to 665 Euros per capita, 20% of which is funded by grants from the central government. The figures for the restricted versions of the data set are similar. Looking at our main controls, the values of the standard deviations suggest that there is a lot of variation within each variable.

Table 4: Descriptive statistics by winning margin

	Full Sample	**Wmg < 5%**	**Wmg < 2%**
Central transfers p.c.	237.5	208.7	218.2
	(126.9)	(124.3)	(129.5)
Current expenditures	664.31	664.97	697.97
	(203.71)	(202.18)	(183.81)
Re-election probability of the same mayor	0.7896	0.6521	0.5010
	(0.4078)	(0.4797)	(0.5107)
Re-election probability of the same party	0.8028	0.6782	0.5294
	(0.3982)	(0.4699)	(0.5066)
Winning margin	21.82	2.53	1.02
	(14.96)	(1.47)	(0.54)
National alignment probability	0.4858	0.4944	0.5249
	(0.4990)	(0.5004)	(0.5005)
Population	55 292	76 601	48 489
	(151.946)	(273.192)	(68.768)
Income	33 851	33 873	33 590
	(3263)	(3409)	(3083)
Electoral cycle	1.84	1.84	1.77
	(1.37)	(1.38)	(1.37)

1.5 Estimation Strategy and Results

Since local elections occur every five years but they are not simultaneous for all the municipalities, we end up having elections occurring every year in our sample. The regression discontinuity design (RDD) model we propose uses political alignment between local and national government as our treatment variable. Then, the level of contestability of a municipality (SW), computed as the difference between the percentage of votes obtained by the winning mayor and the percentage of votes obtained by the runner-up, is the assignment variable. If mayors go through a second ballot, those results are used. We also control for a set of variables which are generally thought to affect local public finance outcomes (Carozzi and Repetto, 2016; Bracco et al., 2015): socio-demographic and geographical characteristics of municipalities (resident population, proportion of population less than 14 and over 65 years old, etc.) and we include municipal fixed effects in all specifications.

Regression discontinuity design is a valuable tool to distinguish between national politicians rewarding their core supporters, through the diversion of funds to cities with strong and supportive political structure at the party level (no matter if the mayor belongs to that party or not), and national politicians targeting municipalities ruled by their party. When the first situation appears, transfers are expected to increase as the vote share for the governing party increases, without any jump if a mayor belonging to that party is elected; on the contrary, in the latter case, the political affiliation of the winning mayor should have a great influence on the amount of transfers received by that municipality.

The regression discontinuity design used ensures that any change in transfers is politically motivated, as it is caused by political alignment between municipalities and central government. As the winning margin reduces, in fact, the electoral outcome can be seen as random.

1.5.1 *Close-race RDD*

As explained in the previous section, we compute the difference in the amount of transfers between municipalities where the elected mayor is politically aligned with those where the mayor is unaligned, when the mayor won the election with a narrow margin. The seminal paper Lee (2001, 2008) proves that when the electoral race is tight, the winning mayor is likely to be determined by pure chance. Thus, RDD can be implemented using several alternatives methods, both parametric and non- parametric(D. S. Lee and Lemieux (2010)). The most immediate approach confronts policy outcomes just around the treatment threshold when the sample size is large enough. Given the relatively small number of observations in our dataset, we prefer to use an alternative approach, based on the regression of the dependent variable on a pth-order polynomial in the control function, in addition to the binary treatment indicator (Bracco et al., 2015).

The close-race RDD model developed by Lee 2008 is particularly adapt to estimate the causal effect of political alignment on the amount of discretionary transfers. We define $\tau_{it}(1)$ as the transfers received by city i at time t when the mayor belongs to the same political party as the government, and $\tau_{it}(0)$ if the mayor is not aligned. Given P_{it} as a measure of political alignment, it is defined as

$$P_{i,t} = \begin{cases} 1, & \text{if municipality } i \text{ changed alignment (AU,UA)} \\ 0, & \text{otherwise (AA,UU)} \end{cases}$$

The observed outcome is $\tau_{it} = P_{it} \cdot \tau_{it}(1) + (1 - P_{it}) \cdot \tau_{it}(0)$, while the variable of interest is $ATE = E[\tau_{it}(1) - \tau_{it}(0)]$. The observed outcome is computed for each category of municipality, as defined by its alignment status (AA, UU, AU, UA). We then calculate the ATE, confronting respectively AU-AA and UA-UU municipalities (i.e. their alignment at $t-1$

was the same), as the difference between the amount of p.c. transfers in municipalities that changed their alignment and those for which it remained unchanged.

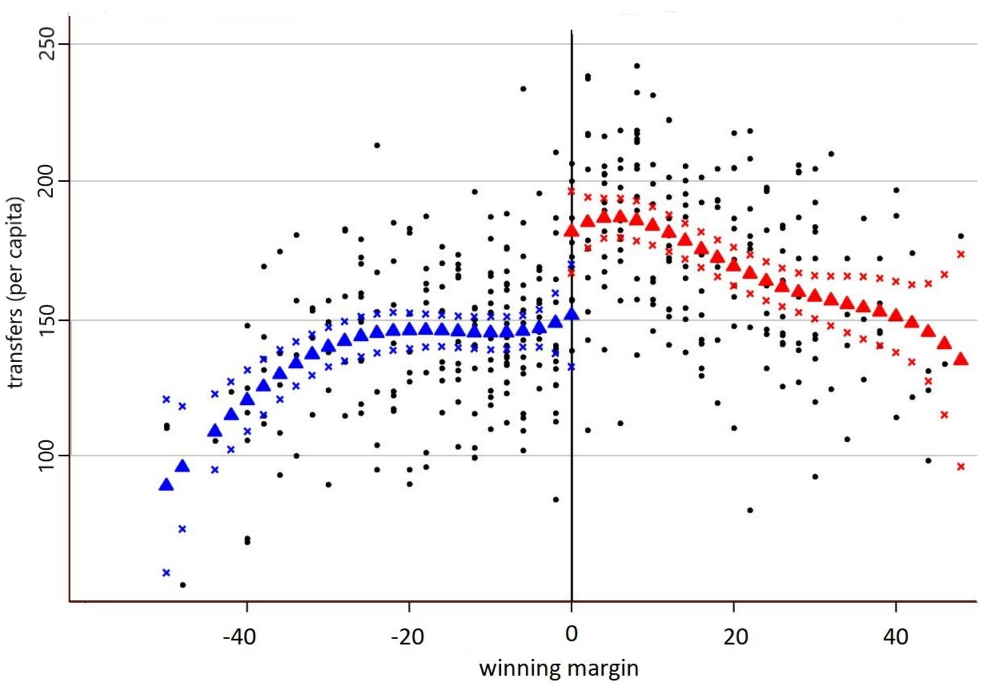
Define W_i as municipality covariates (including state fixed effects), X_{it} as individual characteristics of the mayor and δ_t as term fixed effects. The OLS model takes the form

$$\tau_{it} = \alpha + \pi P_{it} + W_i'\beta + X_{it}'\phi + \delta_t + year_t + \epsilon_{it}$$

the estimated $\hat{\pi}$ could provide a downward biased estimate of the ATE because of a self-selection into political alignment of towns with different unobservables that affect federal transfers.

Figure 2 gives the distribution of central transfers p.c. over the victory margin in the previous elections. The figures show a clear discontinuity in the allocation of transfers between aligned and unaligned municipalities at $Wmg = 0$. It also shows that grants tend to increase even away from the threshold.

Figure 3: Per capita central transfers



Note:The central line splits the polynomial function (triangles) in the margin of alignment fitted over the interval [-40, +40]. The crossed lines represent the 95% confidence intervals.

Table 5 reports the results related to the UA municipalities (compared to UU ones). The unexpected change in alignment that those municipalities experienced had a positive and significant impact on the amount of transfers they received the following year. The increase in grants is quite sizeable as it can be measured between 36% and 43%. The coefficient remain positive and significant for all the model specifications but when considering mayors elected in the second ballot, it shows higher volatility.

Table 5: Close-race RDD results (UA vs UU municipalities)

	OLS Full sample	OLS 2nd round	RDD Full sample	RDD 2nd round
alignment	0.435^{***}	0.275^{**}	0.364^{***}	0.612^{**}
	(0.515)	(0.8143)	(0.6973)	(1.2716)
population	0.138^{***}	0.112	0.134^{***}	0.09
	(0.7796)	(1.357)	(1.3913)	(2.6936)
income	1.257^{**}	1.023^{**}	1.005^{***}	0.998
	(0.0324)	(0.0218)	(0.0314)	(0.0523)
electoral cycle	2.351^{***}	1.601^{***}	2.142^{***}	1.347^{**}
	(0.219)	(0.147)	(0.195)	(0.157)
municipal and year FE	yes	yes	yes	yes
R-adj	0.645	0.532	0.447	0.593
Treated	1908	871	1872	837

Note: Significance at 1% is represented by ***, at 5% by ** and at 10% by *. Robust standard errors in brackets clustered at municipal level.

1.5.2 Second Stage Regression

We now want to investigate if the probability of the incumbent mayor being re-elected is affected by "politically driven" central transfers, i.e. that part of grants which is discretionarily assigned to municipalities, irrespective of the socio-economic criteria established by law. In order to do this, we estimate the following model:

$$Y_{i,e+1} = \gamma_1 \tau_{i,e} + \gamma_2 \hat{\epsilon}_{i,e} + \eta_{i,e}$$

Where our dependent variable is equal to one if the incumbent mayor is reelected or the winning mayor belongs to the same party as the winner in the previous election and the temporal unit is now election years (e). Our coefficient of interest γ_1 measures the difference between the probability of re-election of the aligned incumbent and the unaligned one, caused by the extra-transfers received. We include in the model the predicted error term, as computed in the first stage regression, in order to have γ_1 accounting exclusively for the effect of discretionary transfers on the local electoral outcome.

Table 7 shows the results for different model specification and for the two definitions of incumbency. Using the AIC (Table 6) the polynomial order that fits the data best is the second: our sample size drops to 359 observations if we consider the incumbent party and 210 for the incumbent candidate. The estimated coefficients for the incumbent effect are between 0.20 and 0.30 (without and with controls), meaning that having received higher transfers from the central government in politically aligned municipalities, strongly increases the incumbent advantage at the time of local elections. Results are robust to the inclusion of controls and fixed effects.

Table 6: AIC for incumbent regression

polynomial order	incumbent party	incumbent candidate
0	598.623	59.605
1	599.451	59.576
2	<u>596.785</u>	<u>58.333</u>
3	598.011	59.231
4	599.192	60.035

Table 7: Local Linear Regression results

	Incumbent Party			*Obs*	Incumbent Candidate			*Obs*
Linear Regression	0.0391	0.153**	0.142***	764	0.156***	0.107***	0.119***	650
	(0.0286)	(0.0378)	(0.173)		(0.127)	(0.085)	(0.157)	
Second order polynomial	0.219	0.301***	0.259***	359	0.267***	0.212***	0.147*	210
	(0.141)	(0.091)	(0.315)		(0.120)	(0.084)	(0.168)	
Local Linear Regression (h)	0.648**	0.621		32	0.512*	0.107		25
	(0.397)	(0.366)			(0.238)	(0.096)		
Local Linear Regression (h/2)	0.759**	0.788		19	0.613	0.667		17
	(0.286)	(0.367)			(0.016)	(0.074)		
Local Linear Regression (2h)	0.523***	0.631		53	0.508*	0.202		35
	(0.219)	(0.147)			(0.0523)	(0.0343)		
Controls	no	yes	yes		no	yes	yes	
FE	no	no	yes		no	no	yes	

Note: The sample included all municipal elections where the winner and the runner up belong to the center–left and centre–right coalition. Optimally chosen bandwidth (h) in local linear regressions is+/2.5%. Significance at 1% is represented by ***, at 5% by ** and at 10% by *. Robust standard errors in brackets clustered at municipal level.

The table is divided into two sections: we display results for the municipalities in which in the electoral race, the new mayor belong to the same party that was previously ruling the city or it is the incumbent mayor winning the second mandate. The linear regression model results reported in the table corresponds to the case of zero-order polynomial in the control function. Then, we consider the optimal polynomial order in the control function. Finally, i we report the results for the local linear regression model,where the sample is restricted to observations within an optimally chosen bandwidth, calculated following G. Imbens and Kalyanaraman (2012). We check for the robustness of our results restricting the sample to double and half the optimal bandwidth size. For each model specification we run the regressions with and without additional controls and municipality fixed effects.

1.6 Conclusions

This paper explores the effect of political alignment on local public finance and local electoral outcomes. Consistently with the existing literature, we predict that aligned municipalities are assigned more grants by the central government, thus increasing the probability of their re-election.

We test these predictions using a new data set on Italian local budgets and elections in 2007–2015 period and we propose a new model specification to account for the endogeneity issue arising when estimating the causal impact of political alignment on transfers: the unpredicted change in the government occurred in 2011 after the resignation of Silvio Berlusconi and the following appointment of Mario Monti as prime minister. We implement close-race regression discontinuity design (RDD), as being aligned with the central government changes discontinuously at 50% of the votes in local elections and then we move to Local Linear Regression to assess the effectiveness of extra-transfers in attracting votes.

We find that political alignment with the governing party increases grants between 36% and 43% and that the reelection probability of aligned incumbents is around 20%-30% higher, maybe due to a strategic use of extra-transfers.

Results from the first work are significant for the design of grants allocation. As our empirical analysis demonstrated, when local governments have effective power in the provision of local public goods, it emerges a trade-off between the arbitrariness in central transfers allocation and the regulating role of elections. Hence, when grants are not formula-based and citizens hold the mayor responsible for local public goods supply, then the central government might divert resources toward aligned municipalities for attracting voters, therefore leading to resource misallocation.

Chapter 2

Can Machines Learn Creativity Needs?[1]

″ Computers are able to see, hear and learn.
Welcome to the future.″
- Dave Waters

2.1 Introduction

Since the early 2000s, technological progress has been associated to a crowding-out of cognitive-skill intensive jobs in favour of jobs requiring soft skills, such as social intelligence, flexibility and creativity (Acemoglu and D. Autor, 2011). The growth of occupations characterized by cognitive tasks has been sluggish both in terms of employment and wages (Acemoglu and Autor, 2011; Beaudry, D. A. Green, and Sand, 2016; Deming, 2017). Moreover, the returns to cognitive skills have not risen (Castex and Kogan Dechter, 2014).

Some authors suggest that this phenomenon could be ascribed to a progressive extension of the perimeter of the tasks at risk of automation toward those traditionally performed by high-skill workers (F. Levy and Murnane, 2012; Brynjolfsson and McAfee, 2014; Remus and F. S. Levy, 2016; D. H. Autor, 2014). Indeed, Deming (2017) shows that it is especially the decrease in Science, Technology, Engineering and Mathematics (STEM) jobs, requiring high technical abilities but low social interactions, which has determined the shrinking of high-skill/cognitive share of employment and wage bill. Instead, the cognitive occupations that have fared much better are those involving complex human interaction skills (communication, collaboration, teamwork, flexibility, creativity, etc.).

Those "social skills" are also referred to as "soft skills" or "non-cognitive skills" (Deming, 2017). Soft skills can be defined as interpersonal, human, people or behavioural skills necessary for applying technical skills and knowledge in the workplace (Rainsbury et al., 2002). Soft skills are a new way to describe a set of abilities or talents that an individual can bring to the workplace. Some authors describe soft skills as *"micro social" skills* and categorize them as: *1) intrapersonal and interpersonal skills; 2) personal and social skills; and 3) cognitive skills* (Muzio et al., 2007). The differences between hard and soft skills can be summarized as follows: 1) the majority of people differentiate hard (work with equipment or software) and soft skills (interpersonal or intrapersonal focus) with ease; 2) there is a considerable difference in learning for hard and soft skills; 3) most positions in an organization require not

[1] This chapter is a joint work with my supervisor Prof. Massimo Riccaboni and Prof. Giorgio Gnecco.

only the possession of hard skills for successful execution of work tasks, but also proficiency in the soft skills area (Laker and Powell, 2011).

This change of paradigm toward forms of organization of work characterized by an increased importance of social interactions skills has been noticed across industries and occupations. Bessen et al. (2020) shows that the adoption of automation technologies extends beyond manufacturing firms while Katz and Margo (2014) suggest that the capability of combining the possibilities offered by automation and Information and Communication Technologies (ICTs) for product customization with creativity and communication skills in the relationship with customers is the key factor to explain and sustain the revival of artisanal jobs observed in the United States.

The rapidity and pervasiveness with which economic and organizational changes occur determine an increasing need in reading promptly and efficiently the evolutionary dynamics of all skills in general and soft skills in particular. Indeed, the nature of the soft skills make them hardly replaceable by machine work, because they are a sort of tacit knowledge that human beings apply spontaneously and even unconsciously, built generation after generation, and not codifiable in "closed-form solutions". Instead, cognitive tasks, though complex, are often much easier to codify.

Among soft skills, creativity is assuming increasing importance in shaping the future of employment. Easton and Djumalieva (2018) find that there is a strong demand for creativity in the online advertising job market and, following the work by Bakhshi and Windsor (2015), they are able to claim that creativity itself is consistently the most significant predictor for an occupation's chance of growing, as a percentage of the workforce, by the year 2030. A global study by Adobe, run in 2016, found that businesses which invest in creativity report an increase in employee productivity (78%) and customer satisfaction (80%).

As the European Union recently stated in the *Entrepreneurship Competence Framework*, creativity is a soft skill with a strong strategic components that goes together with other skills such as learning, innovation, project management, proactivity and adaptability, hence the focus on these allow us to reflect upon the possibilities that workers have to be an active part inside firms. Creativity is, in fact, a pillar of the varied concept of entrepreneurship and it represents one of the 15 competences that articulates the entrepreneurship framework (Bacigalupo et al. 2016).

According to the empirical findings of European Working Condition Surveys (EWCS, 2005; 2015), every second workplace involves a form of 'creative work,' which is less threatened by automation, while every fourth worker carries out 'routine' tasks that will be easily replaced by computers.

