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RESEARCH PAPER

COVID-19 and Wage Polarization: a Task-based Approach

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Abstract
The aim of this paper is to estimate the effects of the COVID-19 pandemic on the wage polarization in Italy, combining individual characteristics with their task content in terms of physical proximity within the workplace. We use an innovative dataset which combines data from two sample surveys, the Italian Labor Force Survey and Italian Survey of Professions, which provides information on nature and content of the tasks. First, by employing a non-parametric method (the Relative Distribution) we detect a general increasing wage polarization in the sub-period 2020–2019, driven by lowest deciles, after a reduction in the previous one (2019–10). Different groups have been also isolated. Workers with low education, high proximity to customers job, such as the immigrant, younger and female ones are the categories that more suffered the general downgrading of the Italian wages happened during the COVID-19 crisis.

Keywords Covid19 · Income polarization · Relative distribution · Social conflicts · Tasks

JEL Classification J28 · J81 · H12 · I18

1 Introduction

The Covid-19 emergency affected every country in the world (Bloise and Tancioni 2021; Caselli et al. 2022; Karabulut et al. 2021; Milani 2021; Papageorge et al. 2021) with major consequences for labor markets (Aina et al. 2023, 2024; Alon et al. 2020; Biagetti et al. 2024; Botha et al. 2021, Baert et al. 2020, Esposito et al. 2024, Croce and

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Scicchitano 2022) as governments took shut down non-essential services to combat the pandemic (Caselli et al. 2022; Depalo 2021; Qiu et al. 2020).[1] Social distancing was therefore the key public policy implemented globally during the pandemic, with an important dimension of this being the reduction in proximity between workers s (Carbonero and Scicchitano 2021). Among the different labor market outcomes produced by the COVID-19 crisis, wage polarization has been relatively less investigated, mainly due to the lack of timely and reliable data, since representative datasets on population incomes and living conditions are normally released long after interviews are carried out (Adams-Prassl, et al 2020; Hacıoğlu-Hokeet al. 2021; Gallo and Raitano 2020).

The coronavirus crisis has shown that different types of workers were impacted very differently by the pandemic. Workers whose jobs involve high levels of personal proximity to either co-workers or members of the public are the most economically vulnerable (Mongey et al. 2021; Barbieri et al. 2022). The COVID19 pandemic has added a shadow cost to labor due to the higher risk of physical proximity. More specifically, it increased the cost of physical contact between individuals, something that was particularly clear in the field of healthcare. Moreover, as lockdowns eased, activities intensive in physical proximity were slower to recover as people continued to adopt social distancing precautions (Avdiu and Nayyar 2020).We fill the gap in this literature by analyzing what happened to the wage polarization in Italy during the crisis, merging real-time data up to 2020 from the official Labor Force Survey (LFS) with *task-based* data on the proximity of professions, from the Sample Survey on Professions (ICP), the Italian equivalent of the US Occupational Information Network (O*Net). The main advantages of the ICP data are their richness in terms of job characteristics and their specificity to the Italian context: thus, no international crosswalk (based, for example, on US data) is needed. In this paper, first, we classify the occupations according to the degree of physical proximity involved (first in relation to co-workers and then to external customers and clients). Second, we estimate how and to what extent individuals' characteristics and their tasks contributed to the total polarization of wages in Italy during the Covid-19 pandemic.

Over the last two decades, the relevant literature has increasingly focused on income polarization as a concept that is close to, but distinct from, inequality. The notion of income polarization refers to the tendency of a distribution to concentrate around a number of poles, not necessarily two (Esteban and Ray 1994; Duclos et al. 2004; Duro 2005; Chakravarty 2009; Foster and Wolfson 2010). It has been shown that the concept of polarization can be more informative than that of inequality with respect to income distribution, especially when it is linked to social conflict between clustered groups of a population. Esteban and Ray (1999), for example, report a positive correlation between the level of conflict and polarization. Consequently, polarization is more appropriate than inequality when discussing groups (Esteban and Ray 1994). Other research has examined the impact of the Great Recession (GR) on income polarization (D'Errico et al. 2015; Adelino et al. 2016; Baiardi and Morana 2018), but the empirical evidence of differentiated effects on population groups is still scarce. However, if we limit the analysis to polarization across the entire distribution, without distinguishing on the

[1] A comprehensive review is in Kosteas et al. (2022).

basis of a set of individual characteristics (for example, distinguishing by tasks, gender, education, age, residential area,), we do not provide policymakers with the necessary information about the best policies to adopt (Araar 2008; Ricci and Scicchitano 2021).

Hence, the notion of economic polarization is frequently used to describe those processes of change in income distribution which occur when there is a tendency for concentration at the tails rather than the middle. Two different strands of research are observable within this field. The first assesses income polarization changes by developing quantitative measures called polarization indexes. The second approach uses kernel density estimation and mixture models in order to describe changes in polarization patterns over time and across countries (Clementi and Schettino 2013 and 2015; Clementi et al. 2017, 2018, 2021, 2023a, b; Schettino and Khan 2020; Schettino et al. 2021).

In this paper, we integrate both methods by using the so-called Relative Distribution approach (RD). Our aim is to compare changes both across the whole distribution and across different population groups, classified according to head of household characteristics, between 2000 and 2019, and between 2019 and 2020. Two questions are relevant here: has the change in income polarization been homogeneous during the crisis or have some groups suffered more than others? How have population groups contributed to total polarization during the crisis?

Some institutional reports by Inapp (2020), INPS (2020) and Istat (2021), show from a descriptive point of view that physical proximity in jobs had been penalized before the pandemic. We add to the current literature by investigating income polarization as a result of the Covid-19 crisis between and within population groups, by physical proximity, gender, education, age, residential area. The novelty of our results is due to the fact that we employed a new method – the Relative Distribution method (Handcock and Morris 1998) – that allows for an estimation – rather than a calculation—of wage polarization in a dynamic perspective. We employ the RD by group to evaluate what kinds of changes have occurred in the relative concentration of people at each level over the period 2010–2020. The RD is a non-parametric approach that we use to perform distributional analyses of group differences during the Covid-19 period (Handcock and Morris 1998). The relative distribution method assumes two populations, the ‘reference’ and ‘comparison’ populations, and allows for the calculation of the proportions of the ‘comparison’ population that fall into each quintile of the ‘reference’ population. In this way it is possible to test hypotheses about distributional differences before and during Covid-19 and, using decomposition techniques, to isolate the effects of changes in population mix (a demographic process) from changes in attribute allocation (a social or economic process). Thus, shifts can be due to differences in location (associated with changes in the median or mean of the income distribution) or to differences in shape—the ‘pure’ changes in distributional characteristics that include differences in variance, asymmetry and/or other distributional characteristics that could easily be associated with several other factors. Additionally, it combines the graphical tools of exploratory data analysis with statistical summary, decomposition and inference, and it also provides graphical representations of the results, giving a precise idea of how and to what extent income (or other monetary variables, i.e. wage, consumption etc.) distribution has changed over the period under consideration. Finally, this method allows researchers to test different hypotheses about the drivers of distributional change using the covariates method (Schettino et al. 2021), and, in contrast to traditional statistics such as the DER or FW index, the RD method provides three different indexes able to the detect the polarization from an "absolute" instead of "relative" point of view, a relevant perspective for analyzing contemporary socioeconomic inequalities (Niño-Zarazúa et al. 2016).