In this paper, we exploit similarities in the Italian occupational structure and implement matrix completion – a recently developed machine learning technique which is often used by recommender systems – in order to predict the levels of creative soft skills employed in each occupation and to identify peculiarities of such occupations and such skills. For the purpose of our analysis, we describe creativity along four dimensions and we identify in our data 25 skills associated with creativity. We then formulate a matrix completion optimization problem for creativity levels prediction and we solve it through the soft impute algorithm. In more details, we apply matrix completion to identify a counterfactual value for creative skills across professions. Then we get from the results of our analysis that such counterfactual value is typically in good agreement with the actual level of skills associated with creativity. Finally, for some professions, the observed level deviates positively/negatively from the counterfactual, hence such professions are associated with a surplus/deficit in the creativity level.

To the best of the authors' knowledge, this is the first article in which matrix completion is applied to analyze workers' skills in a whole economy. Our analysis shows that: a) matrix completion demonstrates an excellent prediction capability on the specific dataset, making it meaningful to analyze cases for which the actual creativity level is significantly larger/smaller than the predicted one. Indeed, given the extremely good fit typically obtained, a large error in the prediction of a creativity level for a specific profession may be imputed to peculiarities of that profession, which make it less similar to other professions in the dataset and, as a consequence, more/less "hungry" of creative skills with respect to those professions; b) soft skills associated with creativity are not neatly separated among intellectual and technical workers; c) some professions show a surplus of creativity with respect to its level predicted by their counterfactuals. In this case, their risk of being replaced by machines is deemed to be low; d) on the other hand, we get a deficit of creativity level for other professions. In this case, the risk for such professions of being replaced by artificial intelligence techniques is larger. To reduce this risk, training on creative soft skills might be tailored on these specific professions.

The paper is structured as follows. Section 2 reports a review of related literature. Section 3 describes the dataset used in our analysis. Section 4 summarizes the machine learning approach adopted in the work (more technical details about it are reported in the Appendix). Section 5 provides the main results of the analysis. Section 6 concludes the article with a discussion.

2.2 Related literature

Our work builds on four main streams of existing literature dealing with the relationship between ICT and soft skills, skill relatedness, creativity and matrix completion.

Numerous theoretical and empirical studies investigate the effect of technological progress on jobs, paying particular attention to the growth in importance of social skills in the labour market as an increased interest in social interactions skills has been noticed across all industries and occupations. The diffusion of ICT, and more broadly of "digital technologies", has in fact led to in-depth transformations in the organizational features of firms, industries, production processes, consumption models and labour activities. In the seminal paper by D. H. Autor, F. Levy, and Murnane (2003) the authors claim that digitalization increases the possibility of automating tasks, when tasks are characterized by a high degree of routineness, due to the fact that routine tasks are typically more easily codified (with respect to non-routine tasks).

On a similar trend, Domini et al. (2021) finds that automation spikes are related to increase in firms' contemporaneous net employment growth rate, jointly explained by a higher hiring rate and a lower separation rate, while Harrigan, Reshef, and Toubal (2016) highlights how automation polarized French labor market in France has polarized and this polarization was driven mostly by changes in the composition of firms within industries, specifically they find that techies technology-related occupations were an important force driving aggregate polarization in France, as firms with more techies grew faster.

Skills acquired in one industry can often be used in others. Given the pivotal role of human capital in a firm's strategic asset stocks, a firm will likely focus its diversification efforts in areas that require skills already possessed by its current workforce. In their pioneering work, Neffke and Henning (2013) propose to quantify the similarity of different industries' human capital or skill requirements, that is, the industries' skill relatedness, by using information on cross-industry labor flows. They show that firms are far more likely to diversify into industries that have ties to the firms' core activities in terms of some skill-relatedness measure than into industries without such ties.

Teamwork and creativity require a set of abilities that have been defined as communication and mutual understanding of each other's preferences, motivations and comparative advantages, an ability that has been defined within the theory of mind (Premack and Woodruff, 1978; Baron-Cohen, Tager-Flusberg, and Cohen, 2000). From the work by Autor et al. (2003), tasks requiring creativity have been considered problematic to computerize. Recombining existing features to create new ideas is easily automatable, but recognizing whether these new combinations make sense and are valuable requires encoding an objective set of creative values (Frigotto and Riccaboni, 2011). Indeed, Frey and M. Osborne (2013) and Bakhshi and Windsor (2015) suggest that the creative process is hard to codify and, therefore, that creativity-intensive occupations have been shielded from automation.

The centrality of creativity as the engine of social and scientific progress is witnessed by the plethora of research efforts aimed at understanding its origin and nature. Researchers have taken several approaches to understanding creativity. These approaches include explanations of creativity from the views of mysticism, pragmatism, pyschodynamics, psychometrics, cognition, socio-personality, and a confluence of several factors (R. J. Sternberg, 1999). These different perspectives have provided valuable insights to creativity, but they are also seen as having hindered serious psychological research on the topic. The diffused focus has also limited conceptual agreement on what creativity is. Over the years, creativity has been described as a process, product or personal trait. Some see creativity as a staged process (Amabile, 1983; Basadur, Graen, and S. G. Green, 1982) or a cognitive process of producing divergent ideas (De Bono and Zimbalist, 1970).

The literature review conducted by (Walia, 2019) shows that there seems to be a general agreement among scholars about the fact that creativity involves the production of novel and useful ideas and products (Mumford, 2003). Runco and Jaeger (2012) suggested that the standard definition of creativity (which requires elements of originality and effectiveness) has a long history. Hennessey (2010) argued that the need to implement a creative idea is where the process of innovation takes over. Most of modern day research hinges on novelty and usefulness of ideas as the benchmark of creativity (Mumford, 2003). Novelty refers to originality, that is, the production of something new, and usefulness refers to the appropriateness of an idea in solving the considered problem (see Amabile and Pratt, 2016; Hennessey, 2010). Some definitional proposals of creativity include additional criteria, that is, high quality (R. J. Sternberg and Lubart, 1995), contrast with conformity (Niu and R. Sternberg, 2002), surprise (Boden, 2004), non-obviousness (Simonton, 2012), aestheticism and authenticity (Kharkhurin, 2014).

A possible analytical definition of creativity comes from the seminal work of Edward De Bono and Efrem Zimbalist (De Bono and Zimbalist, 1970). The authors define lateral thinking as a set of processes that provide a deliberate, systematic way of thinking creatively, which results in innovative thinking in a repeatable manner. According to their pioneering research in the field, lateral thinking is strictly related to creativity and it can be described along four dimensions: 1) fluidity, as the ability of a subject to give the highest possible number of answers to a certain question; 2) flexibility, as the number of categories to which one can bring back these questions; 3) originality, as the ability of expressing new and innovative ideas; 4) processing, as the ability of realizing concretely one's ideas. Following this path, many researchers defined creativity as a strategic soft skill, which allows workers to find result-oriented solutions to open problems (Tucciarelli, 2014). Therefore, creativity goes hand in hand wth other competences such as learning, innovation, project management, proactivity and adaptability to change.

We draw upon the work Frey and M. A. Osborne (2017), in which they examine how susceptible jobs are to computerisation, estimating the probability of computerisation for 702 detailed occupations, using a Gaussian process classifier. Their findings imply that as technology races ahead, low-skill workers will reallocate to tasks that are non-susceptible to computerisation – i.e., tasks requiring creative and social intelligence. For workers to win the race, however, they will have to acquire creative and social skills.

In the work, creativity levels of different professions are analyzed based on a recently developed machine learning technique, which is called matrix completion (Hastie et al., 2015). This technique is often used by recommender systems to infer users' preferences, then suggest items to them, based on the inferred preferences. In the present context of the analysis of professions, it has to be mentioned that recommender systems are applied, e.g., for job recommendation (Al-Otaibi and Ykhlef, 2012). In the economic context, matrix completion can be exploited, e.g., to construct synthetic controls, for their possible successive use in counterfactual analysis (Athey et al., 2021). Another possible application is in recommender systems for education. Variations of matrix completion have been also developed in the literature to discover relationships among different databases, assuming that each of them is modeled by a matrix (Klami, Bouchard, and Tripathi, 2013). In the present work, matrix completion is applied for two purposes: in order to assess its prediction capability of the creativity needs of different professions, and with the aim of generating counterfactuals. It has to be remarked, indeed, that in the context of job market analysis, matrix completion has not been applied yet to define theoretical counterfactuals of expected intensity levels of skills' use. Such counterfactuals can be useful, e.g., to identify specific variations in the creativity levels needed for the various professions.

2.3 Data

ICP (*Indagine Campionaria sulle Professioni*, which can be translated into English as *Sample Survey on Professions*) is a survey on workers, promoted by the Italian National Institute of Statistics (ISTAT) and the National Institute for Public Policies Analysis (INAPP). It was last run in 2013 by INAPP on about 16.000 Italian workers in around 800 occupations, according to the 5-digit CP2011 classification (the Italian equivalent of the ISCO-08 ILO's classification)[2]. The sample is stratified so to ensure the representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). The ICP investigates the characteristics of the occupations through a particularly rich and articulated questionnaire structured in six main sections, expressions of a content model that simultaneously provides information from both a job-oriented and a worker-oriented perspective: worker characteristics (enduring abilities and work style of workers), worker requirements (skills and education), occupational requirements (organisational and work context), experience requirements (training, cross functional skills), workforce characteristics (labour market information) and occupation-specifi c information (generalised activities and work context).

[2]The International Standard Classification of Occupations (ISCO) is an International Labour Organization (ILO) classification structure for organizing information on labour and jobs. ISCO is defined by ILO itself as a tool for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in each job. The updated classification was adopted in December 2007 and is known as ISCO-08.

In so doing, descriptors are formulated by making it possible to distinguish, for instance, inner individual abilities from competences acquired on the job. For each question, two rating scales are generally provided: level and importance.

Information in the survey is reported by entrepreneurs and Human Resources (HR) responsibles. Respondents are asked to report skill needs of their employed workforce to be satisfied in the short run. Future trends and new training needs are mainly related to competences and soft skills.

The ICP directly asks workers, rather than experts, to answer the questionnaire in order to focus on the point of view of those who exercise daily occupational activities under consideration and have a direct and concrete assessment of the level of use of certain characteristics essential to carry out one's job (Barbieri, Basso, and Scicchitano, 2020).

The ICP follows the Classification of Occupations (CP2011) produced by ISTAT in 2011 and, along this line, it divides jobs into eight major groups:

1. Legislators, managers and senior officials;
2. Intellectual, scientific and highly specialized professionals;
3. Technicians and associate professionals;
4. Clerical support workers;
5. Service and sales workers;
6. Artisans, specialized and agricultural workers;
7. Plant and machine operators and assemblers;
8. Elementary occupations.

The table below reports some descriptive statistics of our final sample, the occupational matrix of 2013, where the rows are the 800 professional units and columns are the level and intensity in the use of soft skills, as declared when answering the questionnaire.

Table 8: Descriptive statistics of the occupational matrix

Variables	% of the full sample
Age 15-34	22%
Age 35-49	39%
Age $\geq$ 50	38%
Female	42%
Services	37%
Manufacture	19%
Healthcare	7%
Cultural Industry	6%

Given the large availability of information included in the ICP, we decided to consider in our successive analysis not only skills, but also those variables that refer to working attitudes and styles as well as generalized work activities. We ended up identifying 25 items associated with creativity, as highlighted in Table 8, that better fit the 4-dimension definition of creativity given by (De Bono and Zimbalist, 1970). Our resulting occupation matrix, coming from the ICP survey, is given by $m = 796$ rows which refer to professional units and $n = 255$ columns, of which 55 denote skills (25 directly associated with creativity, and the other 30 not directly associated with it), whereas the other 200 columns refer to competences, working conditions, and working styles. Each entry in position (i, j) represents the intensity level (expressed as a percentage) in the use of skill/competence/working condition/working style j by worker type i. The 25 columns associated with the creative skills, on which our successive analysis is focused, form a subset J of columns of our occupation matrix.

Table 9: Soft skills associated to creativity in the ICP dataset

Indicators	Skills	ICP items	Acronym
Fluidity - Flexibility	Solving complex problems	C17A	COMPL
	Solving unexpected problems	C27A	UNEX
	Listening actively	C2A	LIST
	Adaptability	F10	AD
	Service orientation	C16A	SERV
	Classification	D11A	CLASS
	Comprehension	D16A	COMPR
Originality - Processing	Critical sense	C7A	CRIT
	Analytical skills	C18A	ANSK
	Decision making	C31A	DMAK
	Originality	D6A	OR
	Production of ideas	D5A	IDEAS
Learning - Innovation	Learning strategies	C9A	LEAST
	Active learning	C8A	ALEARN
	Teaching	C15A	TEACH
	Creative thinking	G11A	CREAT
	Innovation	F15	INN
Planning - Proactivity	Persuading	C13A	PERS
	Understanding others	C11A	UNDOTH
	Negotiating	C14A	NEG
	Time management	C32A	TIME
	Financial resources management	C33A	FRM
	Material resources management	C34A	MRM
	Human resources management	C35A	HRM
	Coordination with others	C12A	COORD

2.4 Matrix completion

In the following, we apply Matrix Completion (MC) to predict intensity levels of use of skills associated with creativity (or, shortly, creativity levels) for the various professions in our occupation matrix, exploiting the similarity patterns detected automatically by that machine learning technique from its application to the specific dataset.

MC can be defined as the task of filling in the missing entries of a partially observed matrix (Recht, 2011). One well-known example of such a matrix is the rating matrix in a recommender system representing users' tastes on products (e.g., movies). Given a rating matrix in which each entry in position (i, j) represents the rating of movie j by customer i, if customer i has watched movie j and is otherwise missing, one would like to predict the remaining entries in order to make good recommendations to customers on which movie to watch next. In order to do that, one exploits similarities between users (rows) and between products (columns), as one expects that users assigning the same or similar ratings on different products will share similar interests on new products, resulting in the low rank structure of the rating matrix.

In order to apply MC to our occupation matrix, we generate artificially partially observed matrices from it, by obscuring randomly 10%, 25% and 50% of the entries in the columns associated with the creative skills, focusing each time on the prediction capability of matrix completion on each single row (occupation). The procedure is repeated several times (details are in the Appendix).

In summary, we consider the following nuclear-norm regularized MC optimization problem:

$$\underset{\mathbf{Z}\in\mathbb{R}^{m\times n}}{\text{minimize}} \left(\frac{1}{2} \sum_{(i,j)\in\Omega^{\text{tr}}} (M_{i,j} - Z_{i,j})^2 + \lambda \|\mathbf{Z}\|_* \right), \tag{2.1}$$

where Ω^{tr} is a training set of positions (i, j) corresponding to the known entries of the partially observed matrix $\mathbf{M} \in \mathbb{R}^{m\times n}$, $\mathbf{Z} \in \mathbb{R}^{m\times n}$ is the completed matrix, $\|\mathbf{Z}\|_*$ is its nuclear norm, and $\lambda \geq 0$ is a regularization constant. Then, we solve it by applying the Soft Impute algorithm (Mazumder, Hastie, and Tibshirani, 2010). This is proved therein to converge to an optimal solution of the optimization problem (3.1). The optimization problem itself is solved by the Soft Impute algorithm several times, for different choices of the set of obscured entries. For each such repetition, the best value of λ is found by minimizing a suitable error on a validation subset of missing entries, whereas the final performance is evaluated on the remaining test set of other missing entries. Technical details about problem (3.1) and the specific algorithm used to solve it and to choose its regularization parameter are reported in the Appendix.

As a preliminary check for the applicability of MC, we compute the singular value decomposition of our occupation matrix. Figure 4 shows that its singular values decay quite fast to 0. As reported in the Appendix, this is a necessary condition for an effective application of MC, which is satisfied by the dataset under analysis.

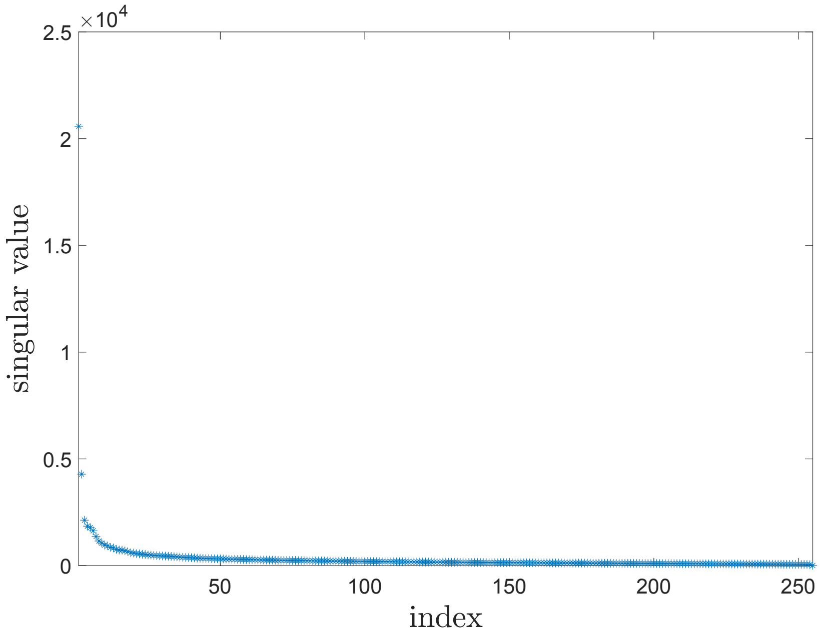


Figure 4: Distribution of the singular values of the occupation matrix considered in the analysis

In order to better illustrate the approach used in our analysis, we consider a specific instance of the optimization problem (3.1), then we visualize its results. Figure 5 shows the original matrix, the locations of the observed and the missing entries in the original matrix (where the green cells denote the elements in the training set, the blue cells refer to the validation set and the red ones are related to the test set), the reconstructed matrix, and the error in absolute value for each cell. As the second subfigure shows, all the obscured entries are at the intersection between specific rows (one of which is associated with the test set) and the set of columns associated with creativity.