We chose Italy as an interesting case study because it is one of the countries most affected by the pandemic, as the early epicenter of the pandemic in Europe. As of March 2021, it was the seventh country in the world in terms of cumulative cases, with about 3.2 million cases, the sixth in terms of the number of deaths, with about 103 thousand, and it was the first Western country to adopt severe lockdown measures, beginning March 11 2020 (Barbieri et al. 2022; Bonacini et al. 2021, 2024). The COVID-19 has had significant effects on low wages and on poverty in Italy. Preliminary estimates indicate a growth in the incidence of absolute poverty both in terms of households (from 6.4% in 2019 to 7.7%, + 335 thousand), amounting to over 2 million families, and in terms of individuals (from 7.7% to 9.4%, over 1 million more), which amounted to 5.6 million. This means that during the pandemic absolute poverty in Italy reached its highest value since 2005, i.e., since the time series for this indicator has been available.[2] The most recent estimates report that in 2022, just over 2.18 million families were in absolute poverty (8.3% of the total up from 7.7% in 2021) while over 5.6 million individuals were in the same condition (9.7% up from 9.1% the previous year). The incidence of relative poverty in 2022 stands at 10.9% (stable compared to 11.0% in 2021) and there are 2.8 million families below the threshold.

To our knowledge, this is the first paper to estimate income polarization during the COVID-19 pandemic by combining a task-based approach. The findings reveal a general strengthening in the tendency toward wage polarization in the sub-period 2020–2019, guided by lowest deciles, following a reduction in the previous one (2019–10). New groups have been also detected. Workers with lower levels of education and working in jobs that involve high proximity to customers, who were also more likely to be immigrant, younger and/or female, were those that were more affected by the general downgrading of wages during the crisis.[3]

The rest of the paper is structured as follows: Sect. 2 Discusses the main literature on the topic; Sect. 3 Describes the datasets, while Sect. 4 Reports the methodology used in the empirical analysis. Sections 5 and 6 Present main results and robustness checks, and Sect. 7 Concludes with some policy implications.

[2] More details are available at https://www.istat.it/it/files//2021/03/STAT_TODAY_stime-preliminari-2020-pov-assoluta_spese.pdf.

[3] Unfortunately, this study is not sufficiently able to separate the effects of the market from those of government policies, mainly due to the type of data employed and the relative closeness in time to the analyzed period. Hopefully, the data that will become available in the coming years will be more useful in looking into this.

2 Theoretical Framework

2.1 Previous Literature on Income Polarization

Our paper relates to different strands of economic literature. First, we build on previous literature on income polarization. Beginning with the studies of Foster and Wolfson (2010), Esteban and Ray (1994), and Wolfson (1994, 1997), various measures of polarization have been defined (Chakravarty and Majumder 2001; Duclos et al. 2004; Esteban et al. 2007; Chakravarty and D'Ambrosio 2010).

In these studies, polarization is related to but distinct from inequality, as shown by Esteban (2002), Duclos et al. (2004) and Lasso de la Vega and Urrutia (2006). Indeed, inequality evaluates the overall dispersion of the distribution, while polarization measures aim to explore whether it is possible to observe "the emergence of groups in a distribution" (Chakravarty 2009) and capture the gap between those at the top and those at the bottom of society in developed and developing countries. This is done through the grouping of community members around more than one pole and through the measuring of their consequent distance from the center, according to specific characteristics.

The literature on polarization lays out a number of sets of axioms. Many authors provide axioms for bipolarization indexes, which consider polarization as the result of a distribution concentrated around two points at its tails. The approach proposed by Foster and Wolfson (2010) looks at the dispersion of the income distribution from the center toward one or both of the tails, dividing the distribution into two income groups: one above and one below the median. Their index is the result of two components: one that measures the distance from the center, the second that evaluates the concentration around each pole. With this tool it is possible to compare different pairs of curves, one for each population being analyzed. If the estimated curves do not cross at any point, it is possible to reach an unambiguous conclusion about the evolution of the middle class without fixing any income boundaries. Otherwise, only the information on the different income ranges that support prior definitions emerges.

Foster and Wolfson also derive a synthetic index of bi-polarization, similar to the Gini index. This index reflects the fact both the fact that an increment in inequality between the two groups increases polarization but, also that an increase in inequality within each group decreases polarization. Alternative ways of measuring of bi-polarization are provided by Bossert and Schworm (2008) and Chakravarty and D'Ambrosio (2010).

On the other hand, Esteban and Ray (1994) and Duclos et al. (2004) propose a set of axioms for general polarization measures, where polarization is explained as a tendency of a distribution to concentrate around two or more poles. This notion of income polarization is more general since it regards the latter as the 'clustering' of a population around two or more poles of the distribution, irrespective of where they are located along the income scale. As reported by Clementi et al. (2017), the notion of income polarization in a multi-group context aims to capture the degree of potential conflict inherent in a given distribution (Esteban and Ray 1994). In this framework, society can be evaluated as an amalgamation of groups, where individuals within the same group share attributes with the other members (i.e. have a mutual sense of 'identification'), but in terms of these same attributes, they are different from the members of other groups (i.e. have a feeling of 'alienation'). Indeed, the coexistence of a high level of homogeneity within each group and a high level of heterogeneity between groups can create social tensions, revolution and revolt, and social unrest in general.

Indexes regarding the concept of income polarization as conflict among groups have been studied in other works (Gradín 2000; Zhang and Kanbur 2001; Duclos et al. 2004; Lasso de la Vega and Urrutia 2006; Esteban et al. 2007). In some cases (e.g. Esteban and Ray 1994), polarization indexes require a pre-grouping of the incomes to be calculated. In others (e.g. Duclos et al. 2004), the number of groups is determined endogenously. In both cases, computing and comparing polarization indexes is useful in characterizing some sort of stylized facts regarding the overall income distribution in one period.

Likewise, the RD approach represents a non-parametric method that links the strengths of summary polarization indexes to the details of distributional change offered by kernel density estimates. The original study in this field is by Jenkins (1995), who proposes an estimation method based on a kernel density approach, looking directly at the changes in the relative concentration of people at each income level over time. Handcock and Morris (1998) further improve this theoretical framework. In this paper, we use their RD approach to disentangle changes in the income distribution by population group during the Covid-19 crisis.

Some empirical studies analyzed income polarization in different countries (Gonzales et al. 2014; Nissanov and Pittau 2016; Clementi and Schettino 2013, 2015; Clementi et al. 2017, 2018, 2021, 2023a, b). Some works have been specifically dedicated to Italy. Boeri and Brandolini (2004) investigated income distribution in Italy in the period of 1993–2002 by assessing income polarization through the Wolfson index. They find that inequality and polarization increased sharply between 1991 and 1993, but unlike inequality, polarization reduced in the following nine years. Massari et al.(2009a)) employ the RD approach to Italian income data between 2002 and 2004: the work obtains a significant location effect, together with a surge in income polarization, driven by incomes below the median. D'Ambrosio (2001) examines Italian income polarization between 1987 and 1995, focusing on changes in the entire distribution rather than only in dispersion. Poggi and Silber (2010), using 1985–2003 Italian data, demonstrate differences between *structural* and *exchange* mobility. Ricci (2016) measures the evolution of the middle-income group in the years from 2002 to 2012, calculating the Esteban, Gradín and Ray (EGR) indexes in Italy between 2002 and 2012. Results from polarization indexes confirm a gradual decline between 2002 and 2006. The period from 2006 to 2012 reports an increase in polarization, which indicates a shrinking of the middle-income group. Simonazzi and Barbieri (2016) looked at the erosion of the Italian middle class, showing that while many typically middle-class jobs are progressively disappearing or becoming increasingly precarious, wages in the last few years have remained substantially stable. The authors demonstrate that while polarization did not change from 1991 to 2006, it increased significantly after this period. Bloise et al. (2018) study wage polarization in Italy between 1985 and

2014 and reveal a clear process of wage accumulation at the extremes of the distribution in the latter years. Likewise, Pianta (2020) shows a clear decline in income for the Italian population over the period of 1994–2016 for all income groups except the top 10% — a stylized tendency that was amplified during the crisis. Brandolini et al.2018) report the evolution of income inequality in Italy from 1989 to 2014. They posit a general downgrading as a clear stylized fact of the GR. Ricci and Scicchitano (2021) report a general downgrading of low-educated, young, southern and foreign heads of household coming out of the GR.[4]

What this strand of literature has ignored are the economic consequences on population subgroups, especially coming out out of the Covid-19 crisis. In this paper, we decompose changes in income polarization during the emergency by population subgroup in Italy. In particular, we present evidence based on the categories of in-work tasks, gender, education, age and residential area.

2.2 Coronavirus Emergency, Task-based Approach, and Income Inequality

The economic literature on COVID-19 is rapidly proliferating. Our paper is related to two strands of this literature. A first line of this literature investigates the distributional consequences of the Covid-19. Using data from a large Fintech company in the United Kingdom, Hacıoğlu-Hoke et al. (2021) indicate that the smallest spending cuts and the largest earning reductions were detected at the lowest quantiles of income distribution. Clark et al. (2021)—using longitudinal data from France, Germany, Italy, Spain, and Sweden—found a decrease in relative inequality between January and September 2020. A possible explanation was posited as the fact that the policy responses to the pandemic converged around the bottom of the income distribution, where the individuals most affected by the pandemic are expected to be found. According to Gambau et al. (2021), without compensating policies, wage inequality would have increased in the US for all social groups and states. They estimate a national potential surge in inequality of 4.1 Gini points with uneven increases by race, gender, and education. A significant positive correlation between income inequality and COVID-19 incidence in OECD countries is found by Wildman (2021) using data from the European Centre for Disease Prevention and Control (ECDC). Angelov and Waldenström (2021) find that income inequality increased in Sweden during the pandemic, because of layoffs and fewer working hours among low-income, part-time employees. Lemieux et al. (2020) study the influence of the pandemic on the Canadian labour market and demonstrate that half of job losses were associated with workers in the bottom earnings quartile.

This strand of literature highlights the importance of the availability of timely and reliable data, something that can be difficult to get hold of as representative datasets on income and living conditions of the population are typically released long after the interviews (Aina et al. 2023). Two exceptions, using real-time ad hoc surveys, are represented by the United Kingdom (Benzeval et al. 2020; Witteveen 2020) and the United States (Berman 2020; Cortes and Forsythe 2020). To resolve this problem, scholars have generally used real-time surveys (e.g., Adams-Prassl et al. 2020; Galasso

[4] Other studies, such as Palacios-Gonzales and Garcia Ferndandez (2012) and Addabbo et al. (2018), have analyzed polarization by group.

2020) or big data from bank records (Aspachs et al. 2020). However, these types of data cannot be considered representative of the entire population and do not allow for reliable estimation of changes along the income distribution (Gallo and Raitano 2020).

The onset of the pandemic has led to another growing body of research characterizing occupations and sectors of economic activity along according to levels of risk or safety for workers during the epidemic. This new area of research classifies jobs and economic activities according to their task content, building on the literature that studies the impact of technological change on labour market outcomes through the tasks performed by workers (Firpo et al. 2009). In particular, many papers have classified jobs according to the degree of physical proximity required to carry them out (Leibovici et al. 2020; Mongey et al. 2021). Montenovo et al. (2020) find that the hardest hit US workers were those in occupations that require physical proximity. Their findings indicate that workers in occupations with a relatively high degree of physical proximity but low risk of illness were more affected in terms of labour market outcomes. Mongey et al. (2021) investigate the socio-economic characteristics of workers who were more exposed to the risk of infections because they were employed in jobs involving a high degree of physical proximity. They further prove that these workers were made more vulnerable due to their low levels of education, low level of income and low home ownership rates. Avdiu and Nayyar (2020) show that jobs requiring intensive face-to-face interactions with consumers were vulnerable even beyond lockdowns. Regarding Italy, Barbieri et al. (2022) rank sectors and occupations in Italy according to the degree of physical proximity and demonstrate that the sectoral lockdown put in place by the Italian Government in March 2020 targeted sectors with a significantly higher degree of physical proximity.

As for Italy, the country seems to have been particularly vulnerable to the effects of the pandemic due to its structural problems, especially in the labour market (Aina et al. 2024). A significant reduction in hiring and an increase in the termination of temporary contracts is evident from the beginning of March 2020 (Casarico and Lattanzio 2020). The same authors also demonstrate that young, temporary and low-skilled workers were more at risk of unemployment due to COVID-19, while gender is not significant. Gallo and Raitano (2020) simulate the impact of the pandemic on Italy for the whole of 2020 under three different scenarios. They find that the crisis caused a relatively larger decline in labour income for those at the bottom of the income distribution, but that this part of the income distribution received higher assistance from the government. As a result, market incomes declined, but social transfers proved effective in reducing the most severe economic consequences of the crisis.[5] Carta and De Philippis (2021) investigate the impact of the pandemic on the distribution of labour income in Italy, using micro data referring to the fourth quarter of 2019, and posit a potential sharp increase in income inequality. Aina et al. (2023) study the effects of the crisis on the total wage distribution in Italy using the quarterly LFS data and find that the coronavirus pandemic positively affected the wages of the entire workforce, and that this result is

[5] In our paper we focus our attention on wage variations due to the COVID-19 pandemic. Those wage variations certainly can be caused by unemployment. Since for each worker the transition from employment, whatever the contract, to unemployment clearly has an impact on their wage, our results appear to be consistent with those of Casarico and Lattanzio (2020).

greater as we move along the wage distribution. They conclude that this improvement in wages is probably due to modifications in the occupational composition.

In summary, the majority of existing evidence on the impact of the crisis on income in Italy is based on simulations using data from before the onset of the pandemic. We add to the existing evidence by showing how the characteristics of individual workers and the particular tasks they were engaged in contributed to the total polarization of wages in Italy during the Covid-19 crisis.

3 Institutional Context and Policies Adopted During the Covid-19 Emergency

With regard to the policies adopted during the emergency, in many European countries, short-time work proved to be an effective measure to cope with the massive layoffs produced by the Covid-19 pandemic. In the case of Italy, a program widely used in previous crises was applied and partially modified: “The Cassa Integrazione Guadagni” (CIG). The Italian short-time work system is based on three pillars: Cassa Integrazione Guadagni Ordinaria (CIGO), Cassa Integrazione Guadagni Straordinaria (CIGS) and Cassa Integrazione Guadagni in Deroga (CIGD).

During the Covid-19 pandemic the CIG scheme had four objectives. First, to help companies finance reductions in working hours (although the subsidy is paid to the employee, not the company). Second, to pay subsidies to employees for hours not worked. Third, to allow companies to temporarily lay off part of their workforce, since in Italy short-time work can be used to subsidize both partial and full reductions in hours. And fourth, to spread the costs of adjustment across the workforce.

The emergency legislation approved in February 2020 had to respond to the rapid onset of the health emergency, intervening to protect employment, particularly in the sectors that were in lockdown. The law of April 24, 2020, n. 27 (the so-called *Cura Italia* Decree) guaranteed economic integration to alleviate the contraction of wages, according to a timetable, with the aim of preventing massive layoffs. A new form of ordinary fund was introduced (CIGO), initially for a maximum of nine weeks and then, after various revisions and in particular with the Legislative Decree of March 22, 2021, n. 41 (the so-called "Support Decree"), until 2022. The expansion of existing protection schemes also related to the sectors covered, with the universality of this same integration treatment extended to all employers in the private sector (including agriculture, fishing and the third sector), but not domestic work (Filippi et al 2021).

In addition to the strengthening of the CIG, which had been used extensively in the past to address sectoral or structural crises, the *Cura Italia* Decree also introduced a completely innovative measure, which, in the specificity of its field of application, testified to the diversity and pervasiveness of the pandemic crisis. It represents a recognition of the characteristics of those sectors of the labour market most affected by the crisis. It was a social security benefit designed to protect the income of self-employed workers in the business sector, as well as some special categories of employees (seasonal workers in tourism and agriculture and workers in the entertainment industry).