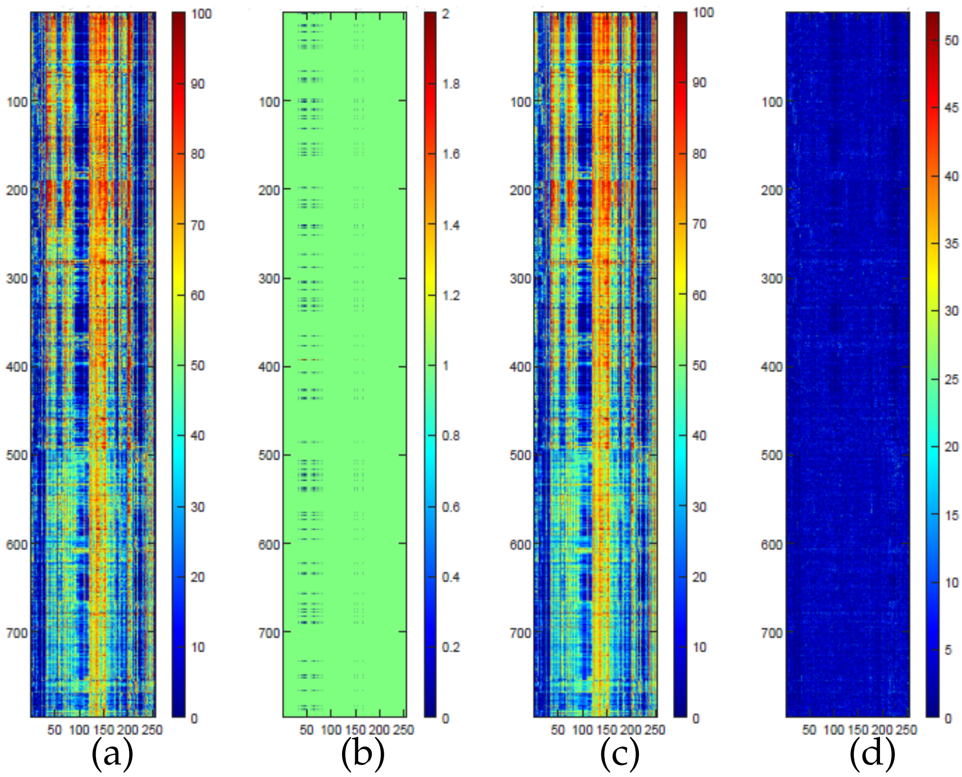
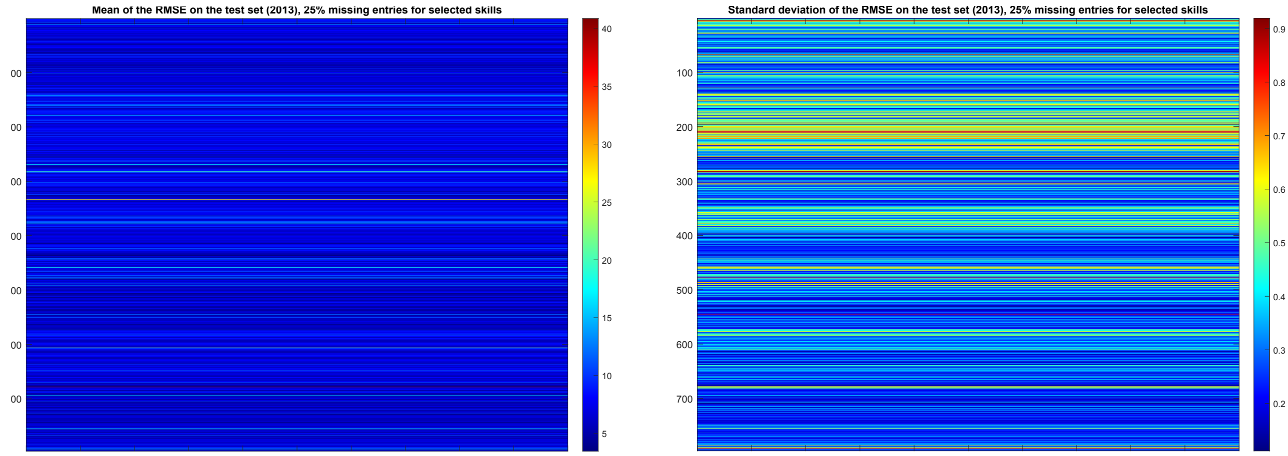


Figure 5: Visual representation of (a) the original matrix, (b) the locations of its observed (green) and missing entries (blue: validation; red: test), (c) the reconstructed matrix for a specific repetition, and (d) the absolute value of the prediction error for the same repetition

Then, Figure 6 presents a visual representation of the mean and standard deviation of the Root Mean Square Error (RMSE) of MC prediction on the test set (see the Appendix for details on its definition), where each row (profession) refers to the mean and standard deviation computed with respect to the repetitions having as test set elements belonging only to that specific row of the original matrix. As the figure shows, both the mean and standard deviation are typically small (taking into account that the entries of the original matrix are numbers between 0 and 100).



(a) (b)

Figure 6: (a) Mean and (b) standard deviation of the RMSE of prediction on the test set for a specific choice of the percentage of missing entries in the columns associated with creativity

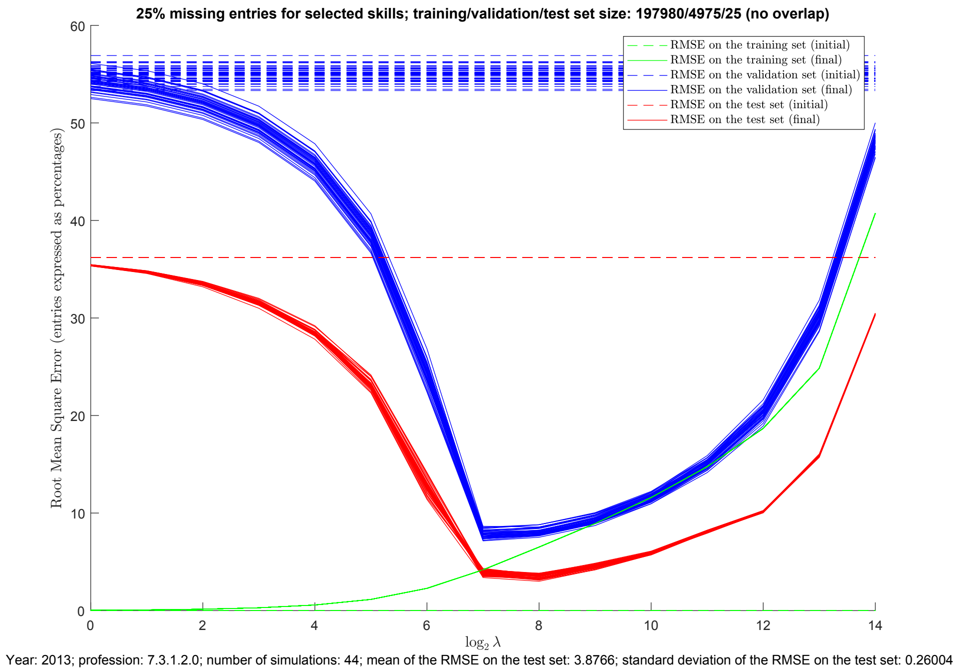


Figure 7: RMSE of prediction on the training, validation and test sets as functions of the regularization parameter λ, for all the repetitions associated with the same test related to a specific profession

Figure 7 reports more detailed results for all the repetitions for which the elements of the test set refer to a specific profession. In particular, the figure shows how the RMSE of MC prediction (evaluated, respectively, on the training set, validation set, and test set) changes as a function of the regularization parameter λ. As the figure reveals, the optimal value of λ (which is computed based on the RMSE of MC prediction on the validation set) is associated with a quite small RMSE of MC prediction for both the validation and test sets. Moreover, for each of the two cases, the variability of the RMSE curve with respect to changing the training set (i.e., performing another repetition of the analysis, for the same choice of the test set) is very small, whereas the variability of the RMSE curve of MC prediction for the training set itself is negligible.

It is worth mentioning that, for the specific case reported in Figure 7, the performance of the method on the test set is slightly better than the one on the validation set. This is likely due to the fact that the elements of the two sets are sampled from different portions of the occupation matrix. Moreover, the test set has much smaller cardinality (since its elements come from a specific row of the occupation matrix). In any case, the behaviour of the RMSE curve as a function of the regularization parameter λ is similar for both sets, being also the minima of these two curves achieved for almost the same values of λ.

Finally, Figure 8 reports, for each of the three percentages of missing values in the 25 selected columns, the boxplots of MRE_i for 4 subsets of professions i. Such subsets correspond to the 4 quartiles of the average true value $\frac{1}{25}\sum_{j\in J} true_{i,j}$, where the average is limited to the 25 skills directly associated with creativity. The figure clearly shows that the surplus tends to be larger for the professions with a larger average true value of creative skill levels. This holds for each of the three percentages of missing values.

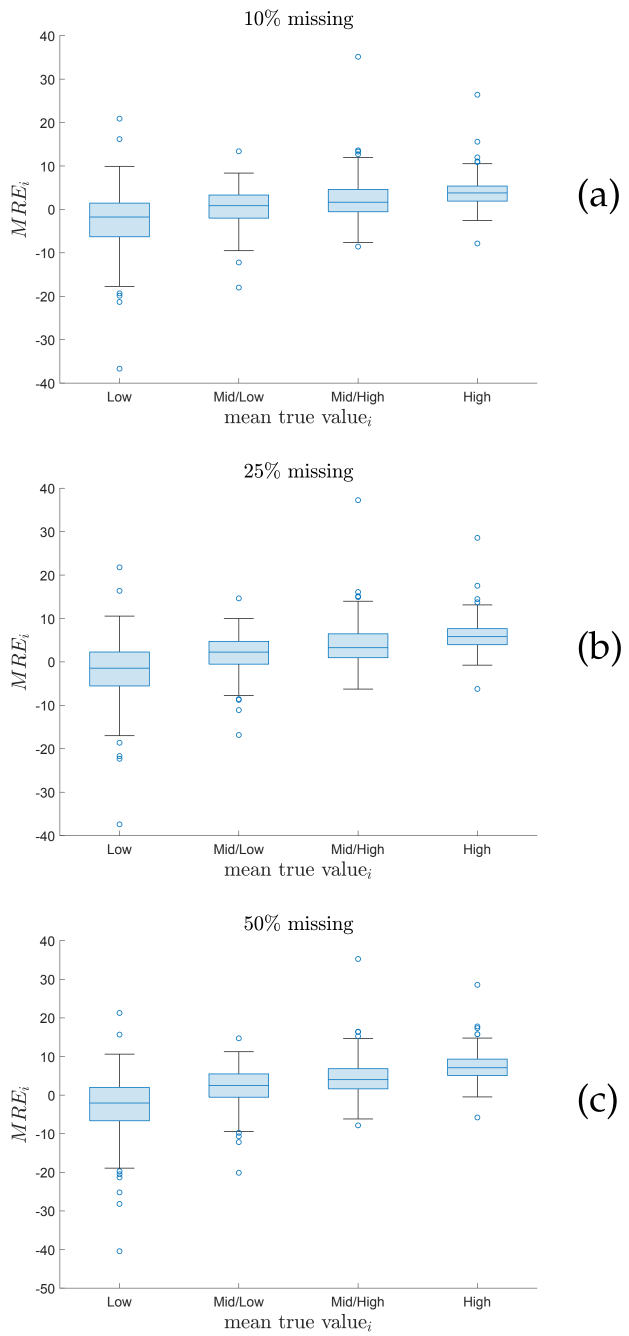


Figure 8: Boxplots of MRE_i for 4 subsets of professions i corresponding to the 4 quartiles of the average true value $\frac{1}{25}\sum_{\in J} true_{i,j}$ of the skill levels, for the skills directly associated with creativity: (a) 10% missing values in the selected columns; (b) 25% missing in the selected columns; (c) 50% missing in the selected columns

2.5 Results

For each profession i, we predict (via the MC estimate $predicted_{i,j,r}$) the missing entry $true_{i,j}$ of each creative skill j (for $j \in J$) in each repetition r belonging to the set of r_i repetitions in which such elements of row i are in the test set. Then, we compute the associated Mean

Relative Error, defined as follows (and expressed as a percentage):

$$MRE_i = \frac{1}{r_i}\sum_{r=1}^{r_i}\left[\frac{\sum_{j\in J}(true_{i,j} - predicted_{i,j,r})}{\sum_{j\in J} true_{i,j}}\right] \times 100 \quad (2.2)$$

To avoid burdening the notation, the dependence on the percentage of missing elements in the 25 selected columns is not reported in equation (3.2). We say that for a specific profession i there is a surplus (deficit) of creativity when $MRE_i > 0$ (when $MRE_i < 0$).
What we find (see Figure 11 for the histograms of the MRE_i in the three cases) is that around 65% of occupations deviate positively (i.e., they have positive MRE_i). Moreover, deviations are concentrated in the interval (-1%,+5%). For instance, in the case of 10% missing entries associated with creativity, about 52% of the observations of the MRE_i fall in this interval, meaning that the prediction error is typically very small (see also Table 10 for summary statistics, and Table 16 for results at the level of each major group).

Table 10: Summary statistics for the distribution of MRE_i in the full dataset of professions, for different percentages of missing entries in the columns associated to creativity

	10% missing		**25% missing**		**50% missing**	
	# professions	%	**# professions**	%	**# professions**	%
$MRE_i > 5\%$	151	18,94	265	33,24	315	39,52
$MRE_i \in [-1\%; +5\%]$	419	52,57	367	46,04	308	38,64
$MRE_i < -1\%$	227	28,48	165	20,70	174	21,83
Total	797	100	797	100	797	100

Referring to the list reported in Section 4, the professional groups experiencing most of the positive deviations are: the second (intellectual, scientific, highly specialized professions), the third (technical professions), the sixth (artisans, specialized workers, agriculturalists) and the seventh (plant operators, machinery workers, drivers of vehicles), while the main skills explaining these results (i.e., which contribute to the summation in equation (3.2) with the largest positive terms) are: listening, human resources management and creative thinking.

The remaining professions whose predictions deviate negatively are mostly in the first (legislators, entrepreneurs, senior management), third (technical professions), sixth (artisans, specialized workers, agriculturalists), seventh (plant operators, machinery workers, drivers of vehicles) group, while the associated skills that motivate the negative differences are analytical skills and solving unexpected problems.

In summary, there is a need of reinforcing competences such as solving unexpected problems, listening actively, critical sense, adaptability and service orientation concerns transversely all the professional groups, including technicians and associate professionals as well as service and sales workers, artisans, specialized workers and agriculturalists and, to a smaller extent, plant and machine operators and assemblers.

The most intense skill upgrading needs are observed in the high-tech manufacture sector (chemical and pharmaceutical, electronic, energetic, engineering industry) but they are

Table 11: Distribution of MRE_i in the interval $[-1\%; +5\%]$ by major group, for different percentages of missing entries in the columns associated to creativity. The total number of professions for each major group is also reported in the table

Major groups Professions with MRE_i in $[-1\%; +5\%]$	**10% missing** % professions	**25% missing** % professions	**50% missing** % professions	**Observations** total # professions
1. Legislators, managers and senior officials	62,31	48,52	36,76	68
2. Intellectual, scientific and highly specialized professionals	68	48,57	37,14	175
3. Technicians and associate professionals	53,14	48,75	45	160
4. Clerical support workers	30	33,34	36,67	30
5. Service and sales workers	39,68	38,09	30,16	63
6.Artisans, specialized and agricultural workers	44,70	45,88	39,41	170
7. Plant and machine operators and assemblers	47,57	48,54	41,74	103
8. Elementary occupations	32,14	32,14	21,43	28

quite relevant also in the service sector when related to education, health, communication, financial activities and other services.

To address the issue above in more details, in Table 17 we report 4 professions for each major group whose MRE_i is among the largest in absolute value, and the relative skills in which they deviate the most, both positively and negatively.

Table 12: Professions, means of the observed values of creative soft skills, MRE_i (in the case of 10% missing observations in the selected columns) and skills which contribute most to the positive/negative deviation

Professions	**Mean true values**	MRE_i **10%**	**Largest pos. dev. skills**	**Largest neg. dev. skills**
Police chiefs	82.52	7.15	ANSK, INN, CREAT	LEAST, UNDOTH, UNEX
PA managers	79.20	8.21	AD, DES	NEG, SERV, UNEX
Firm managers (manufacture)	55.05	-3.16	SERV, MRM, DES	CRIT, NEG, DMAK
Firm managers (building)	59	-1.82	SERV, ANSK, CREAT	LEAST, FRM, HRM
Cartographers	46.05	-6.16	UNDOTH, PERS, SERV	ANSK, CLASS, INN
Dietologists	57.80	-6.17	CRIT, UNDOTH, NEG	PERS, TEACH, DES
Lawyers	62.05	11.04	ANSK, SERV, CREAT	PERS, NEG, DMAK
Dialogists	51.87	11.29	PERS, FRM, HRM	AD, INN, CREAT
IT Technicians	63	26.40	CRIT, TIME, HRM	LIST, LEAST, UNDOTH
Interviewers	16.50	-36.67	CRIT, AD, SERV	LIST, TIME, AD
Athletes	29	-15.22	MRM, DES, CREAT	ALEARN, NEG, DMAK
Presentators	53.84	13.60	CRIT, SERV, COMPL	DES, CREAT
Typists	28.20	-21.31	UNDOTH, PERS, COMPL	MRM
Data entry officers	35.90	15.55	ALEARN, UNDOTH, DES	TIME
Purchasing managers	49.82	6.18	CRIT, CREAT	DMAK, FRM, DES
Post office workers	34.82	6.44	UNDOTH, AD, ANSK	TIME, DES
Shop assistants	19.90	-19.87	CRIT, ALEARN, UNDOTH	LIST, LEAST, TIME
Remote sellers	35.60	20.89	TEACH, UNEX, FRM	PERS, NEG, DES
Waiters	32.31	-14.97	UNDOTH, NEG, FRM	UNEX, HRM, AD
Hairdressers	52.20	13.31	AD, NEG, TEACH	ALEARN, UNDOTH, PERS
Tilers	27.75	13.38	UNDOTH, NEG, DES	LIST, CRIT, AD
Tunnel owners	46.62	-19.33	TEACH, COMPL	UNDOTH, NEG, ANSK
Planes mechanics	45.87	-18.01	UNDOTH, NEG, SERV	AD, INN
Engravers	54.35	11.92	ALEARN, PERS, TIME	CRIT, NEG, FRM
Electrochemical plant workers	52	35.14	LEAST, UNDOTH, NEG	LIST, CRIT, AD
Machinery operators	34.36	16.18	UNEX, DMAK, CREAT	ALEARN, LEAST, SERV
Bus conductors	24	-14.64	LEAST, AD, DMAK	UNDOTH, FRM, DES
Boiler conductors	29	-15.98	ALEARN, LEAST, AD	DES, INI
Cleaning staff	25.10	-15.08	CRIT, ALEARN, AD	TIME, MRM
Forestry personnel	52.33	11.75	LIST, CRIT, UNEX	NEG, SERV, DES
Fishing/hunting personnel	65	15.58	LIST	ALEARN, UNDOTH, NEG
Industrial activity personnel	30.35	-13.78	PERS, NEG, SERV	LIST, AD, CLASS

2.5.1 Results related to specific economic sectors

In this subsection, we focus our analysis on two economic sectors, the health system and the cultural industry. These two sectors are chosen for the following reasons. In the case of the health system, we are interested to identify professions at a high risk of being automated, due to actual creativity levels smaller the ones predicted by the counterfactuals generated by matrix completion. The healthcare sector is a working context in which creativity is often assumed to play a limited role (at least in the cases for which routine tasks are common). On the other hand, the analysis of the cultural industry is performed to get a further validation of the method, since the creativity levels for the professions in this sector are typically expected to be higher than the ones of the professions belonging to other sectors. So, in this case, we check that the predictions of MC are consistent with this expectation.

Figure 9 shows that the creative behaviour of professions in the healthcare sector is highly heterogeneous: categories of health workers dealing with patients on a daily basis are used to interact more with people, thus the need for soft skills in general and creativity in particular is higher. This also implies that MC negative deviations (i.e., underestimates of the true creativity level) are likely to occur.

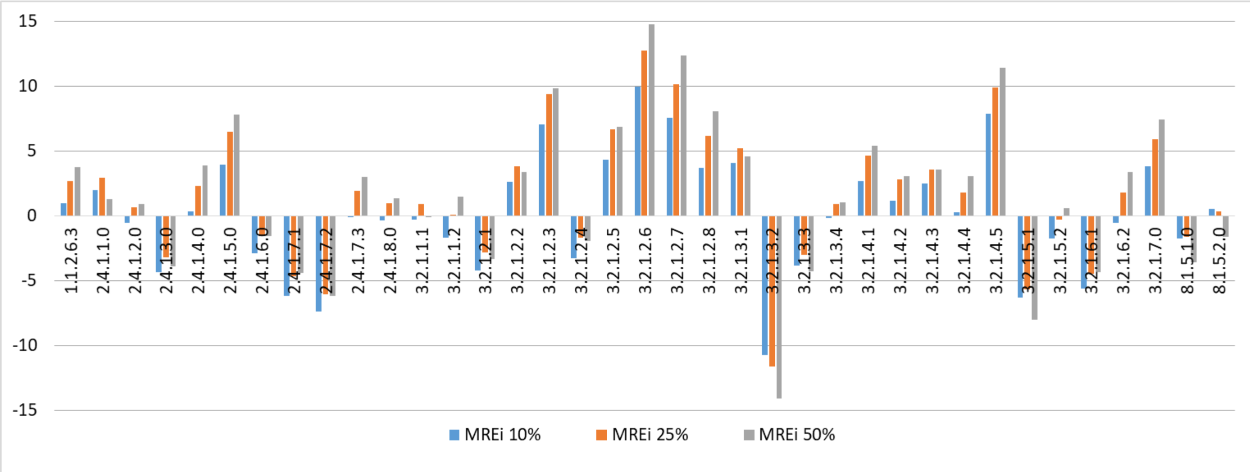


Figure 9: MRE_i in the Health Sector - ADA 19 (ADA stands for *Area di Attività*, or *Area of Activity*), The correspondence between codes and professions is reported in Table 18 in the Appendix

That is exactly the case for jobs like Therapists in neuropsychomotricity (3.2.1.2.5), Therapists in psychiatric rehabilitation (3.2.1.2.6), Social educators (3.2.1.2.7) and Occupational therapists (3.2.1.2.8). On the other end of the distribution we find jobs that are mainly dealing with technical diagnostic, such as Diagnostic imaging and radiotherapy specialists (2.4.1.6.0) and Biomedical laboratory assistants (3.2.1.3.2).

In the case of the cultural sector, instead, the distribution is smoother and creativity patterns are more homogeneous among professions (see Figure 10). In particular, the MC predictions for almost all kinds of workers in this sector deviate positively and the magnitude of these deviations is quite large.

The most creative occupations, according to the results of our analysis above, are Dialogists (2.5.4.1.2), Set designers (2.5.5.2.5), Artistic performances presenters (3.4.3.1.2) and Stage builders (3.4.4.1.2), while Painters and sculptors (2.5.5.1.1), Directors (2.5.5.2.1), Actors (2.5.5.2.2), Artistic directors (2.5.5.2.3), Scriptwriters (2.5.5.2.4) take values in the middle of the distribution.

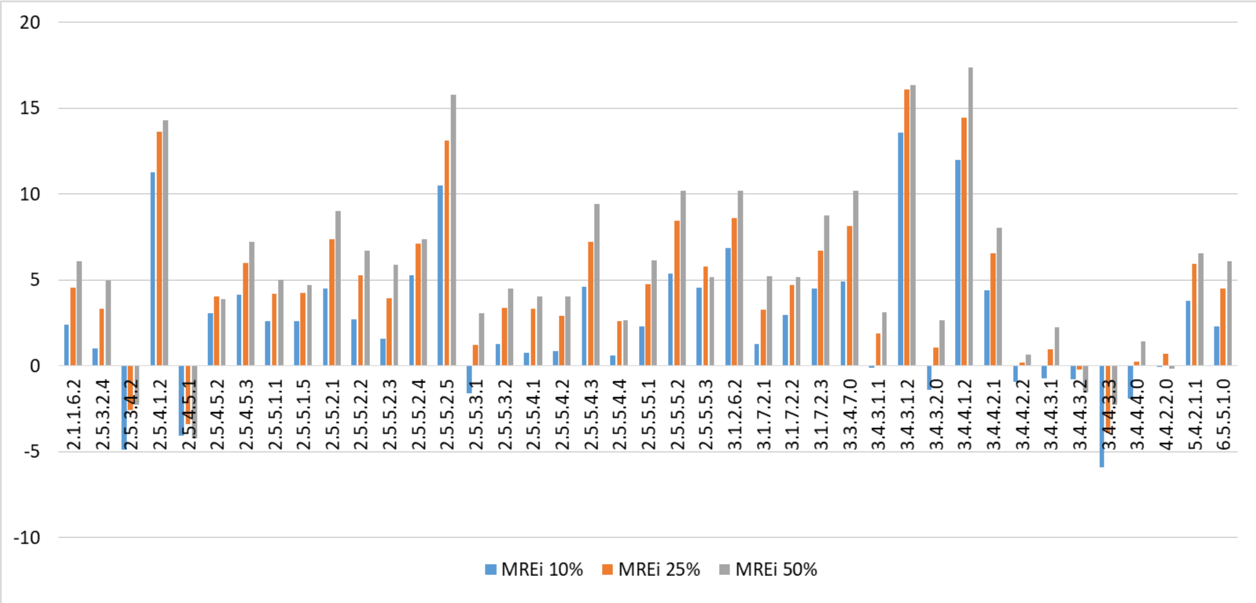


Figure 10: MRE_i in the Cultural Industry - ADA 22 (ADA stands for *Area di Attività*, or *Area of Activity*). The correspondence between codes and professions is reported in Table 19 in the Appendix

2.5.2 The evolution of creativity needs

Recent developments in the MC literature extend the range of applications of this method to causal inference with panel data (Athey et al., 2021). They show that MC outperforms other synthetic control methods, as its simulations are based on real data. Thanks to the availability of the first edition of the *Survey on Occupations*, which was run in 2007, in this subsection we extend our analysis to this year, in order to assess whether our model has some predictive power over time, when the results of the MC analysis of the 2007 dataset are used to predict creativity levels observed later in 2013.

The first edition of the ICP adopted a slightly different occupation classification (*Classificazione delle Professioni 2001* or *Classification of Professions 2001*, CP2001), as this was subject to changes operated by ISTAT in 2011. Even though occupations are clustered into the same major groups in both editions of the survey, the two different classification criteria adopted do not allow to get a perfect one-to-one matching of professions at the 5-th digit occupational level. As a consequence, we reduce the rows of our two datasets (related to the years 2007 and 2013, respectively) to those professions for which there was either no change in the classification code, or a negligible change in the job description occurred. In this way, the two occupation matrices are reduced to 510 closely matching professions. Then, we apply to each of the reduced 2007 and 2013 occupation matrices the same kind of MC analysis described in Section 4 and in the Appendix. As before, the analysis is performed for each of the three percentages of missing observations in the columns associated with creative skills (10%, 25%, 50%). In particular, for each pair (i, j), where i denotes a profession in the reduced subset of 510 professions, and j one of the selected creative skills, we compare the mean MC prediction of the skill level j of the profession i based on the 2013 and 2007 datasets, respectively, i.e., we compute[3]

$$\Delta\overline{predicted}_{i,j} = \frac{1}{r_i}\sum_{r=1}^{r_i}\left(predicted^{(2013)}_{i,j,r} - predicted^{(2007)}_{i,j,r}\right) \tag{2.3}$$

(again, to avoid burdening the notation, the dependence on the percentage of missing elements in the selected 25 columns is not reported in equation (2.3)).

Figures 12, 13, and 14 report, for the three cases, and for each creative soft skill j, the resulting histograms of the variations $\Delta\overline{predicted}_{i,j}$ (in each histogram, j is fixed, whereas i varies). These figures show that the creative soft skills for which the largest positive variations are obtained are persuading, creative thinking, financial resource management and classification, while the creative soft skills with the largest negative variations are listening actively, teaching, time management and solving unexpected problems.

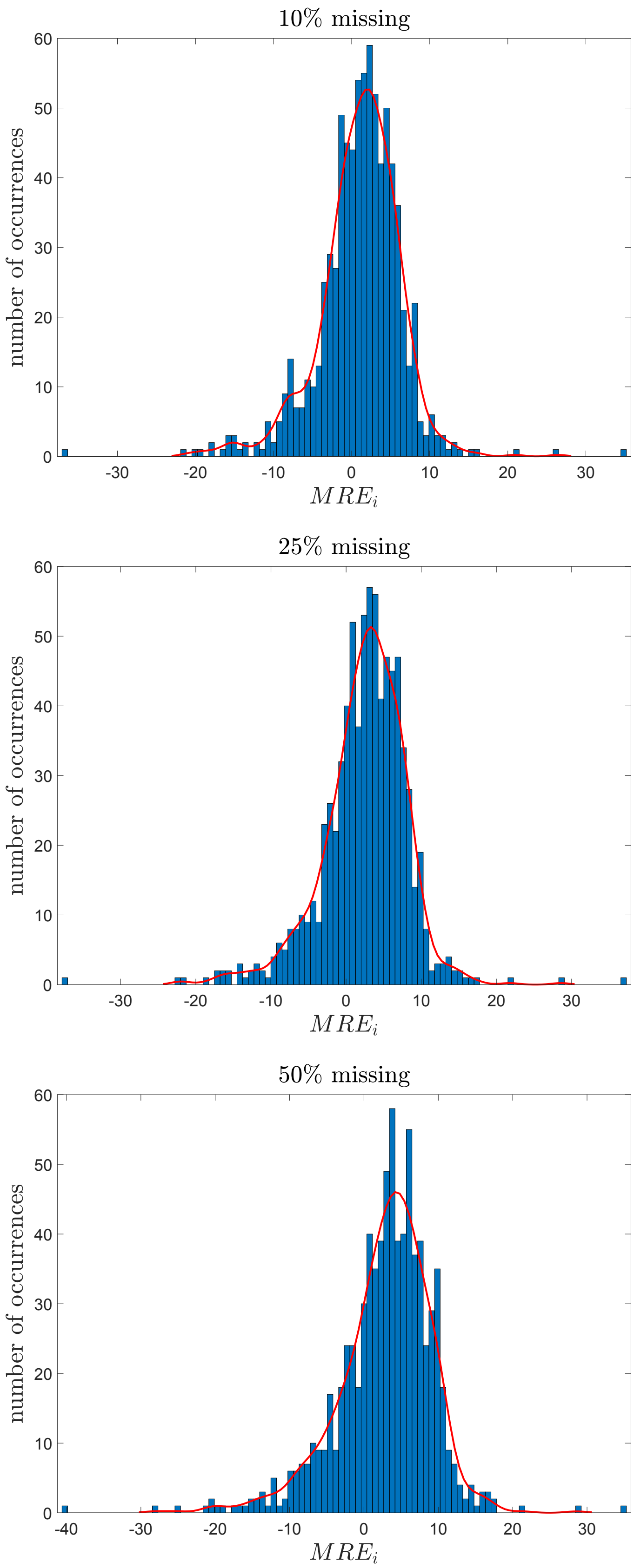
As a further comparison, Figure 15 reports the boxplots of the averages

$$\Delta\overline{predicted}_{i} = \frac{1}{25}\sum_{j\in J}\Delta\overline{predicted}_{i,j} \tag{2.4}$$

over the creative soft skills, for the three cases considered in the analysis. The figure also shows that the [first quartile, third quartile] intervals of $\Delta\overline{predicted}_i$ are, in the three cases, $[-7.64\%, 1.00\%]$, $[-7.51\%, 0.96\%]$, $[-7.13\%, 0.55\%]$, respectively. Hence, the predictions – based on the MC analysis of the reduced 2007 dataset – of the creativity levels for the professions considered in the two analyses are quite similar to the corresponding predictions based on the reduced 2013 dataset.

The professions i in the reduced datasets for which the average $\Delta\overline{predicted}_i$ assumes the largest negative values are: Shop assistants (5.1.2.2.0), Meter readers (8.1.1.2.0), Remote sellers (5.1.2.5.2), Biomedical laboratory technicians (3.2.1.3.2) and Plant operators in sugar refining (7.3.2.5.0). Similarly, the ones for which the average $\Delta\overline{predicted}_i$ assumes the largest positive values are: Plant operators in pottery production (7.1.3.3.1), Flame welders (6.2.1.2.0), Electric welders (6.2.1.7.0), Assemblers of composite industrial articles (7.2.7.9.0) and Hunters (6.4.5.4.0). In the period 2007-2013, the professions that experienced the largest increase in the predictions of the intensity levels of use of creative soft skills belong mainly to the 6-th (Artisans, specialized and agricultural workers) and 7-th (Plant and machine operators and assemblers) major groups. These are major groups characterized by a high level of routinary (manual and cognitive) tasks (Gualtieri et al., 2019). Thus, these results suggest that technological change, advances in ICTs, the advent of Industry 4.0 and the last developments in artificial intelligence, which might lead to a substitution of mechanical and repetitive jobs, are forcing these same jobs to adapt and reshape their soft skills provision.

[3]The same seed for pseudo-random number generation has been used for the simulations based on the reduced 2007 and 2013 datasets. So, for each profession i considered, the number r_i is the same for the two analyses.



(a)

(b)

(c)

Figure 11: Histograms (and kernel-fitted histograms) of MRE_i in the full dataset of professions, for different percentages of missing entries in the columns associated to creativity: (a) 10% missing entries in the selected columns; (a) 25% missing entries in the selected columns; (a) 50% missing entries in the selected columns

2.6 Final discussion

In this paper, we exploit similarities in the Italian occupational structure and implement a recently developed machine learning technique to predict the levels of creative skills employed in each occupation and to identify the creativity needs of occupations. We find that professions belonging to the major group of legislators, senior officials and managers, as well as intellectual professionals have a greater surplus of creative soft skills. Nevertheless, creativity patterns and trends are extremely heterogeneous and idiosyncratic and this means that there is no clear separation among technical and intellectual skills with respect to creative soft skills. Our results suggest that creativity gaps in the labor market are so peculiar that training might be tailored specifically for every occupation, to reduce its risk of being automated. In our application, matrix completion has demonstrated an excellent prediction capability, making it meaningful to further analyze cases for which the actual creativity levels are significantly larger/smaller than the predicted ones, as the errors are possibly related to specific features of professions that distinguish them from other professions in the dataset. As a possible extension of our analysis, as soon as the data collected in the last edition of ICP (conducted in 2019) will be made publicly available, the method used in this article could be also applied to predict the most recent trends in the labour market, and possibly also to make a forecast analysis for the future trends after the current COVID-19 pandemic (Barbieri et al., 2020).