The duration of the subsidy was repeatedly extended by decree over the course of the pandemic, without prejudice to the duration of future use of short-time work for reasons not related to Covid-19. The legal level of the subsidy replacement rate was not changed. In addition, the CIGD was reintroduced to cover firms and sectors not eligible for the CIGO.

The *Cura Italia* Decree also had the purpose of preventing massive layoffs, with a package of measures representing a total amount of 25 billion in terms of net balance. A temporary ban was ordered, starting from 17 March 2020, of collective and individual dismissals for economic reasons, i.e. linked to company performance (those for just cause were still possible). Beyond liquidity support, other measures introduced in the Decree include: (a) measures to ensure business continuity, with particular regard to businesses that were healthy before the emergency, whereby the drop or loss of share capital would not any lead to company dissolution and with a loosening of insolvency proceedings; (b) the deferral of tax obligations by workers and companies (e.g. VAT, withholding tax and social contributions) (OECD 2020).

4 Data

Our analysis relies on an innovative dataset built recently by merging two Italian surveys. First, in order to calculate the *physical proximity* we use data produced by the ICP. This dataset adapts the traditional approach by focusing on nature and content of the work. The survey reports information on about 16,000 workers and describes all the 5-digit occupations (i.e. 811 occupational codes) existing in the Italian labour market.

The ICP asks workers to answer the questionnaire themselves, rather than relying on experts. This places the focus on the point of view of those who carry out the daily occupational activities under consideration and who have a direct and concrete assessment of the level of certain characteristics essential for carrying out the job. The survey describes all the occupations present in the Italian labour market: those in private companies, those in public institutions and state-owned companies, and those carried out by the self-employed and regulated professionals. The survey is based on the Occupational Information Network (O*Net) of the U.S. Department of Labor. As the ICP is based on Italian occupations and not those of the United States, it is more reliable in capturing the characteristics of the Italian production structure, and the Italian context in terms of technology and industrial relations. In this way, we may be able to avoid the potential biases that arise when information on the U.S. occupational structure (contained in the U.S. O*Net repertoire) is combined with labour market data that refer to different economies, such as European economies.[6]

Following the US O*Net conceptual framework, ICP questions model each profession as a multi-dimensional concept that can be analysed according to four thematic areas: (a) worker requirements (e.g. skills, knowledge, educational level); (b) worker characteristics (e.g. traits, working styles); (c) profession requirements (i.e. generalized work activities and working context); d) experience requirements (i.e. training

[6] It is relevant to note that Italy is the only country to have a dictionary of occupations similar to the US O*NET, based specifically on the Italian context. This allows us to avoid potential biases which may arise when matching information on occupational structures (e.g. those contained in the US O*Net repertoire) to labor markets of a different country.

and experience).[7] The ICP survey includes questions that are particularly relevant for shedding light on the potential risks for workers in the current COVID-19 emergency. In particular, the survey directly asks about physical proximity for every profession in the question: “Are you close to other people during your work?” The score that goes from a 0 to 100 (from less to more intense) is then calculated for each 5-digit occupation. The survey also reports information on the importance of dealing with the public, and of directly interacting with co-workers. This additional information is useful to disentangle the source of physical proximity (colleagues or external customers) and thus to examine more precisely which measures should be adopted or reinforced to keep workers safe. Thus—in line with Barbieri et al. (2022), and Carbonero and Scicchitano (2021)—we first compute a “proximity to colleagues” index as a weighted average between degree of physical proximity and interaction with colleagues (with weights respectively of 0.75 and 0.25). Then, we calculate a “proximity to the public” index averaging over the degree of physical proximity and interactions with the public (with weights respectively of 0.75 and 0.25). Both the “proximity to colleagues” and the “proximity to the public” index are composite indexes where a weight of 0.75 is attributed to the physical proximity component and a 0.25 weight is attributed to the degree of interaction with colleagues or with the public.[8] The indexes derived from the ICP dataset are finally aggregated at the ISCO 4-digits level to allow this information to be merged with data from the Italian Labour Force survey (ILFS).

Following this, we employ cross-sectional quarterly data (2010Q1–2020Q4) derived from the ILFS by ISTAT (Italian National Institute of Statistics). This is the largest survey in Italy monitoring the quarterly dynamics of the labour market. Each year, it collects information on almost 280,000 households, for a total of 700,000 individuals. Our sample includes individuals (wage earners) from the age of 15 to the age of 64 and it is representative of the overall population, as we use the provided population weights. The population weights for the Italian LFS are estimated in three steps. In the first step, the initial weights are designed as the inverse of the probability of selection; in the second step, non-response adjustment factors are considered by household characteristic; in the last step, the final weights are calculated using a calibration estimator with the help of auxiliary demographic information such as sex, five-year age groups, nationality, and region (NUTS 2 and NUTS 3 level). Final weights are assessed at the household level, which means that each component of the same household has the same final weight as all the others (household weight). This method permits us to produce coherent estimates at both individual and household level (Aina et al. 2023).

Table 1 contains the principal descriptive statistics for wages in the three surveys considered. In particular, the last two years are also presented in a quarterly form. In sum, in the decade before the pandemic crisis, the real wage of Italian workers declined both in terms of mean and median, following the substantial stagnation of the Italian

[7] A further description of the ICP survey is in the Appendix A.

[8] The weights have been chosen according to the criteria of using the degree of physical proximity as the main explanatory factor for the ranking. Different weights (e.g., a weight of 0.5 for each component) lead to rankings that give too little emphasis to the physical proximity component (e.g., a certain profession may score highly because it requires a very high degree of interactions with colleagues, but mainly on the phone).

Table 1 Summary measures of monthly net wages (RETRIB) distribution, inflation adjusted in 2013 euros (RCFL–Istat)

	Y2020	Q201	Q202	Q203	Q204	Y2019	Q191	Q192	Q193	Q194	Y2010
Obs	**138,368**	34,431	33,110	34,540	36,287	**149,396**	37,473	37,828	37,098	36,997	**133,986**
Min	**29**	39	29	39	29	**19**	39	49	24	19	**27**
Mean	**1336**	1339	1316	1335	1355	**1321**	1317	1320	1323	1325	**1351**
Median	**1283**	1286	1266	1272	1315	**1262**	1262	1262	1262	1262	**1275**
Max	**14,606**	9737	11,685	14,606	10,711	**15,534**	11,650	11,650	15,534	9951	**15,940**
BottomShare05	**1.3**	1.3	1.2	1.3	1.3	**1.3**	1.3	1.3	1.3	1.3	**1.3**
BottomShare10	**3.5**	3.6	3.3	3.6	3.5	**3.6**	3.6	3.6	3.5	3.6	**3.5**
BottomShare20	**9.4**	9.6	9.1	9.6	9.5	**9.6**	9.6	9.6	9.5	9.6	**9.3**
TopShare20	**32.4**	32.2	32.7	32.4	32.4	**32.2**	32.1	32.2	32.2	32.2	**33.2**
TopShare10	**19.1**	18.9	19.3	19.1	19	**18.9**	18.8	18.9	18.9	18.8	**19.7**
TopShare05	**11.3**	11.2	11.5	11.3	11.2	**11.1**	11	11.1	11.2	11.1	**11.6**
Gini	**0.2256**	0.2212	0.2332	0.2239	0.2239	**0.2215**	0.2206	0.2212	0.2230	0.2213	**0.2337**
Theil	**0.0919**	0.0889	0.0980	0.0906	0.0903	**0.0881**	0.0868	0.0881	0.0899	0.0877	**0.0967**
Wolfson_ind	**0.1611**	0.1563	0.1335	0.1592	0.1815	**0.1385**	0.1340	0.1289	0.1411	0.1500	**0.0876**

Annual values in bold

GDP. The principal distributional parameters (such as share of consumption) did not significantly move from 2010. Therefore, both the Gini and Theil indexes for the period slightly decreased, while the Foster-Wolfson index captures an important increase in wage polarization over the 2019–2010 period already. Moreover, notwithstanding the slight increase of mean and median, the 2020–2019 presents a general worsening of all the distributional indicators, including the Gini and Theil indexes. The Gini index decreases from 2010 to 2019 by 1.22 percentage points and increases from 2019 to 2020 by 0.41 percentage points. The Wolfson index increases from 2010 to 2019 by 5.1 percentage points and increases from 2019 to 2020 by 2.26 percentage points. It is important to remark that all the indexes shown in Table 1 are "relatives". In the next sections we propose a different methodology (RD, by Handcock and Morris 1998) to the inquire into distributional changes, from an "absolute" perspective (for a wider debate on this see Clementi et al. 2022).