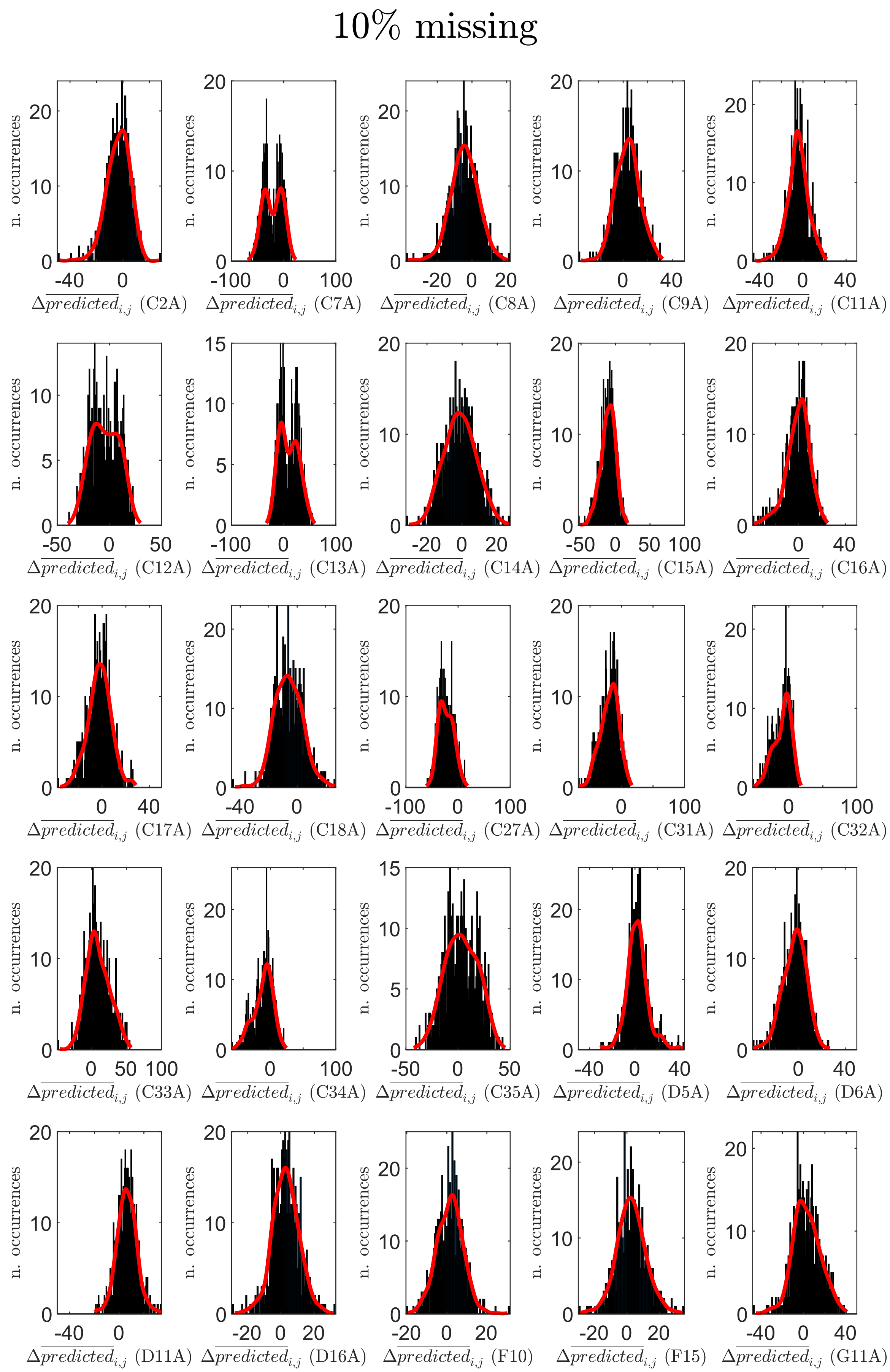


Figure 12: Histograms of the variations $\Delta\overline{predicted}_{i,j}$ for the various creative soft skills j: case of 10% missing entries in selected columns

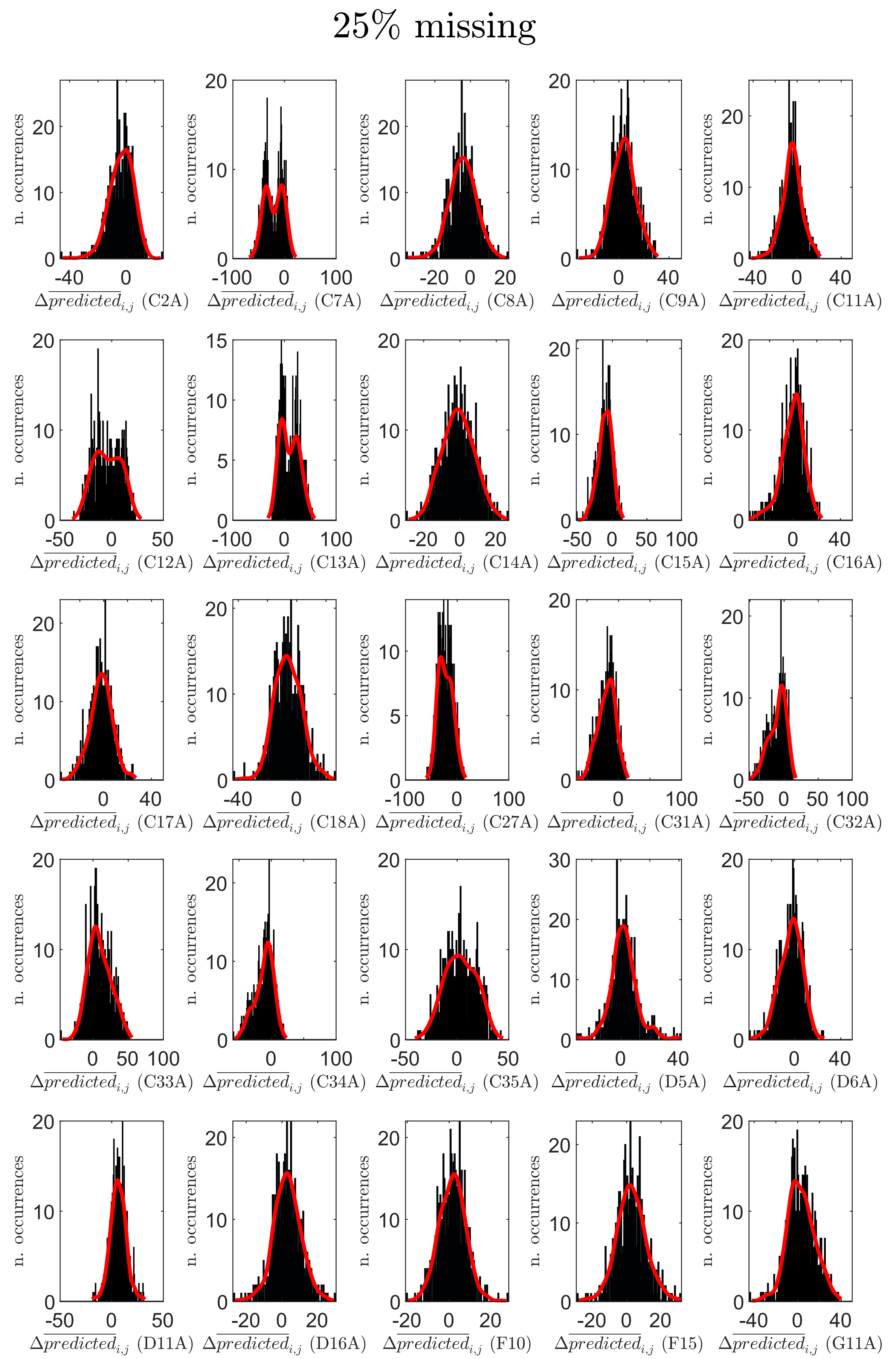


Figure 13: Histograms of the variations $\Delta\overline{predicted}_{i,j}$ for the various creative soft skills j: case of 25% missing entries in selected columns

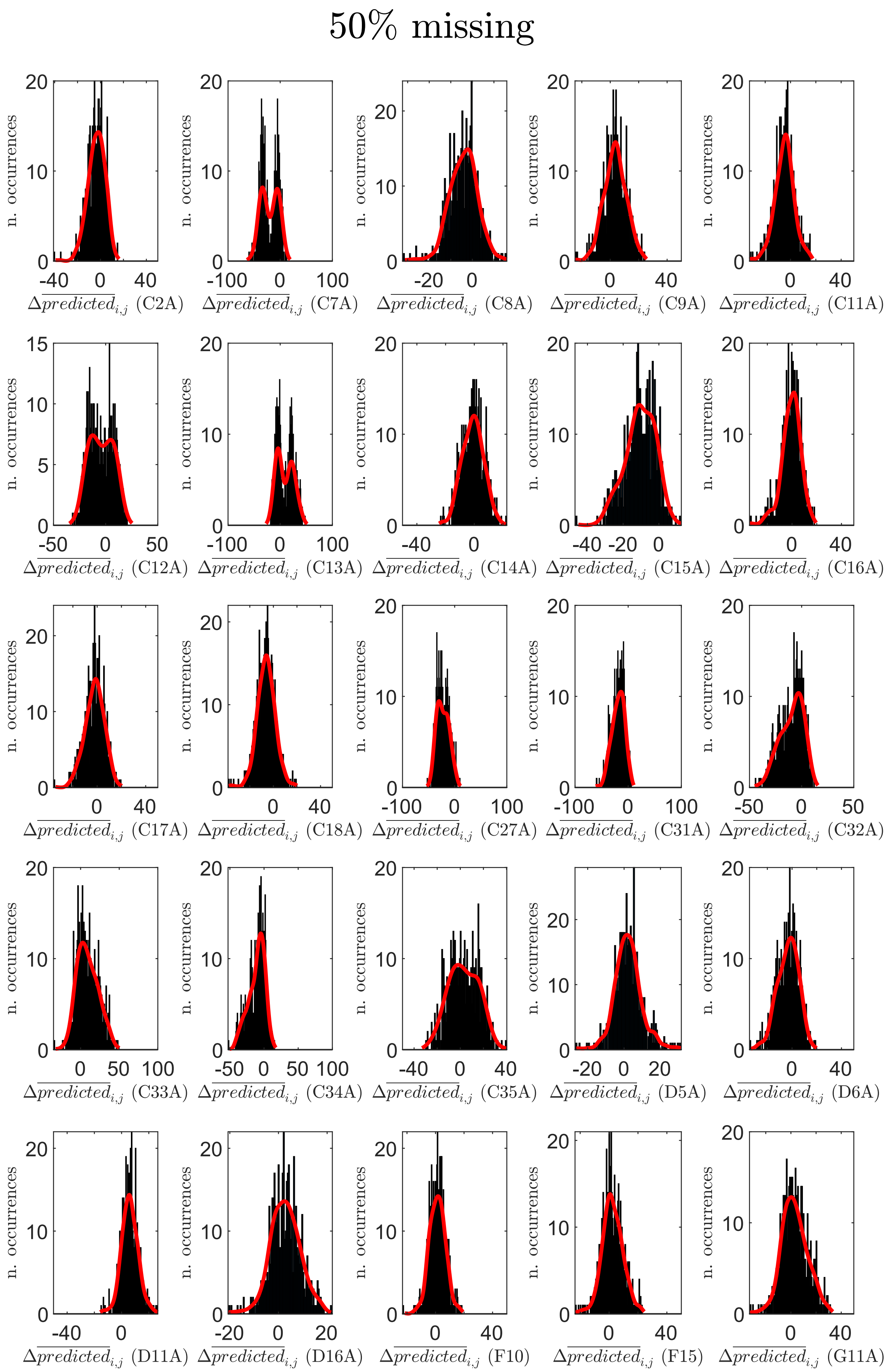


Figure 14: Histograms of the variations $\Delta\overline{predicted}_{i,j}$ for the various creative soft skills j: case of 50% missing entries in selected columns

Figure 15: Boxplots of the variations $\Delta\overline{predicted}_i$ for the three cases considered in the analysis

Chapter 3

The emergence of soft skill needs of Italian workers in the post-covid era[1]

" For all those sitting in traffic right now "
- Jason Fried

3.1 Introduction

The Covid-19 pandemic originated from the city of Wuhan in China in December 2019 and spread rapidly across the world, reaching around 213 countries (Roser et al., 2020). The spillover effects of this pandemic have been devastating, especially in terms of deaths and job losses. In order to reduce the spread of the virus and contain the burden on health-care systems, governments around the world have enforced lockdowns and quarantines, i.e. restrictive physical distancing measures that have also raised issues about the negative effects on the economy and social well-being. For instance, Covid-19 pandemic had a severe impact on labor market, employers, employees, and also graduates. There is a need for highly skilled employees and graduated to deal with the effects of Covid-19 pandemic, helping a quick recovery for the labor market. Furthermore, governments have required most non-essential businesses to close, impacting negatively national economies and leading to a significant drop in employment (Khalid, Okafor, and Burzynska, 2021). While many of the implications of lockdown on the economy are negative, there have been some positive progresses as firms adapted to a 'new normality'. Now banks are dealing with increased credit risks, while the insurance companies are expanding their digital assets. Some traditional office-based businesses were experiencing significant cost reductions by shifting to remote working, while restaurants and bars moved towards takeaway and delivery services.

Particular attention was devoted on the concept of smartworking during the COVID-19 pandemic, a period that has proven how more flexible working conditions are possible without necessarily affecting workers' productivity and how much these flexible working conditions are desired by workers, insofar as embracing them does not put remote workers at a disadvantage or negatively affect their well-being. In other words, the forced lock-down 'experiment' that pushed masses of workers to work remotely at the same time has shown that more coordination and improved working relationships and thus efficiency gains are possible.

[1]This chapter is a joint work with my supervisor Prof. Massimo Riccaboni and Prof. Giorgio Gnecco.

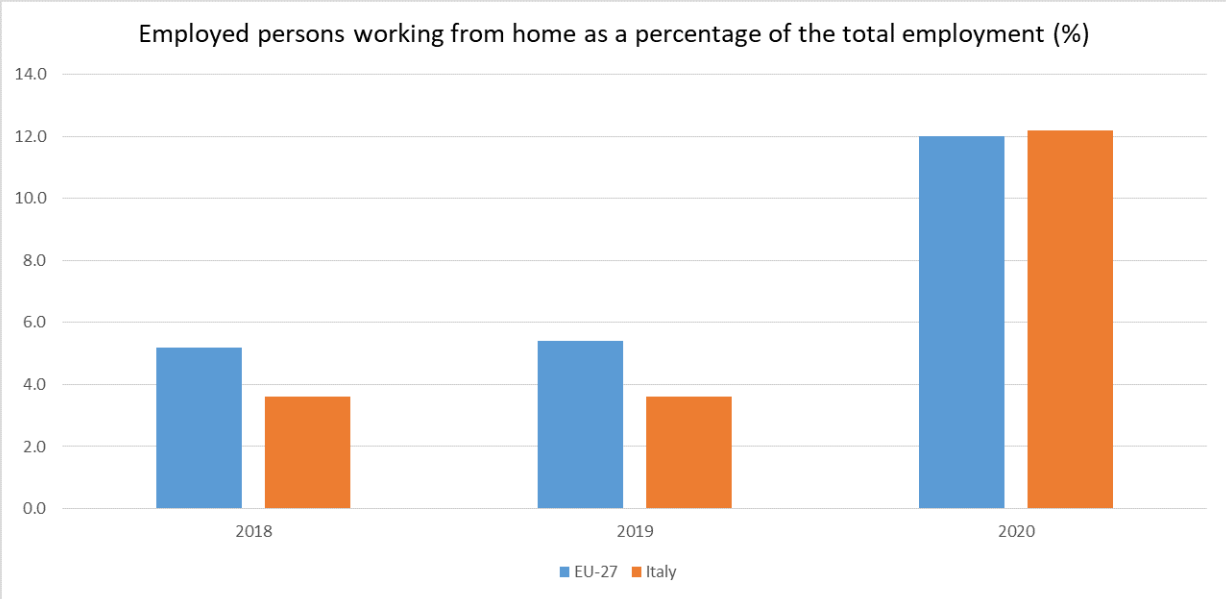


Figure 16: Telework in Italy vs EU countries (% of total employment)

Eurostat data show that in 2019, before the pandemic only about 3% of the EU workforce usually worked from home and 8% of workers sometimes worked from home (Grzegorczyk et al., 2021). Moreover, the work by Sostero et al. (2020) proposes a new index to measure 'teleworkability', meaning the possibility of a job to be done remotely, based on the task contents (physical, intellectual and social interaction tasks), the methods and tools of work. The authors calculations suggest that before COVID-19, telework was not adopted at its best, as many 'teleworkable jobs' where still performed in a traditional office or firm. In addition to this, the gap between teleworkability and the real usage of telework is larger for clerical support workers than for managers and professionals, pointing to what they define as a 'hierarchy effect': before the pandemic, *"access to telework depended more on occupational hierarchy and associated privileges than the task composition of the work"* (Sostero et al, 2020). These are the reasons why pre-pandemic levels of telework were regularly minimal, while they reached the maximum during the pandemic.

Adaptability goes hand in hand with other skills and competences which were defined as "soft" in comparison with hard skills, that include every skill related to scientific knowledge. The definition of soft skills is knowledge that is in the human mind and is very personal, difficult to be formalized and difficult to acquire naturally as its transformation requires personal interaction (P. Lee, 2019). Soft skills are rooted in one's actions and experiences, including idealism, values, and emotionality (Cirillo et al., 2021). Based on this understanding, soft skills are categorized as personal knowledge or in other words knowledge obtained from other individuals or by personal experience. For example, the experience gained by each teacher is certainly different based on situations and conditions that cannot be predicted (Mohajan, 2016; Prasarnphanich, Janz, and Patel, 2016). Online classes have made it more difficult for academic staff to cope up with this deteriorating situation. Business organizations have been already reporting that they need to conduct special training sessions for fresh graduates to learn and adapt to the business requirements (Tang, 2020).

The Covid-19 emergency in Italy expanded extremely rapidly and government adopted serious social and economic measures to preserve public health including locking down several industrial sectors(Baldwin and Di Mauro, 2020). In this severe situation, those workers employed in sectors that require physical proximity to customers or colleagues, as well as those who are exposed to diseases and infections were the most at risk. For all the other categories, it was possible to keep performing their daily job working from home. The Italian legislative setting was modified in 2017 with Law 81 with the precise purpose of fostering smartworking, defined by this law as a "new method of forming a subordinated employment relationship without precise constraints on time or location of work and with the use of technological tools in the workers' duties and activities". In this framework, Italy is a curious environment to carry out our analysis: the country labor market is characterized by high rigidity in work organization but in the last years firms started to show some level of interest in smart-working, even if this approach remain confined to a few number of workers.

Social distancing was fundamental for addressing the shock caused by Covid-19, as it reshaped the landscape of economic activities, with an heterogeneous impact across occupations. Specifically, nonessential jobs characterized by a high degree of physical interaction are those that suffered the most because consumers reduced their demand for them due to social distancing. Similarly, essential workers were compelled to remain in their workplaces so increasing the risk of contagion among them while the possibility of carrying out some of their work from home allowed them to absorb the negative effects of the lockdown. The difficulties faced during the lockdown have been an excellent opportunity to test and develop soft skills. Among these skills adaptability, communication skills, empathy and relationship building are those who suffered most and needed much attention both from the employer and employee perspective. Soft skills already play an increasingly important role in the job market but after the coronavirus crisis, the demand for them is expected to boost.