We report in Table 2 all the variables used in the subsequent analyses with their main descriptive statistics. Retrib is the average monthly wage; SOUTHISL is a dummy that takes the value 1 if the interviewee lives in the South of Italy or in the Islands, otherwise it takes the value 0; CITITA is a dummy that takes the value 1 if the interviewee is an Italian citizen and is 0 otherwise; FEMALE is a dummy that takes the value 1 if the interviewee is female and the value 0 if he is male; Age1534 is a dummy that takes the value 1 if the interviewee is between 15 and 34 years old and the value 0 if he is older; LowEDU is a dummy that takes the value 1 if the interviewee has a level of education lower than or equal to lower secondary school and the value 0 if he has a higher level of education; proximity, proximity with work colleagues (proximityColl) and proximity with the public (proximityPub) are dummies that assume the value one if the respective proximity level exceeds 66%, otherwise they assume the value 0. To build these dummies we extracted the three-digit codes of Istat professions (CP2011 profession classification) from the main database of wages and we averaged the risk levels (proximity) of the professions based on this coding. We then added these average values to the wages database (using the three-digit CP2011 code to merge) and created the dummy by means of the threshold described above.[9]

5 Methodology: the Relative Distribution Approach (RD)

We employ the Relative Distribution (RD) approach (Handcock and Morris 1998), which combines the strengths of summary polarization indexes with the details of distributional change offered by the Kernel density estimates (see also Clementi and Schettino 2013 and 2015; Clementi et al. 2017, 2018, 2021, 2023a, b; Massari et al. 2009a,b; Nissanov and Pittau 2016; Nissanov 2017; Schettino and Khan 2020; Schettino et al. 2021). This technique can be helpful to evaluate the dynamic evolution of the middle class by capturing income polarization, and also by providing the possibility to decompose the overall effects of the pandemic into location and shape components.

[9] We ran the same estimations of Tables 4 and 5 employing two different cutoffs (75% and 50%): the results—available upon request – do not change significantly.

Table 2 Descriptive statistics by year

	Min	Q1	Median	Mean	Q3	Max
Year 2010—N.Obs 133,986						
Retrib	26.57	1009.56	1275.24	1350.83	1594.05	15,940.49
SOUTHISL	0	0	0	0.25	0	1
CITITA	0	1	1	0.9	1	1
FEMALE	0	0	0	0.46	1	1
Age1534	0	0	0	0.3	1	1
LowEDU	0	0	0	0.33	1	1
Proximity	0	0	0	0.26	1	1
ProximityColl	0	0	0	0.29	1	1
ProximityPub	0	0	0	0.27	1	1
Year 2019—N.Obs 149,396						
Retrib	19.42	970.87	1262.14	1321.23	1553.4	15,533.98
SOUTHISL	0	0	0	0.25	1	1
CITITA	0	1	1	0.88	1	1
FEMALE	0	0	0	0.46	1	1
Age1534	0	0	0	0.24	0	1
LowEDU	0	0	0	0.3	1	1
Proximity	0	0	0	0.28	1	1
ProximityColl	0	0	0	0.29	1	1
ProximityPub	0	0	0	0.25	0	1
Year 2020—N.Obs 138,368						
Retrib	29.21	976.63	1283.35	1336.22	1557.94	14,605.65
SOUTHISL	0	0	0	0.25	1	1
CITITA	0	1	1	0.88	1	1
FEMALE	0	0	0	0.46	1	1
Age1534	0	0	0	0.24	0	1
LowEDU	0	0	0	0.29	1	1
Proximity	0	0	0	0.27	1	1
ProximityColl	0	0	0	0.28	1	1
ProximityPub	0	0	0	0.24	0	1

The location component can be considered a "growth" effect, while the shape component represents the "pure distributional" effect. The RD methodology also allows for the estimation of the median relative polarization index (MRP) using a numerical value ranging between -1 and 1, taking value equal to 0 when no changes in the distribution have occurred. Positive values indicate relative polarization while negative ones denote convergence toward the center of the distribution. The MRP can be driven by the deciles of the distribution above and below the median, determining, respectively, an upper relative polarization index (URP) and a lower relative polarization index (LRP).[10]

We take Y_0 as a continuous random variable for the reference population (e.g. monthly net wage distribution in 2019) and Y as the comparison population (e.g. monthly net wage distribution in 2020). The cumulative distribution function (CDF) and the probability density function (PDF) are F and f respectively. The aim is to investigate the differences between the distributions of Y and Y_0 using Y_0 as the reference. The 'relative rank' is defined as $R = F_0(y)$ with $R \epsilon$ [0; 1]. The CDF of the relative data R is $G(r) = F\left(F_0^{-1}(r)\right)$ with $0 \leq r \leq 1$.

The corresponding PDF is

$$g_r = \frac{f\left(F_0^{-1}(r)\right)}{f_0\left(F_0^{-1}(r)\right)} = \frac{f(y_r)}{f_0(y_r)}, \quad 0 \leq r \leq 1,\ y_r \geq 0,$$

where f and f_0 are the density functions of Y and Y_0, while r represents the proportion of values. On the one hand, $G(r)$ represents the proportion of the target population that is below the level of a proportion r of the reference population. On the other hand, $g(r)$ is the ratio of the frequency of the target population to the frequency of the reference population at the r^{th} quantile of the reference population level $\left[F_0^{-1}(r)\right]$. If the two distributions are identical, then the relative distribution is uniform on [0; 1].

A value of $g(r)$ higher (lower) than 1 means a higher (lower) share of households in the comparison population with respect to the reference population at the r^{th} quantile of the latter distribution. Estimating the density functions with a non-parametric kernel method allows for the obtaining of relative density functions for different realizations of R. Then a local polynomial model can be fitted for each estimated point to obtain a correct description of the relative density. In this way, it is possible to decompose the relative distribution into a location effect, generally associated with changes in the mean of the income distribution, and a shape effect, which identifies changes in the covariate–outcome relationships.

We take $Y_{0L} = Y_0 + \rho$ as an *additive* location-adjusted population with shape as the reference distribution and the median as the comparison distribution, where ρ is the difference between the medians of Y and Y_0. Thus, the CDF of F_{0L} is defined as $F_{0L}(y_r) = F_0(y + \rho)$, and its derivative PDF is f_{0L}.

Formally,

$$\frac{f(y_r)}{f_0(y_r)} = \frac{f_{0L}(y_r)}{f_0(y_r)} \times \frac{f(y_r)}{f_{0L}(y_r)}.$$

Thus, we can decompose the relative distribution into a *location effect* (the first right-hand term), generally associated with changes in the median of the income

[10] Our calculations have been made using a reldist Stata package. For a wider explanation on the model's calibration see Jann 2021.

distribution, and a *shape effect* (the second right-hand term), which captures changes in the covariate–outcome relationships.

To isolate the shape component in the relative distribution, the median relative polarization (MRP) index of Y with respect to Y_0 has been developed. It is formally defined as it follows:

$$MRP(F, F_0) = 4\int_0^1 \left|r - \frac{1}{2}\right| g(r)dr - 1.$$

Finally, the MRP index can be decomposed into a lower relative polarization (LRP) index and an upper relative polarization (URP) index, which examine change in the overall polarization due to income above and below the median of the relative distribution.

They are defined by:

$$LRP(F, F_0) = 8\int_0^{\frac{1}{2}} \left|r - \frac{1}{2}\right| g(r)dr - 1,$$

$$URP(F, F_0) = 8\int_{\frac{1}{2}}^1 \left|r - \frac{1}{2}\right| g(r)dr - 1,$$

and can be estimated in a similar way.

6 Results and Discussion

As described previously, the strongest features of the RD tools are arguably: (1) its capacity for capturing the dynamic evolution of distributional changes over two different points in time by comparing two Kernel densities non-parametrically; (2) the possibility of decomposing the overall effect into the location effect (the "growth" component) and the shape effect (the "pure distributional" component). Having data for three distinct waves (2010–2019–2020), we can exploit these characteristics by analyzing what happened during the development of the pandemic in detail. In sum, our aim is to inquire principally into the extent to which the previous distributional trend was modified by COVID19 public restriction policies and their direct and indirect consequences. Therefore, we apply the RD method to three different periods: the first (2010–2019) describes the distributional changes that occurred prior to the pandemic; the second (2010–2020) describes the potential changes that the pandemic determined on the previously detected trend (2019–2020); the third (2020–2019) tries to specifically isolate the effects of the pandemic on the wage distribution in Italy. The results, by indicator, are summarized in Table 3.

Figure 1, 2, 3 provides the results of the RD analysis showing the overall (panel a), the location (panel b) and the shape effects (panel c) for the three selected subperiods.

In the period before the spread of COVID-19 (2019–2010), a more equal wage distribution appears only when we are looking at the MRP value. Regardless, observing the indicators, such as panel c in Fig. 1, we see a relative enlargement of the deciles

Table 3 RD indicators

	2019–2010	2020–2010	2020–2019
MRP	– 0.0433***	– 0.0135***	0.0148***
LRP	0.055***	0.0157***	0.0574***
URP	– 0.124***	– 0.0427***	– 0.0278***

Source: Authors' elaboration using IFLS-ICP data
***$p < 0.01$

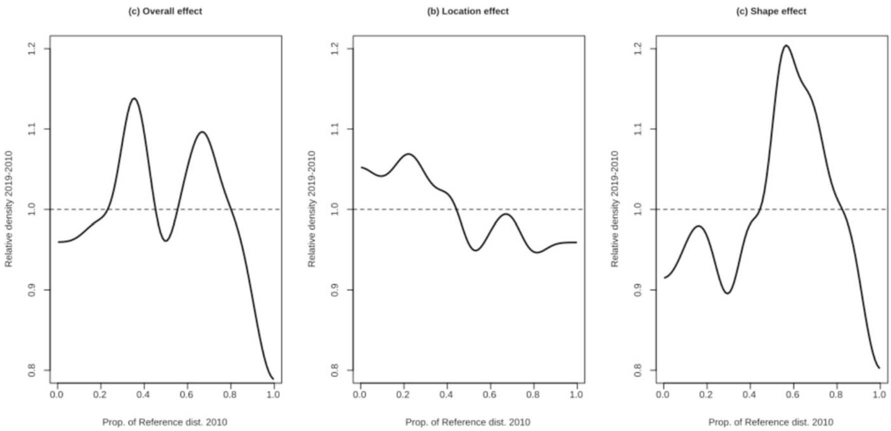

Fig. 1 The Relative Distribution analysis (Ref2010–Comp2019)

close to the median which is mainly due to the downgrading of the highest deciles (URP < 0), while the bottom part of the distribution is also enlarged. In other words, the general downgrading of the top deciles is not completely counterbalanced by the enlargement of the bottom ones, determining a negative MRP value. This confirms the recent widespread tendency towards a deterioration in Italian wages, as discussed previously. This medium-period trend is confirmed if we use the 2020 data as the comparison distribution (column 2, Table 3 and Fig. 2). Isolating the 2020/2019 sub-period (panel c, Fig. 3 and column 3, Table 3) we see a sharp general downgrading in the whole distribution. Notwithstanding a slight increase in the median real wage (panel b, Fig. 3),[11] the increase in the bottom deciles is not counterbalanced by the hollowing out of the top deciles, producing a positive MRP. These results could be interpreted as a *downgrading* of wages during the first wave of COVID-19. In contrast to the analysis employed on the whole distribution, which in our case does not consider profits or rents earners, the negative score for the URP index must be interpreted as a

[11] This effect, to some extent counterintuitive, is presumably due to the far-reaching public policies adopted by the Italian government to alleviate the conditions of workers, both employees and self-employed. In particular, the CIG (*Cassa integrazione guadagni*), which provided for millions of dependent workers, jointly with the ban on layoffs during the first phases of pandemic, played an important role in counterbalancing the negative effects of COVID-19 (see Sect. 3).

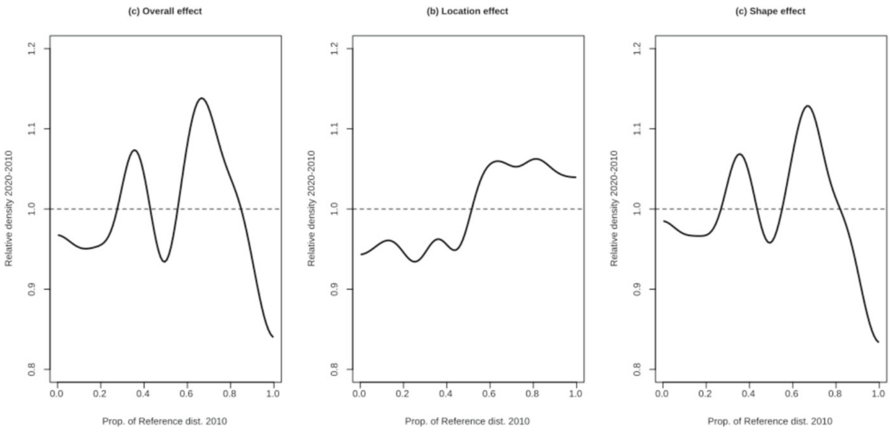

Fig. 2 The Relative Distribution analysis (Ref 2010–Comp2020)

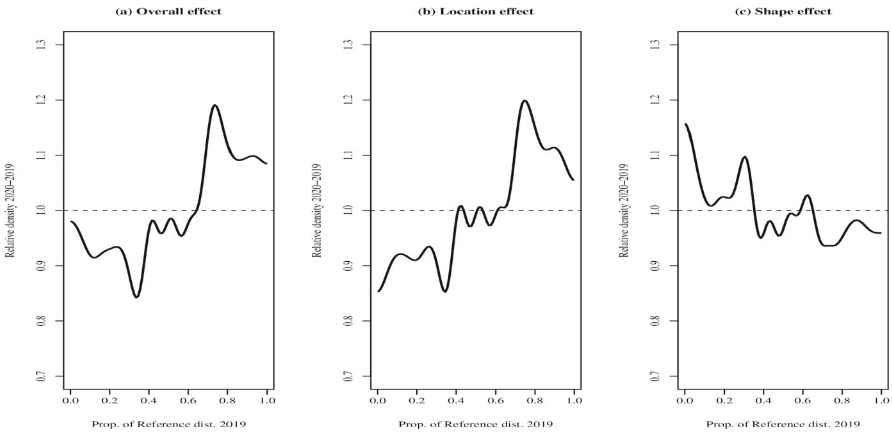

Fig. 3 The Relative Distribution analysis (Ref2019–Comp2020)

convergence towards the middle\lower class by workers previously belonging to the upper-middle class.