We make use of the original data coming from the Survey on Occupations (ICP, Indagine Campionaria delle Professioni) which represents, for every profession, its percentage of use of each soft skill and we combine it with the European Labour Force Survey, which gives us the economic sector or activity workers are associated with. The ICP survey contains variables that are extremely useful to illustrate the potential risks workers faced during the Covid-19 emergency, as well as formulate hypothesis and make predictions on how the labor market will move on in the near future. Following Barbieri, Basso, and Scicchitano (2020)we identify 5 working conditions that were mostly affected by the spread of the pandemic and the lockdown measures. We then create three possible scenarios based on how strong the pandemic affected the above conditions: 25% (low), 50% (medium), 100% (high). In each of them we reduced or increased the values of the elements of the corresponding columns in the original ICP matrix. Then we formulate and solve a Matrix Completion (MC) optimization problem to predict elements in the ICP matrix based on a subset of its other elements. The same method was applied in our previous work Gnecco, Landi and Riccaboni (2021) in a similar context, in which, however, no matrix perturbation induced by a simulated Covid scenario was considered. The results obtained in the present work show that the public sector was highly affected by the simulated Covid scenarios and its workers had to adapt several of their soft skills in order to be able to keep performing their tasks.

3.2 Related literature

This work builds on the existing literature on three main topics: working from home, soft skills and matrix completion. Many researchers studied the prevalence and consequences of working from home. The seminal paper by Oettinger (2011) analyses how home-work grew in the period 1980-2000, as documented in the US census of population and how this is related to changes in the frequency of face-to-face interactions, as measured in the O*NET survey. The work by Bloom et al. (2015) uses a randomized controlled trial within a Chinese travel agency to estimate the effects of home-based work on productivity. Mas and Pallais (2020) proposed a detailed overview of the prevalence, features and demand for alternative working arrangements, including the ability to work from home. In this study, they report data from the Quality of Worklife Survey and the Understanding American Study and they show that less than 13% of full- and part-time jobs have formal arrangements for the smartworking, even if more than 25% of workers often work from home. According to the two scholars, the median worker claims that only 6% of jobs could be feasibly done from home, although plenty of occupations, including those in computer and mathematics and business and financial operations can be carried out from home.

On the contrary, making use of the Skills Toward Employability and Productivity (STEP) survey on workers' tasks, Saltiel (2020) measures the share of jobs that can be done from home and finds that only few jobs can be done remotely, from 5% to 23% across the ten developing countries considered. He also shows that there is a positive correlation between the smartworking share and GDP per capita. In a deeper analysis on the characteristics of jobs that can be done at home, Mongey, Pilossoph, and Weinberg (2020) use O*NET data to build a measure of physical proximity in the workplace, for each occupation. Baker et al. (2020) and Koren and Pető (2020) use the same data to propose measures of which occupations cannot be done at home or will be affected by social distancing. More recent research uses surveys to create real-time measures of smartworking. In the US context, Brynjolfsson, Horton, et al. (2020) document that almost half of the people interviewed said they were working from home during the first week of April 2020, while McLaren and Wang (2020) report that 35 percent of their US respondents worked entirely from home in May 2020. The Decision Maker Panel, an entity set up by the Bank of England, conducted a real-time survey of U.K. firms and showed that 37 percent of employees were reported to be working from home in both April and May 2020.

The value of soft skills in the workplace has been documented for decades and the literature is putting more emphasis on the importance of 'soft' skills as complementary to 'hard' skills (Hendarman and Cantner, 2018). Soft skills are skills often referred to as interpersonal, human, people, or behavioral skills, and rely on personal behavior.

Lastly, we follow the seminal paper by Athey et al. (2021) on the application of matrix completion for estimating causal effects in settings with panel data. Matrix completion is the task of filling in the missing entries of a partially observed matrix and this technique is widely applied in recommendation systems (Ricci at al., 2011) to derive users' preferences knowing the tastes of similar users and/or to suggest products that could match these preferences. Missing data is a problem that researchers frequently encounter. As Ma and Chen (2019) point out, we can expect more occurrence of incomplete observations in the era of big data. One can always work with a balanced panel but this effectively throws away information in many series and cannot be efficient. This has led to the development of simple methods that replace the missing values with zero or the mean as well as sophisticated methods that fully specify the data generating process and the missing data mechanism. In the paper by Athey et al. (2021), the application of matrix completion was extended to causal inference, overcoming the two prevalent approaches to missing outcomes in econometrics: unconfoundedness (G. W. Imbens and Rubin, 2015), that imputes missing potential outcomes using observed outcomes for units with similar values for observed outcomes in previous periods; and synthetic control (Abadie, Diamond, and Hainmueller, 2015; Doudchenko and G. W. Imbens, 2016), that imputes missing control outcomes for treated units by finding weighted averages of control units that match the treated units in terms of lagged outcomes. Athey et al. (2021) propose matrix completion estimators in a context where a subset of units undergo a treatment for a finite period of time, and the objective is estimating counterfactual (i.e., untreated) outcomes for the treated unit/period combinations and finally use them to predict the missing entries of the matrix, corresponding to treated units/periods. The most recent literature on matrix completion (Candès and Recht, 2009; Candes and Plan, 2010; Mazumder et al. (2010)) attempts imputing the missing entries of a matrix assuming that the complete, partially observed one is a low rank matrix plus noise and that the missingness is random. The low rank structure of the matrix requires the addition of a regularization parameter to the objective function, which might come easier to compute through nuclear norm minimization, especially in the case of complex missing data patterns (Athey et al., 2021).

Similarly, in this work we use data on occupations and skills, treating our units with three different levels of the impact of COVID-19 on those working conditions related to physical proximity, exposure to disease and infections and working remotely so to estimate differences in the intensity of use of soft skills due to the spread of the pandemic. Hence, we apply matrix completion, formulated as a nuclear norm minimization problem and solve it via the soft impute algorithm. Tuis allows us to compare pre and post Covid-19 skill levels, thus deriving our counterfactual units.

3.3 Data

We combine data from two data sources: first, we make use of the Italian O*Net database, namely the *Survey on Occupations* (ICP, Indagine Campionaria sulle Professioni), run by the Italian National Institute for the Analysis of Public Policy (INAPP); secondly, we derive he distribution of occupational employment at the 3-digit level across 87 economic sectors (ATECO[2]) from the 2018 Labour Force Survey. These employment-based occupation weights are then used to predict the effect of Covid-19 on the skill endowment of the different production sectors.

The ICP (*Indagine Campionaria sulle Professioni* is a survey on workers last run in 2013. It encloses a sample of 16.000 Italian workers clustered in around 800 occupations, following the CP2011 classification (the Italian equivalent of the ISCO-08 ILO's classification)[3]. The sample stratification is representative of sector, occupation, firm size and geography. The ICP collects the answers of the sample workers with an exceptionally detailed questionnaire which includes knowledge, skills, attitudes, generalized work activities, values, work styles, and working conditions. Respondents, entrepreneurs and HR managers, also report skill needs of their employees in the near future trends and new training needs related to competences and soft skills.

The European Union Labour Force Survey (EU LFS), started by Eurostat in 1983, is a large household survey that provides statistics on labour participation. The national surveys are

[2]The ATECO (ATtività ECOnomiche) classification of economic activities was adopted in 2007 by the Italian National Institute of Statistics (ISTAT) for the national statistical summaries on the economic landscape. It is the translation of the Eurostat NACE Rev. 2

[3]The International Standard Classification of Occupations (ISCO) is an International Labour Organization (ILO) classification structure for organizing information on labour and jobs. ISCO is defined by ILO itself as a tool for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in each job. The updated classification was adopted in December 2007 and is known as ISCO-08.

Section	ICP items	Skills
Skills and competences	C2a	Listening actively
	C4a	Speaking
	C10a	Monitoring
	C11a	Social perception
	C12a	Coordination with others
	C13a	Persuading
	C14a	Negotiating
	C15a	Teaching
	C16a	Service orientation
	C32a	Time management
	C35a	HR management
Working styles	F4	Leadership
	F5	Cooperating
	F6	Taking care of others
	F7	Team working
Generalized working activities	G33a	Coordinating
	G34a	Managing working groups
	G35a	Training
	G36a	Guiding, directing and motivating the subordinates
	G37a	Making people grow
	G38a	Consultancy

Table 13: Social soft skills in the ICP dataset.

conducted by the national statistical institutes of the member states, which are also responsible for the sample selection, the preparation of the questionnaires and the interviews. Results are then forwarded and assembled by the European institution. The EU-LFS covers all industries and occupations. Thanks to the large amount of information contained in the ICP, we are able to focus not only on skills, but also on those variables that account for working attitudes and styles as well as generalized work activities. Among those, we identify the 5 conditions that were impacted by the spread of COVID-19 and 21 items associated with social skills, as reported in Table 3.3. The identification of these skills stems from the consideration that in order to employ them, workers need to interact and relate with other people, otherwise it is impossible to make use of them.

The final occupation matrix considered in our analysis contains $m = 796$ rows which refer to professions and $n = 255$ columns, of which 55 denote skills, while the other 200 columns refer to competences, working conditions, and working styles. Each entry in position (i, j) represents the intensity level (expressed as a percentage) in the use of skill/competence/work condition/working style j by worker type i.

3.4 Methodology

The ICP survey contains variables that are extremely useful to illustrate the potential risks workers faced during the Covid-19 emergency, as well as formulate hypothesis on how the labor market will move on in the near future. In particular, the survey directly asks about physical proximity and disease exposure for every profession, based on the following questions, respectively: “During your work are you physically close to other people?” and “How often does your job expose you to diseases and infections?”. A score that belongs to a 0 to 100 scale (from less to more intense) is then calculated for each 5-digit occupation. Following Barbieri et al. (2020), we identify 5 working conditions which were mostly affected (negatively or positively) by the spread of the coronavirus pandemic:

1. exposure to disease or infection (”How often does this job require exposure to disease/infections?”);

2. physical proximity (”To what extent does this job require the worker to perform job tasks in close physical proximity to other people?”, ”How often do you have to have face-to-face discussions with individuals or teams in this job?”, ”How important is it in carrying out your work to interact in first person with external customers or in general with the public?”);

3. working remotely (using computers to process information).

We assume that with the surge and the spread of the epidemic, workers would face a higher exposure to disease and infection as well as higher levels of working remotely while physical proximity would be reduced together with the possibility of having face-to-face discussions. Therefore, in our simulated matrices, entries in the columns related to point 1 and 3 would be increased while entries in the remaining treated columns would be reduced, as shown in Table 14.

ICP item	Conditions	Sign
H.29	Exposure to disease/infections	Positive
H.21	Phisical proximity	Negative
G.19	Working with computers	Positive
H.1	Face-to-face discussions	Negative
H.8	Deal with external customers	Negative

Table 14: Variables description.

Since we do not exactly know how much the single working conditions have been affected by the spread of the COVID-19 pandemic and the consequent lockdown measures, we simulate its possible effects by considering the following scenarios:

- *Low impact: 25%*, entries in the columns related to the working conditions affected by COVID-19 are reduced (increased) by 25%;

- *Medium impact: 50%* entries in the columns related to the working conditions affected by COVID-19 are reduced (increased) by 50%;

- *High impact: 75%* entries in the columns related to the working conditions affected by COVID-19 are reduced (increased) by 75%.

(All variables in the matrix are expressed as percentages, thus if any entries goes above 100% due to the simulated increase, we set it at 100%). Assuming that it will take long for workers to get back to the traditional way of performing their job, when not impossible, the results relative to the above scenarios could be read as predictions of what would imply for professions and soft skills a reduction (increase) of face-to-face contact, proximity, smartworking and so on. While it is true that the pandemic has been a once in a lifetime experience and that some measures and precautions will be removed, it is also true that the shock it causes brought about some permanent changes in the society as a whole and in all the economic sectors.

3.5 Matrix completion

We apply Matrix Completion (MC) to estimate the difference in the intensity levels of use of social skills before and after the spread of Coronavirus in the Italian economic sectors. In order to apply MC to our occupation matrix, we generate artificially partially observed matrices from it, by obscuring randomly 10%, 25% and 50% of the entries in the columns associated with the social skills, focusing each time on the prediction capability of matrix completion on each single row (occupation). Details on the specific application of matrix completion are similar to those reported more extensively in Gnecco, Landi, and Riccaboni (2021).

In summary, we consider the following nuclear-norm regularized MC optimization problem:

$$\underset{\mathbf{Z}\in\mathbb{R}^{m\times n}}{\text{minimize}} \left(\frac{1}{2} \sum_{(i,j)\in\Omega^{\text{tr}}} (M_{i,j} - Z_{i,j})^2 + \lambda \|\mathbf{Z}\|_* \right) , \tag{3.1}$$

where Ω^{tr} is a training set of positions (i, j) corresponding to the known entries of the partially observed matrix $\mathbf{M} \in \mathbb{R}^{m\times n}$, $\mathbf{Z} \in \mathbb{R}^{m\times n}$ is the completed matrix, $\|\mathbf{Z}\|_*$ is its nuclear norm, and $\lambda \geq 0$ is a regularization constant. The rank of the resulting completed matrix is implicitly determined by the regularization through the addition of a penalty term to the objective function. Then, we solve the optimization problem (3.1) by applying the Soft Impute algorithm (Mazumder et al., 2009). This is proved therein to converge to an optimal solution of that optimization problem. Several instances of such problem are solved by the Soft Impute algorithm, by considering different choices of the set of obscured entries. For each such choice, the best value of λ is found by minimizing a suitable error on a validation subset of obscured entries, whereas the final performance is evaluated on a test set made of the remaining obscured entries.

Figure 17 shows that the algorithm employed has good prediction capability, as the prediction error is always smaller than 15%, and its standard deviation is even much smaller.

3.6 Results

For each profession i, we define the Mean Relative Error (MRE) associated with the application of matrix completion as the following percentage:

$$MRE_i = \frac{1}{r_i} \sum_{r=1}^{r_i} \left[\frac{\sum_{j\in J}(true_{i,j} - predicted_{i,j,r})}{\sum_{j\in J} true_{i,j}} \right] \times 100 \tag{3.2}$$

where $j \in J$ denotes one of the social skills, and $r \in \{1, \ldots, r_i\}$ the MC repetitions for which elements of row i are in the test set, $predicted_{i,j,r}$ is the MC prediction, and $true_{i,j}$

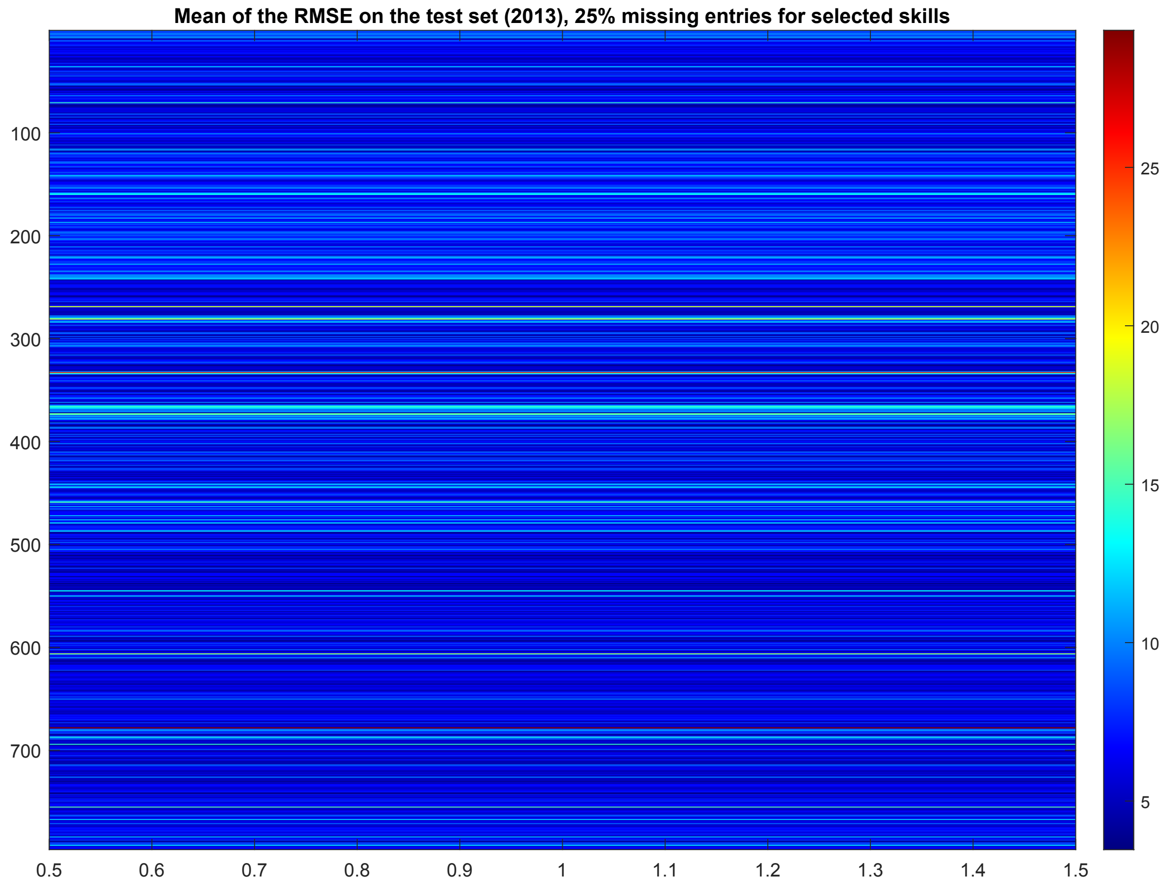


Figure 17: Mean and standard deviation of the RMSE of prediction on the test set for a specific choice of the percentage of missing entries in the columns associated with social skills.

is the corresponding missing entry. Then, occupations at the 5-digits level are clustered in economic sectors at the 3-digits level: to each ATECO code, we assign a weight based on the percentage of professions belonging to that sector. When aggregating results at the first digit of the ATECO classification (sections), where we find only the general characteristics of the goods and services produced, we notice that the average MRE, computed as a weighted average of the single mean relative errors of the professions belonging to that section, is always negative and concentrated in a small interval $\sim (-16; -8)$. Sign and magnitude are consistent in the three scenarios considerated.
To go more into details, Table 16 reports MC results for the highest and lowest Mean Relative Error averaged on each ATECO sector.