In Table 4 the results have been presented through a splitting of the sample by subperiod, and employee characteristic and task. To begin, a simple comparison between the second and the third column clearly confirms that during the first few months of the pandemic the (only apparent) improvement in distribution which had occurred during the 2010–2019 subperiod was completely subverted, independently of the subsamples feature. The MRP value is also higher for employees living in Central\North Italy, confirming that areas more dedicated to manufacturing activities were greater impacted. The results of Table 4, moreover, indicate that non-citizen, female, and younger workers were more aversely affected by this overall downgrading. They report the highest coefficients, equal to 0.0761, 0.0567 and 0.0621 respectively. This relative situation in

Table 4 Median relative polarization indexes by employee characteristics (2020–2019-2010)

Characteristics	MRP 2019–2010	MRP 2020–2019	LRP 2020–2019	URP 2020–2019	N. 2020	N. 2019	N. 2010
General index	− 0.0433***	0.0148***	0.0574***	− 0.0278***	138,368	149,396	133,986
SOUTHISL = 1	− 0.0352***	0.0027	0.0247**	− 0.0193*	36,455	39,552	37,415
SOUTHISL = 0	− 0.0279***	0.0176***	0.0734***	− 0.0381***	101,913	109,844	96,571
CITITA = 1	− 0.0315***	0.0132***	0.0685***	− 0.0421***	123,565	131,989	120,943
CITITA = 0	− 0.0076	0.0761***	0.0686***	0.0833***	14,803	17,407	13,043
FEMALE = 1	− 0.0547***	0.0567***	0.1013***	0.0194**	66,202	71,177	62,197
FEMALE = 0	− 0.0443***	0.0476***	0.1377***	− 0.0279***	72,166	78,219	71,789
Age1534 = 1	− 0.0073	0.0621***	0.0372***	0.0852***	28,233	32,020	36,054
Age1534 = 0	− 0.0566***	0.0507***	0.0577***	0.0439***	110,135	117,376	97,932
LowEDU = 1	− 0.0187***	0.0467***	0.1277***	− 0.0216**	39,903	45,914	45,006
LowEDU = 0	− 0.0606***	0.0485***	0.0564***	0.0413***	98,465	103,482	88,980
proximity = 1	− 0.0562***	0.0144***	0.0604***	− 0.0316***	39,757	43,321	36,366
proximity = 0	− 0.015***	0.015***	0.0641***	− 0.0341***	98,611	106,075	97,620
proximityColl = 1	− 0.0605***	0.0009	0.0502***	− 0.0454***	40,656	44,277	40,934
proximityColl = 0	− 0.0271***	0.0465***	0.0028	0.0933***	97,712	105,119	93,052
proximityPub = 1	− 0.0269***	0.0179***	0.0681***	− 0.0322***	34,287	37,698	37,502
proximityPub = 0	− 0.0217***	0.0502***	0.0539***	0.0467***	104,081	111,698	96,484
FEMALE = 0:proximity = 0	− 0.016***	0.0216***	0.0829***	− 0.0398***	61,086	66,110	61,288
FEMALE = 0:proximity = 1	− 0.0535***	0.0509***	0.0137	0.0905***	11,080	12,109	10,501
FEMALE = 1:proximity = 0	− 0.0272***	0.045***	0.1308***	− 0.0231**	37,525	39,965	36,332
FEMALE = 1:proximity = 1	− 0.0597***	0.0704***	0.0604***	0.0794***	28,677	31,212	25,865

Table 4 (continued)

Characteristics	MRP 2019–2010	MRP 2020–2019	LRP 2020–2019	URP 2020–2019	N. 2020	N. 2019	N. 2010
Age1534 = 0:proximity = 0	– 0.0626***	0.0467***	0.114***	– 0.0121*	79,931	85,257	71,933
Age1534 = 0:proximity = 1	– 0.0544***	0.0577***	0.0078	0.1092***	30,204	32,119	25,999
Age1534 = 1:proximity = 0	– 0.0168***	0.0152**	0.0609***	– 0.0306**	18,680	20,818	25,687
Age1534 = 1:proximity = 1	– 0.0111	0.0255***	0.0708***	– 0.0197	9553	11,202	10,367
LowEDU = 0:proximity = 0	– 0.0812***	0.0206***	0.0733***	– 0.0321***	67,456	70,474	60,821
LowEDU = 0:proximity = 1	– 0.0514***	0.0527***	– 0.037***	0.1515***	31,009	33,008	28,159
LowEDU = 1:proximity = 0	0.0016	0.0115**	– 0.0338***	0.0568***	31,155	35,601	36,799
LowEDU = 1:proximity = 1	– 0.0435***	0.0231**	0.0955***	– 0.0492**	8748	10,313	8207

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$..$p < 0.1$

Source: Authors' elaboration using IFLS-ICPdata terms of increasing polarisation is even clearer if we look at the upper relative polarisation index (URP): non-citizen, female and young workers have the highest positive coefficients, equal to 0.0833, 0.0194 and 0.0852 respectively, while Italian and male workers have negative values. From a structural point of view, a higher degree of physical proximity in the workplace alone does not imply a clear trend in terms of relative polarization measures. This is probably due to the very different jobs which involve the same level of "indistinct" proximity (i.e. University professors and Bartenders). To overcome this problem, we considered two separate variables, giving different weights to proximity to colleagues (*ProximityColl*) or proximity to customers (*ProximityPub*). As expected, employees whose jobs involved a higher proximity with customers suffered the effects of the pandemic more in terms of earnings (Table 4). This trend is reinforced for all three categories—women, young people and workers with lower levels of education—when considering interaction with the proximity variable. Table 4 shows that the MRP index assumes positive values for each type of worker. This means that polarization increases for roles requiring work is carried out in conditions of physical proximity (to the public or to colleagues). Looking at the LRP and URP indexes, the strongest downgrading due to proximity is suffered by workers with low levels of education, (LRP is equal to 0.0955 URP is -0.0492).

To better quantify the effects of COVID19 on wages, we estimated the quantile treatment effects, as proposed by Firpo (2007). Considering COVID19 as the treatment, and using a propensity score re-weighting procedure to satisfy the conditional independence assumption, our results show that the bottom 35 percentiles suffered a reduction in wages ranging from 40 to 10 euros, from 2019 to 2020. Immigrants, young people, women and workers with low levels of education suffered significantly more than the other categories.[12]

The results summarized in Table 4 were checked for robustness using an unconditional (RIFREG) quantile regression approach (Firpo et al. 2009, see also Clementi et al. 2018).[13] This method allows us to directly compare the results of wage differences between years at different quantiles of the wage distribution without imposing path dependence in the estimation of the gap at different quantiles. The dependent variable of our regressions is the re-centered influence function (RIF, Firpo et al. 2009) of a statistic ν calculated on the RD's CDF (y):

$$y = F\left(F_0^{-1}(r)\right) = F(Q_0(r))$$

where r ∈ [0,1] is the realization of the relative distribution of wages. F and F_0 are the CDF of the comparison and the reference year respectively. Since ${F_0}^{-1}$ is the inverse of F_0, Q_0 is the reference year wage quantile function. Denoting with G the CDF of

[12] In the selection of comparisons (matching procedure) based on the propensity score, the following variables have been selected: temporary worker status, age, level of education, sex, immigrant or Italian citizen status, presence of children in the household, geographical location. All results are available on request in the form of a spreadsheet.

[13] In Appendix B another test for robustness is provided.

Table 5 MRP RIF-REG results by RP indicator (2020–2019)

	MRP	LRP	URP
Proximitypub	0.0001041***	0.0004019***	– 0.000194***
Immigrant	0.0000709***	0.0001235***	0.0000183***
Northern Regions	0.0003089***	0.0012528***	– 0.000635***
Age (15 to 34)	0.0001138***	0.0004622***	– 0.000235***
Female	0.000198***	0.0006557***	– 0.00026***
Low Education	0.0001621***	0.0006758***	– 0.000352***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$..$p < 0.1$

y, for any statistical measure ν on the distribution of y the general expression of the RIF is:

$$Y_i = RIF(y_i; v, G) = v(G) + IF(y_i; v, G)$$
$$= v(G) + \lim_{\varepsilon \downarrow 0} \frac{v((1-\varepsilon)G + \varepsilon \Delta y_i) - v(G)}{\varepsilon}, \forall y_i \in y$$

where the value of ν depends on G and IF is the influence function. In such a way, Y "can be loosely interpreted as the relative contribution that observation y_i has on the construction of the statistic ν" (Rios-Avila 2020).