ATECO sectors (sections)	**COVID-19 impact** 25%	50%	75%
A Agriculture, forestry and fisheries	-16.01	- 17.23	-17.94
B Mining and minerals from quarries and mines	-14.33	-13.69	-15.54
C Manufacturing activities	-11.10	-12.75	-13.99
D Supply of electricity, gas, steam and air conditioning	-13.90	-13.86	-14.94
E Water supply, sewerage, waste management and remediation	-8.52	-9.06	-10.15
F Construction	-9.31	-9.59	-11.44
G Wholesale and retail trade	-8.32	-9.63	-10.65
H Transportation and storage	-10.24	-10.35	-11.19
I Accomodation and catering services	-15.13	-16.17	-16.97
J Information and communication services	-11.10	-11.23	-11.57
K Financial and insurance activities	-16.13	-18.84	-20.05
L Real estate activities	-18.78	-19.92	-21.49
M Professional, scientific, and technical activities	-13.60	-15.33	-15.76
N Rental, travel agencies, business support services	-10.19	-13.34	-13.07
O Public administration and defense; social security	-15.78	-14.52	-14.77
P Education	-14.88	-18.25	-19.01
Q Healthcare and social services	-17.74	-17.98	-19.82
R Art, sport and entertainment	-10.75	-10.33	-11.02
S Other service activities	-12.98	-14.21	-14.83
T Activities of households as employers of domestic personnel	-9.23	-12.18	-13.24
U Extraterritorial organisations and bodies	-8.53	-9.37	-9.68

Table 15: Average MRE by ATECO sectors

The results reported in Table 16 show that the simulated Covid-19 scenarios impacted more the entire public administration industry, especially the education sector, which had to perform its everyday activities online. The same happened to the healthcare system, which was put under huge pressure during the crisis, and had to reallocate some wards in order to serve a larger number of people. The negative MRE underlines that there might have been a deficit in social skills (true values were smaller then predicted ones) in these sectors, maybe due to the rapid and unexpected change of working conditions.

As Table 17 shows, the ability of adapting to the new normality of working from home, lockdown and social distancing required workers a certain capacity of coordinating with others, working under unexpected deadlines, and setting priorities. Time management, in fact, is becoming crucial, since when working from home it is important to be able to adjust

ATECO Sectors	COVID-19 impact 25%	50%	75%
94 *(Membership organisation services)*	-77.92	-81.48	-82.78
85 *(Education)*	-54.98	-59.61	-58.90
51 *(Air Transport)*	-36.02	-39.58	-30.73
86 *(Healthcare)*	-31.53	-27.01	-38.33
84 *(Public Administration)*	-25.69	-24.31	-28.10
59 *(Movie, radio, video production)*	16.94	13.36	17.18
3 *(Fishing)*	15.86	12.27	8.52
18 *(Printing and reproduction of media)*	12.98	12.71	15.74
50 *(Maritime transport)*	17.01	14.84	16.99
97 *(Activities of households as employers of domestic personnel)*	41.04	42.55	33.19

Table 16: Top 5 lowest and highest MRE averaged by economic sector.

working hours to family needs. Together with these, leadership qualities are required as they reflect in soft skills such as human resources management, teaching and training skills. Lastly, support among colleagues as well as coordination and empathy are fundamental for the motivation of workers.

Soft skills	COVID-19 impact 25%	50%	75%
Understanding others	-43.49	-42.94	-37.37
Persuading	-42.51	-42.36	-39.59
Service orientation	-37.88	-38.70	-43.59
HR management	-34.03	-34.14	-35.73
Consultancy	-23.88	-23.81	-23.19
Coordination with others	17.04	16.76	18.34
Time management	22.78	23.05	25.53
Teaching	29.80	29.99	31.27
Taking care of others	31.36	31.02	33.01
Training	33.04	32.20	36.52

Table 17: Top 5 highest and lowest MRE by soft skills.

3.7 Robustness checks

The Root Mean Square Error (RMSE) of the MC prediction, as evaluated on the validation and set test, is decreasing in the regularization parameter λ up to its minimum value of, as shown in Figure 18. The optimal value of λ is associated with the smallest RMSE on the validation set. A similar behavior is obtained on the test set. The variability of the curves with respect to changing the training and validation sets is quite small. So, for this specific application, MC shows high generalization capability.
Figure 19 reports, as an example for the Covid 25% scenario and 10% missing entries in the selected columns, the histograms of the variations $\Delta\overline{predicted}_{i,j}$ for each social skill (in each

histogram, j is fixed, whereas i varies).

$$\Delta\overline{predicted}_i = \frac{1}{25}\sum_{j\in J}\Delta\overline{predicted}_{i,j} \tag{3.3}$$

These figures corroborates our results showing that the social skills for which the largest positive variations are obtained are teaching and time management, while the social skills with the largest negative variations are persuading and understanding others.

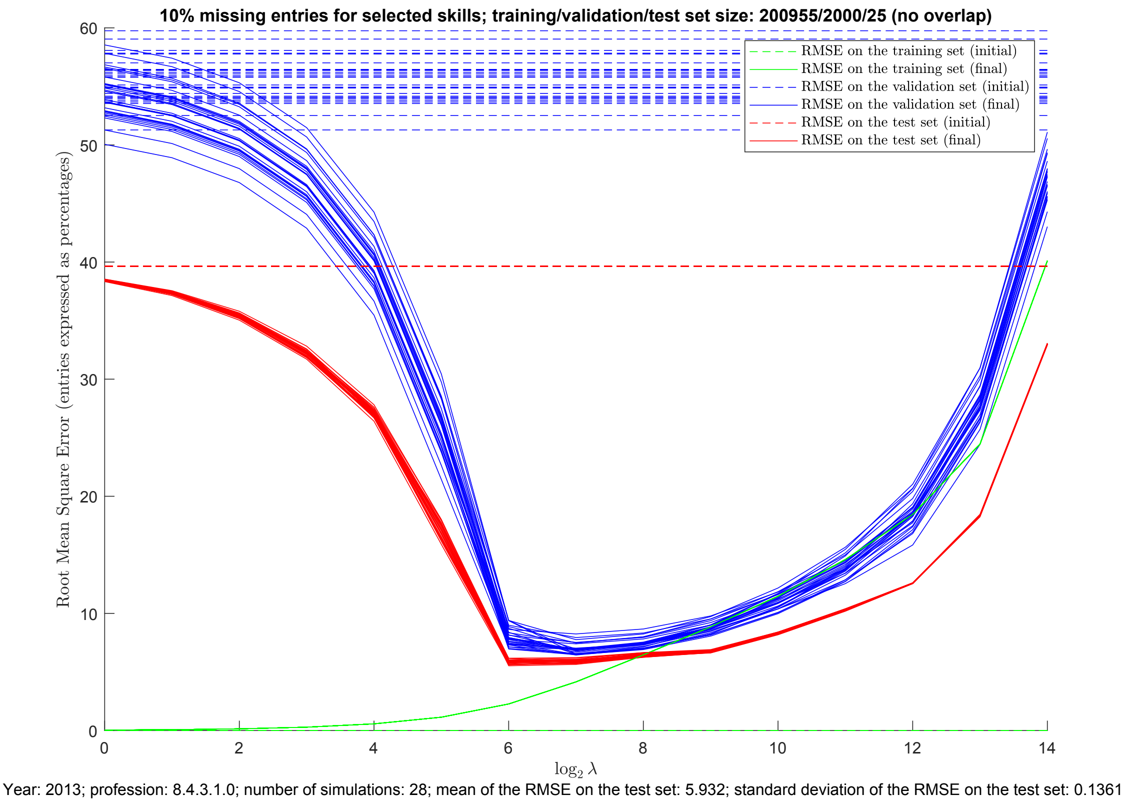


Figure 18: RMSE of prediction on the training, validation and test sets as functions of the regularization parameter λ, for all the repetitions associated with the same test related to a specific profession.

3.8 Final discussion

In this paper, we have exploited similarities in the Italian occupational structure and implemented a recently developed matrix completion technique to predict the levels of creative skills employed in each occupation and to identify the creativity needs of occupations. We could only simulate three possible scenarios for the impact of COVID-19, yet our results could give us a preliminary insight on trends in the labor market in the near future. Our results suggest that professions belonging to the public administration sector, healthcare system and education suffered a huge deficit in social skills due to social distancing and smartworking. Contrarily, people working in the media sectors were able to perform their job quite well, even in times of crisis, possibly thanks to a surplus in the endowment of social skills. Among social skills, we report a deficit in understanding others, persuading and service orientation while the ability of coordinating with others, teaching and training were the most effective in carrying out the work during the pandemic. When the COVID-19 pandemic will be over, it will be primary interest for the public and the business sectors to formulate effective alternatives to maintain and promote the favourable mutations in labour markets that the crisis has provoked. A composite and hybrid working model might become dominant, a model in which workers can decide whether to work at the office or from home, even blending these two during the working week. In accordance with the content of tasks, together with personal needs or preferences, employees and managers will be asked to find new working conditions that merge the advantages of direct personal and physical contact with the flexibility of telework. Definitely, smartworking is not suitable for everyone and the quantity of smartworking adopted during the pandemic might have been disproportionate. A balance between employer-employees preferences is desirable, as well as some minor changes in the organisation of work. This consideration has to be tackled by policy makers after the lesson we learned from the COVID-19 pandemic: there is an unexploited capability, wich might result as a gain in efficiency for employers and employees who are willing to telework more, if frictions in the national legislation and internal organization of workplaces are addressed. All those changes related to digitalisation, artificial intelligence, smartworking and the platform economy go hand in hand with a reinforcement in workers' rights, social security systems and occupational health and safety (European Council Porto Declaration, May 2021). Pandemic has been a stress test, in the sense that it has highlighted where to invest more in order to improve connectivity or upskilling of workers and at the same time it has dismantled psychological and cultural barriers to smartworking, as it has obliged both employers and employees to win their previous reluctance about smartworking, and in fact they are now expressing preferences for higher shares of teleworking hours with respect to pre-pandemic levels. Our results suggest which are the skills that required an update and upgrade in the labor market and highlight skill needs that must be addressed by the public agent for the future of work. Soft skills, in fact, might need some time to adjust to these rapid changes the organizational structure and labor market, thus workers needs to undertake specific and tailored training that goes in this direction. In our application, matrix completion has demonstrated an excellent prediction capability, as well as making us able of carrying out a conterfactual analysis of pre and post Covid occupational structure. The path for future research is wide as more data will be made publicly available at the end of the pandemic so to confront these results with the actual values. The methodology proposed in this article could be also applied to predict other recent trends in the labour market, and possibly also to make a forecast analysis for the future trends.

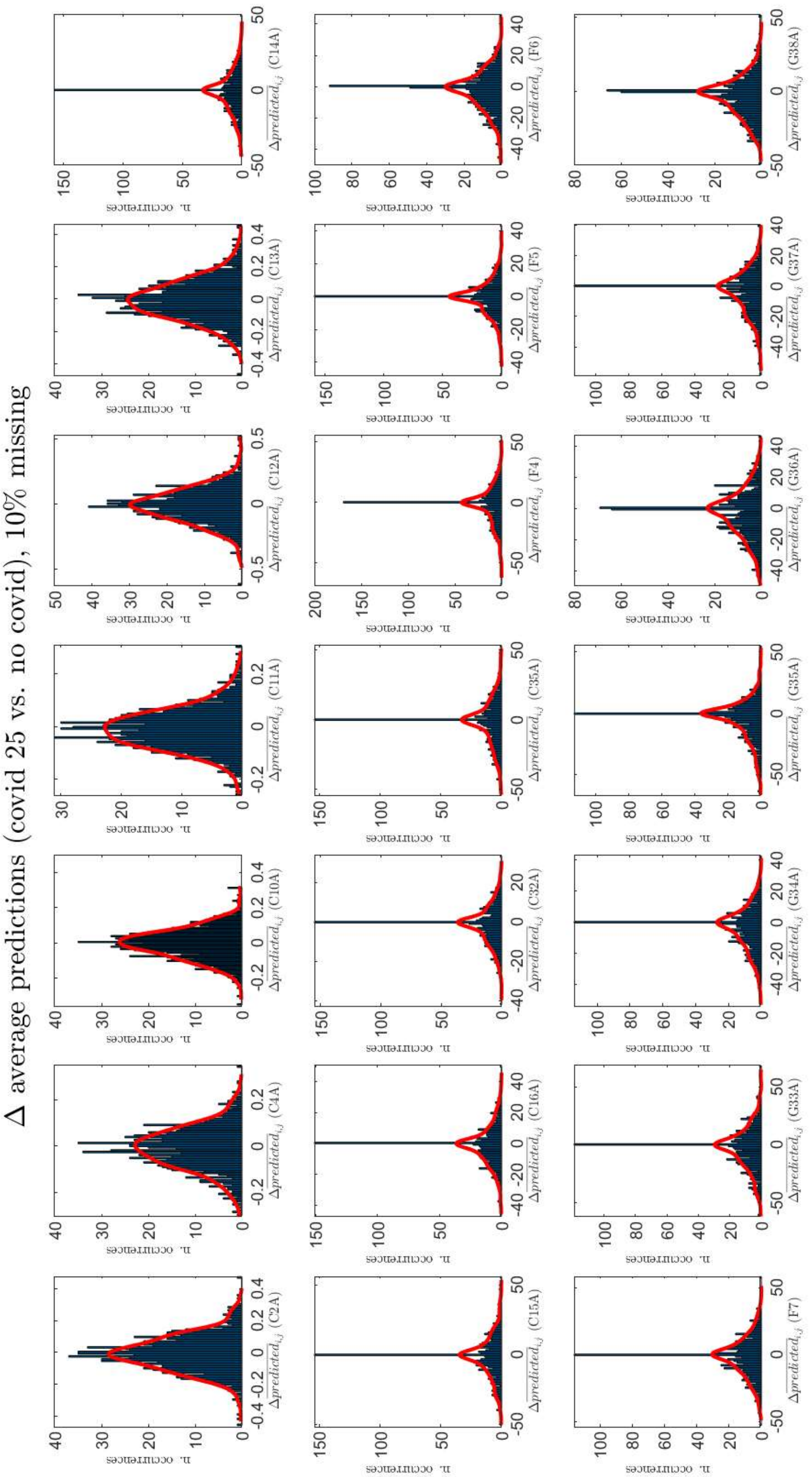


Figure 19: Histograms of the variations $\Delta\overline{predicted}_{i,j}$ for the various social soft skills j.

Conclusions

In this thesis we perform an empirical analysis on the Italian institutional setting both in a political competition context and in the occupational structure. We propose new methods to tackle some of the most disputed questions in the literature of political and labour economics.

The first paper explores the relationship between transfers from central state to political aligned municipalities and the effect of these transfers on local electoral consensus. This study contributes to the empirical literature of the political determinants of spikes in central transfers in pre-electoral periods and of the electoral benefits of pork barrel measures for incumbent politicians. We focus on the so called swing municipalities, defined as those in which the probability of winning is close to one-half, analysing data of Italian comuni with more than 15 000 inhabitants, in the period 2007-2014.

Here we address the endogeneity issue arising in the estimation of the causal impact of political alignment on the amount of federal transfers. Without a credible source of exogenous variation in political alignment, in fact, the empirical correlation between alignment and transfers (if any) can be completely driven by socio-economic factors influencing both dimensions. We proposed, then, to exploit the unpredicted change in the government occurred in 2011 after the resignation of Silvio Berlusconi and the following appointment of Mario Monti as prime minister. Assuming that an unforeseen change in the government or the unexpected dissolution of the two parliament houses could be considered as an exogenous shock for the political alignment of the mayor, and that this shock is not correlated with the political party the mayor is associated with, but it could potentially affect subsequent local elections, the the designation of Monti would be the random device on our treatment variable (political alignment).

We proceed with the empirical estimation in two steps: first, we apply the close-race RDD setup (Lee 2008) to assess the impact of political alignment on transfers. Results from the close-race RDD show that aligned municipalities receive more grants, with this effect being stronger before elections. At a second empirical stage, we perform a local linear regression of the re-election probability of the local incumbent on transfers, including the first stage error term to have our coefficient of interest measuring only the effect of politically-driven transfers on electoral outcomes, and we conclude that this probability increases as grants increase.

The second paper moves our analysis on current trends in the labour market. The idea stems from the observation of the most recent phenomena in the domestic and foreign labour market: technological progress has been associated to a crowding-out of cognitive-skill intensive jobs in favour of jobs requiring soft skills, such as social intelligence, flexibility and creativity. Soft skills can be defined as interpersonal, human, people or behavioural skills necessary for applying technical skills and knowledge in the workplace. The nature of the soft skills make them hardly replaceable by machine work, and Among soft skills, creativity is one of the hardest to define and to codify, therefore, creativity-intensive occupations have been shielded from automation. In our work, we focus on creativity, starting from its definition in order to get significant insights on which occupational profiles in Italy can be considered creative and to explore their dynamics in the labour market.

For the sake of our analysis, we first give a definition of creativity, based on the seminal work of Edward De Bono, and we describe it along four dimensions: 1) fluidity, as the ability of a subject to give the highest possible number of answers to a certain question; 2) flexibility, as the number of categories to which we can bring back these questions; 3) originality: ability of expressing new and innovative ideas; 4) processing: ability of realizing concretely one's ideas. We apply this definition to a uniquely detailed occupational dataset on tasks, skills, work attitudes, and working conditions regarding all Italian occupations: the Inapp-Istat Survey on Occupations (Indagine Campionaria sulle Professioni, ICP hereafter), an O*NET-type dataset developed by the Italian National Institute for Public Policy Analysis. Among the variables included in the survey, we identify 25 skills associated to creativity and we formulate a Matrix Completion (MC) optimization problem, as discussed theoretically in Mazumder (2010).

Matrix Completion is the task of filling in the missing entries of a partially observed matrix, which we generate by obscuring randomly 10%, 25% and 50% of the entries in the columns associated with the creative skills, given a fixed row (occupation). In our analysis, we use a formulation of the problem known as Nuclear Norm Minimization and we solve it with the Soft Impute Algorithm.

We conclude our analysis on social skills in our third paper where we analyse the effects of Covid-19 pandemic on soft skills in the context of Italian occupations, operating in about 100 economic sectors. We leverage detailed information from ICP, the Italian O*Net, and we simulate the impact of Covid-19 on those workplace characteristics and working style that were more seriously hit by the lockdown measures and the new sanitary dispositions (physical proximity, face-to-face discussions, working remotely, ecc.). Since real data on the impact of Covid-19 on the labour market outcomes are not available yet, we decided to simulate three possible scenarios based on the intensity of the effects of COVID-19 on some working conditions, such as working from home, keeping physical distance and so on. This way we can also attempt in predicting the evolution of work in the near future. It might be possible that some of the changes brought about by the pandemic will be adopted permanently both from firms and the public sector. We then apply again matrix completion in order to predict the levels of soft skills required for each occupation when working conditions change. Professions showing a lower intensity in the use of soft skills, with respect to the predicted one, are exposed to a deficit in their soft-skill endowment, which might ultimately lead to lower productivity or higher unemployment, thus enhancing the negative effects of the pandemic.

Results from the first work are significant for the design of grants allocation. As our empirical analysis demonstrated, when local governments have effective power in the provision of local public goods, it emerges a trade-off between the arbitrariness in central transfers allocation and the regulating role of elections. Hence, when grants are not formula-based and citizens hold the mayor responsible for local public goods supply, then the central government might divert resources toward aligned municipalities for attracting voters, therefore leading to resource misallocation.

To the best of our knowledge, the second paper is the first article proposing the application of matrix completion to the analysis of workers' skills. Results show that matrix completion, as we implemented it on the occupational database we employed, has an excellent prediction capability. We also find that soft skills associated with creativity are not neatly separated among intellectual and technical workers, as one might expect. Lastly, some professions show a surplus of creativity with respect to its level predicted by their counterfactuals, meaning that their risk of being replaced by machines is deemed to be low. The opposite happen for profession exhibiting a deficit in creativity: the risk for such professions of being replaced by artificial intelligence techniques is larger. In order to reduce this risk, training on creative soft skills might be tailored on these specific professions and on specific skill needs.

Finally, results of our third work are relevant to imagine the most recent trends in the Italian economy after the huge crisis caused by the pandemic. Our estimates are just an attempt to hypothesize which skills would be required most in the upcoming future where we assume that some working conditions imposed by the pandemic will remain persistent, at least for a few years (Ichino et al., 2020). Policy makers both at national and international level would be asked to foster the formation and training on those exact skills that help workers overcome physical distance and maintain high productivity standard, even when working in a complicated environment, such as their own house.

The thesis leave room for several paths of further research. The relationship between local governments and national transfers might suffer also from criminal infiltration, that are not so infrequent in the Italian landscape. Thus, once endogeneity is overcome, other crucial dimensions undermining an equal distribution of State funds should be taken into account. As far as the labor market is concerned, skill upgrading and skill mismatch are becoming increasingly important in the research agenda and this attention should be transferred to policy makers so to adopt effective strategies in training citizens, starting from the secondary school, empower the digital capabilities of workers and firms, design internal mechanism to foster organizational changes that not only boost employers productivity but also their well being.

Appendix

Further details on matrix completion and on its application to the prediction of creativity levels for different professions

In the work, we consider the following formulation for the Matrix Completion (MC) optimization problem, which was investigated theoretically in Mazumder et al. (2010):

$$\underset{\mathbf{Z}\in\mathbb{R}^{m\times n}}{\text{minimize}} \left(\frac{1}{2} \sum_{(i,j)\in\Omega^{\text{tr}}} (M_{i,j} - Z_{i,j})^2 + \lambda \|\mathbf{Z}\|_* \right) , \tag{4}$$

where Ω^{tr} (which, using a machine-learning expression, may be called training set) is a subset of pairs of indices (i, j) corresponding to positions of known entries of the partially observed matrix $\mathbf{M} \in \mathbb{R}^{m\times n}$, $\mathbf{Z}$ is the completed matrix (to be optimized), $\lambda \geq 0$ is a regularization constant, and $\|\mathbf{Z}\|_*$ is the nuclear norm of the matrix $\mathbf{Z}$, i.e., the sum of all its singular values. The regularization constant λ controls the trade-off between fitting the known entries of the matrix $\mathbf{M}$ and achieving a small nuclear norm. The latter requirement is often related to getting a small rank of the optimal matrix $\mathbf{Z}^\circ$, which follows by geometric arguments similar to the ones typically adopted to justify how the classical LASSO (Least Absolute Shrinkage and Selection Operator) penalty term achieves effective feature selection in linear regression (Tibshirani, 1996).

The optimization problem (4) can be also written as

$$\underset{\mathbf{Z}\in\mathbb{R}^{m\times n}}{\text{minimize}} \left(\frac{1}{2} \|\mathbf{P}_{\Omega^{\text{tr}}}(\mathbf{M}) - \mathbf{P}_{\Omega^{\text{tr}}}(\mathbf{Z})\|_F^2 + \lambda \|\mathbf{Z}\|_* \right) , \tag{5}$$

where, for a matrix $\mathbf{Y} \in \mathbb{R}^{m\times n}$,

$$(P_{\Omega^{\text{tr}}}(\mathbf{Y}))_{i,j} := \begin{cases} Y_{i,j} & \text{if } (i,j) \in \Omega^{\text{tr}} , \\ 0 & \text{if } (i,j) \notin \Omega^{\text{tr}} \end{cases} \tag{6}$$

represents the projection of $\mathbf{Y}$ onto the set of positions of observed entries of the matrix $\mathbf{M}$, and $\|\mathbf{Y}\|_F$ denotes the Frobenius norm of $\mathbf{Y}$ (i.e., the square root of the summation of squares of all its entries).

It is shown in Mazumder et al. (2010) that the optimization problem (5) can be solved by applying the following Algorithm 1, named Soft Impute therein:[4]

Algorithm 1: Soft Impute (Mazumder et al., 2010)

Input: Partially observed matrix $\mathbf{P}_{\Omega^{\mathrm{tr}}}(\mathbf{M})$, regularization constant $\lambda \geq 0$, tolerance $\varepsilon > 0$, maximal number of iterations N^{it}

Output: Completed matrix $\mathbf{Z}_\lambda \in \mathbb{R}^{m \times n}$

1. Initialize $\mathbf{Z}$ as $\mathbf{Z}^{\mathrm{old}} = \mathbf{0} \in \mathbb{R}^{m \times n}$
2. Repeat for at most N^{it} iterations:
   (a) Set $\mathbf{Z}^{\mathrm{new}} \leftarrow \mathbf{S}_\lambda \left(\mathbf{P}_{\Omega^{\mathrm{tr}}}(\mathbf{M}) + \mathbf{P}^{\perp}_{\Omega^{\mathrm{tr}}}(\mathbf{Z}^{\mathrm{old}}) \right)$
   (b) If $\frac{\|\mathbf{Z}^{\mathrm{new}} - \mathbf{Z}^{\mathrm{old}}\|_F^2}{\|\mathbf{Z}^{\mathrm{old}}\|_F^2} < \varepsilon$, exit
   (c) Set $\mathbf{Z}^{\mathrm{old}} \leftarrow \mathbf{Z}^{\mathrm{new}}$
3. Set $\mathbf{Z}_\lambda \leftarrow \mathbf{Z}^{new}$

In Algorithm 1, for a matrix $\mathbf{Y} \in \mathbb{R}^{m \times n}$, $\mathbf{P}^{\perp}_{\Omega^{\mathrm{tr}}}(\mathbf{Y})$ represents the projection of $\mathbf{Y}$ onto the complement of Ω^{tr}, whereas

$$\mathbf{S}_\lambda(\mathbf{Y}) := \mathbf{U}\boldsymbol{\Sigma}_\lambda \mathbf{V}^T \,, \tag{7}$$

being

$$\mathbf{Y} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T \tag{8}$$

(with $\boldsymbol{\Sigma} = \mathrm{diag}[\sigma_1, \ldots, \sigma_r]$) the singular value decomposition of $\mathbf{Y}$, and

$$\boldsymbol{\Sigma}_\lambda := \mathrm{diag}[(\sigma_1 - \lambda)_+, \ldots, (\sigma_r - \lambda)_+] \,, \tag{9}$$

with $t_+ := \max(t, 0)$.

In Li and Zhou (2017), a particularly efficient implementation of the operator $\mathbf{S}_\lambda(\cdot)$ defined in Equation (7) is proposed (by means of the MATLAB function `svt.m` reported therein), which is based on the determination of only the singular values σ_i of $\mathbf{Y}$ that are larger than λ, and of their corresponding left-singular vectors $\mathbf{u}_i$ and right-singular vectors $\mathbf{v}_i$. Indeed, all the other singular values of $\mathbf{Y}$ are annihilated in $\boldsymbol{\Sigma}_\lambda$ (see Equation (9)).

The connection between MC and singular values, which has been highlighted above, is actually even stronger. Indeed, given a nonzero matrix $\mathbf{M} \in \mathbb{R}^{m \times n}$, and denoting its rank by $\mathrm{rank}(\mathbf{M})$, it is well-known – by Eckart-Young theorem, see Theorem 2.1.2 in Moitra (2018) – that, for any $k \in \{1, \ldots, \mathrm{rank}(\mathbf{M})\}$, the best rank-$k$ approximation of $\mathbf{M}$ according to the Frobenius norm is provided by its truncated singular value decomposition, in which one keeps only the k-largest singular values of $\mathbf{M}$, and zeroes all the others. So, for an effective application of MC, one needs a quite rapid decay to 0 of the singular values of the matrix $\mathbf{M}$ to be completed. This is an important necessary condition for such an effective application. However, such condition is not sufficient when the matrix is only partially observed, since computing the singular value decomposition itself requires knowing the whole matrix.

In our application of the Soft Impute algorithm to an occupation matrix, we combine the original MATLAB implementation of Soft Impute from Mazumder et al. (2010) with the

[4]Compared to the original version, here we have included a maximal number of iterations N^{it}, which can be helpful to reduce the computational effort – at the cost of possibly stopping before convergence – when one has to run the algorithm multiple times, e.g., for several choices of the matrix $\mathbf{M}$ to be reconstructed and several values of the regularization constant λ.

MATLAB function `svt.m` from Li and Zhou (2017). First, a specific row (profession) is fixed. All its entries in 25 given columns related to creativity are obscured, and form the test set (their set of positions is denoted by Ω^{test}). Then, one selects a percentage (respectively, 10%, 25%, 50%) of the rows of the matrix, excluding the given row. The entries in such rows are obscured in correspondence of the 25 given columns. These obscured entries form the validation set (their set of positions is denoted by Ω^{val}). All the remaining entries of the matrix form the training set. It is worth observing that, by the construction above, there is no overlap among the training, test, and validation sets. To avoid overfitting, we select the regularization constant λ via the following validation method. The optimization problem (5) is solved for several choices λ_k for λ, exponentially distributed as $\lambda_k = 2^{k-1}$, for $k = 1, \ldots, 15$. For each λ_k, the Root Mean Square Error (RMSE) of matrix reconstruction on the validation set is computed as

$$RMSE^{\text{val}}_{\lambda_k} := \sqrt{\frac{1}{|\Omega^{\text{val}}|} \sum_{(i,j)\in\Omega^{\text{val}}} \left(M_{i,j} - Z_{\lambda_k,i,j}\right)^2}\,, \tag{10}$$

then the choice λ_k° that minimizes $RMSE^{\text{val}}_{\lambda_k}$ for $k = 1, \ldots, 15$ is found. Finally, the RMSE of matrix reconstruction on the test set is computed in correspondence of the optimal value λ_k° as

$$RMSE^{\text{test}}_{\lambda_k^\circ} := \sqrt{\frac{1}{|\Omega^{\text{test}}|} \sum_{(i,j)\in\Omega^{\text{test}}} \left(M_{i,j} - Z_{\lambda_k^\circ,i,j}\right)^2}\,. \tag{11}$$

The whole procedure is repeated a sufficiently large number of times for each profession. This number is not the same for each profession due to the following method employed to reduce the total simulation time. Since the MC optimization problem (5) depends only on the training set, 200 random permutations of the rows of the matrix are generated. Each permutation is associated with a single training set. At the same time, it is associated with various different choices for the validation and test sets. More precisely, for each permutation, the first $h\%$ among such rows (with $h = 10$, 25, 50), plus the successive row in the permutation, form a set $\mathcal{S}$ of rows, which is used to generate the union of the validation and test sets, by including in such union all the elements at the intersection between such rows and the selected columns. All the remaining elements of the matrix constitute the training set (one for each permutation). Then, $|\mathcal{S}|$ different test sets are constructed by including in each of them all the elements at the intersection between the selected columns and one specific row belonging to $\mathcal{S}$, in all possible $|\mathcal{S}|$ ways. The corresponding $|\mathcal{S}|$ validation sets are constructed by including in them all the elements at the intersection between the selected columns and the remaining rows of $\mathcal{S}$, in all possible $|\mathcal{S}|$ ways. As already mentioned, in all these $|\mathcal{S}|$ cases, the training set is always the same, so the MC optimization problem (5) is solved once for each choice of $\mathcal{S}$. It is also clear that, in this way, the number of times a specific row appears in $\mathcal{S}$ is not guaranteed to be the same for each row, because it depends on the specific set of random permutations generated. The number of such permutations (200) is selected in order to include each row in the sets $\mathcal{S}$ with high probability for a sufficiently large number of times. Indeed, the expected number of times this occurs is about 20, 50, 100, respectively for $h = 10$, 25, 50. In this way, it is possible in principle to assess how the prediction on the test set associated with each row changes by varying the training and corresponding validation sets (see Figure 7 in the main text for an example of this kind of analysis).

It is worth mentioning that in our application of MC to occupation matrices, all the very few missing entries of such matrices in the training set (when they are present) are replaced by zeros before running Algorithm 1. The tolerance is chosen as $\varepsilon = 10^{-7}$. Moreover, when convergence is not achieved, in order to reduce the simulation time, the algorithm is stopped after $N^{\text{it}} = 50$ iterations. An additional post-processing step is included, thresholding to 0 any negative element (when present) of the completed matrices, and to 100 any element (when present) larger than 100. This is justified by the fact that the elements of the occupation matrices represent percentages.

A final remark has to be made about the trade-off between prediction capability and biasedness of the method. According to Foucart et al. (2017) and Ma and Chen (2019), biasedness in MC depends, e.g., on the way the selection of unobserved entries is made (in our case, only entries associated to selected skills are obscured, and for the professions for which this occurs, all the entries associated to such skills are actually obscured). For some algorithms, de-biasing is possible (Foucart et al., 2017), and can even improve prediction capability. Nevertheless, in general biasedness can be beneficial to prediction capability, due to the well-known trade-off between bias and variance (Hastie et al., 2009). In the particular case of MC achieved via Algorithm 1, biasedness can be ascribed also to the presence of the regularization constant λ (indeed, for both $\lambda \to 0$ and $\lambda \to +\infty$, the predictions of the optimal solution to the optimization problem (5) tend to 0 for the unobserved entries), and to the fact that Algorithm 1 is initialized by a matrix with all entries equal to 0, and terminated at most after a given number of iterations.

Appendix

Correspondence between codes and selected professions in Figures 9 and 10

Table 18: Correspondence between codes and professions; healthcare sector, Figure 9

Code	Profession
1.1.2.6.3	Health care directors
2.4.1.1.0	General doctors
2.4.1.2.0	Medical care specialists
2.4.1.3.0	Surgical care specialists
2.4.1.4.0	Laboratorians and clynical pathologists
2.4.1.5.0	Dentists and oral surgeons
2.4.1.6.0	Diagnostic imaging and radiotherapy specialists
2.4.1.7.1	Dietologists and hygienists
2.4.1.7.2	Social and occupational health specialists
2.4.1.7.3	Epidemiologists
2.4.1.8.0	Anaesthetists and critical care specialists
3.2.1.1.1	Nursing professions
3.2.1.1.2	Obstetrical professions
3.2.1.2.1	Podiatrists
3.2.1.2.2	Physioterapists
3.2.1.2.3	Logopedists
3.2.1.2.4	Optometrists
3.2.1.2.5	Therapists in neuropsychomotricity
3.2.1.2.6	Therapists in psychiatric rehabilitation
3.2.1.2.7	Social educators
3.2.1.2.8	Occupational therapists
3.2.1.3.1	Audiologists
3.2.1.3.2	Biomedical laboratory assistants
3.2.1.3.3	Radiographers
3.2.1.3.4	Neurophysiopathologists
3.2.1.4.1	Orthopaedic technicians
3.2.1.4.2	Hearing care professionals
3.2.1.4.3	Dental hygienists
3.2.1.4.4	Cardiovascular pathophysiology and perfusion technicians
3.2.1.4.5	Dieticians
3.2.1.5.1	Technicians in prevention in the environment and the workplace
3.2.1.5.2	Health visitors
3.2.1.6.1	Opticians
3.2.1.6.2	Dental technicians
3.2.1.7.0	Popular medicine technicians
8.1.5.1.0	Janitors and assimilated
8.1.5.2.0	Aides and assimilated

Table 19: Correspondence between codes and professions; cultural sector, Figure 10

Code	Profession
2.1.1.6.2	Paleontologists
2.5.3.2.4	Archaeologists
2.5.3.4.2	Art experts
2.5.4.1.2	Dialogists
2.5.4.5.1	Archivists
2.5.4.5.2	Librarians
2.5.4.5.3	Curators
2.5.5.1.1	Painters and sculptors
2.5.5.1.5	Conservators
2.5.5.2.1	Directors
2.5.5.2.2	Actors
2.5.5.2.3	Artistic directors
2.5.5.2.4	Screenwriters
2.5.5.2.5	Scenographers
2.5.5.3.1	Choreographers
2.5.5.3.2	Dancers
2.5.5.4.1	Composers
2.5.5.4.2	Conductors
2.5.5.4.3	Instrumentalists
2.5.5.4.4	Singers
2.5.5.5.1	Folk artists
2.5.5.5.2	Variety artists
2.5.5.5.3	Acrobats
3.1.2.6.2	Radio or TV broadcasters
3.1.7.2.1	Audio-video equipment and video shoots technicians
3.1.7.2.2	Sound technicians
3.1.7.2.3	Audio-video editors
3.3.4.7.0	Agents and representatives of artists and athletes
3.4.3.1.1	Radio or TV announcers
3.4.3.1.2	Presenters
3.4.3.2.0	Radio, television, cinema and theaters production technicians
3.4.4.1.2	Set designers
3.4.4.2.1	Museum technicians
3.4.4.2.2	Library technicians
3.4.4.3.1	Art estimators
3.4.4.3.2	Philatelic and numismatic experts
3.4.4.3.3	Calligraphy experts
3.4.4.4.0	Restoration technicians
4.4.2.2.0	Library officers
5.4.2.1.1	Cinema and theatre merchants
6.5.5.1.0	Stagehands and property workers

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