Parameters estimated by the linear regression of the dependent variable $\boldsymbol{Y} = [Y_1, \ldots, Y_n]'$on the k explanatory variables $\boldsymbol{X} = [X_{ij}]$(for $i = 1, \ldots, n$ and $j = 1, \ldots, k$), specified as

$$Y_i = X_i \beta + \epsilon_i$$

with the stochastic term ϵ_i and k parameters β_j measuring the marginal effect of each explanatory variable on the distributional statistic v.

We apply in the RIF, in place of v, the relative polarization indexes (MRP, LRP and URP), calculated for the period 2020–2019, following the methodology suggested by Rios-Avila (2020), Jann (2021), Clementi and Fabiani (2023a). Table 5 presents the results confirming substantially what yet analysed and commented in previous sections. In sum, the features of working in jobs requiring high proximity to the public, of being a non-citizen (immigrant), of residing in the North of the country, being young, being female, or having a lower level of education, all increased the probability of suffering a downgrading in wages during the COVID-19 pandemic.

7 Conclusions

This paper aims to present an original estimation of the distributional movements among wage earners in Italy, before and during the COVID-19 pandemic. While it is well known that Italian wages have not grown significantly over recent decades, in this paper we look at the distributional movements within the wage earners class. The traditional tools used to measure these changes do not present significant modifications in the considered period, excepting the Foster Wolfson polarization index. However, applying a non-parametric method (RD, Handcock and Morris 1998) to two datasets produced by ICP and IFLS/ISTAT, we detect a general increase in the polarization of wages in the sub-period 2020–2019, driven by lowest deciles, which counterbalanced the slight reduction of previous decades. The economic consequences of COVID-19 in the labour market have been severe across the world, but obviously workers that are required by the nature of their role to work near other people have been more at risk than the others. This paper also aims at inquiring into how and to what extent both individual characteristics (independent of job role) and the tasks workers are required to carry out as part of their role contributed to the total polarization of wages in Italy during the COVID-19 pandemic. It was found that workers with low levels of education, whose job involves a high level of physical proximity to customers, and who are non-citizens, younger or female were worse affected by the general downgrading of wages that occurred in Italy during the COVID-19 crisis.

It is clear that the changes in inter-group polarisation cannot be attributed solely to the recent pandemic crisis, given that there have been many institutional events in Italy during the period under study, including a series of political elections. Polarisation can be seen as an early warning sign, warranting targeted corrective measures for specific subgroups of the population (Schettino and Kahn 2020). If some groups have suffered more than others during the crisis, polarisation indicators can be evidence of this and thus become predictors of future social conflicts. We show that during the economic crisis two groups experienced a deterioration in their relative conditions: young people and, above all, immigrants. Our results are in line with those of Brandolini et al. (2018), who reported that the gap between the young and the old increased as a result of the financial crisis, and that the living conditions of those living with a foreign-born head of household worsened. Evidence of a significant deterioration in the living conditions of young people during the financial crisis was also found by Ghoshray et al. (2016) and Pastore (2018). This seems to confirm low levels of intergenerational social mobility and the deterioration of their expectations for their future on the part of younger generations (Simonazzi and Barbieri 2016; Ricci and Scicchitano 2021).

The evidence presented here can be adapted for all countries trying to contain the epidemic while minimising the impact on economic activity. Our results make it possible to identify which activities posed risks to workers, where workplace safety measures need to be implemented or strengthened, and are flexible enough to allow policymakers to choose the risk tolerance they are willing to bear. With restrictions on economic activities now lifted, our results could be useful for determining which categories of workers have suffered most in the recent crisis.

Our results make clear that the structural characteristics of the Italian labour market shaped significantly the ways in which the pandemic crisis impacted income polarisation in Italy. The worse relative economic situation of migrants compared to citizens, of the young compared to the old, of women compared to men, and of workers whose jobs require a higher degree of physical proximity has been exacerbated during the crisis. The widespread phenomenon of insecurity and impoverishment thus reinforces the need for an approach based on income distribution, since occupational categories can only reveal some of the characteristics that might define a status group (Bagnasco 2005).

Income polarization can be seen as a warning sign that requires targeted corrective action for specific subgroups of the population (Schettino 2020). Evidently, some social groups have suffered more than others during the COVID-19 crisis: from this point of view, polarization indicators can act as predictors on which to base the design of policies aimed at improving social cohesion. However, evaluating and calculating the total polarization of income at a given moment, or in each period, is not sufficient to provide the necessary information to design appropriate redistributive policies in favour of the most disadvantaged population groups. Therefore, a decomposition of the polarization indexes by population groups and in-work task content is provided to give specific policy indications, tailored to groups' needs. Perceptions of inequality among the population are of utmost importance: the long-lasting absence of strong and effective public interventions may further exacerbate the already fragile social cohesion in Italy, with a consequent risk of social conflicts.

Appendix A

Yun (2006) synthesizes two decomposition methodologies based on earnings equations provided by Juhn et al. (1993) and Fields (2003). A multiple regression analysis is applied to decompose in three components changes in earnings inequality: 1. on regression coefficients (called price or value effect), 2. on individual characteristics (quantity effect), and 3. on the distribution of not-observables variables (residuals effect). The Fields' methodology proceeds on two subsequent steps: 1. decomposes inequality into contributions of individual factors at a point in time (levels question), 2. compares inequalities across time using the results of the first step (differences question). Yun (2006) unifies these methodologies allowing to comprehensively evaluate the price and quantity effects of various factors on changes in earnings inequality.

The starting point is the following earning equation (applied to *pseudo-panel* – or *repeated cross sectional* – data)[14]:

$$y = \beta_{0t} + \sum_{k=1}^{K} \beta_{kt} x_{ikt} + e, \forall i \in \{1, 2, \ldots, N\}$$

where y_{it} is the log of individuals wage at time t, x_{ikt} are K individual characteristics, β_{kt} are the parameters to estimate for each period t, and e_{it} are unexplained residuals for the same observation i at the period t.

Table 6 and 7 presents measures of inequality (the Gini index, the Mean log deviation, the Theil index and the variance of logs): consistently with Table 4, they slightly decrease from the year 2010 to the year 2019. From 2019 to 2020, they suddenly raise. Table 8 shows in the first three columns, the contribution of each explanatory factors (and unexplained residuals) to the total dispersion of (log)wages, by year. In the subsequent four columns the changes of these contributions from 2010 to 2019 and from

[14] For this methodology see also Brewer and Wren-Lewis (2016).

Table 6 Inequality measures

	Gini	MLD	Theil	Variance of LogWage
Year 2010	0.2337	0.1042	0.0967	0.233
Year 2019	0.2215	0.0969	0.0881	0.2216
Year 2020	0.2256	0.1005	0.0919	0.229

Table 7 Log of wages variance and its change

Variance Y2010	Variance Y2019	Variance Y2020	Change 2010–2019	Change 2019–2020
0.233	0.2216	0.229	− 0.0114	0.0074

2019 to 2020 are presented. These effects can be decomposed into value change and quantity change. The first represents how the influence of each single characteristic on the dependent variable (for instance a higher income for the Female) varied. The second reports the relative change of each group size.

This inequality analysis confirms the principal results of the paper already obtained in terms of wage polarization: between 2019 and 2020 some subgroups of workers suffered much more than others the sanitary public policies anti-COVID19 and their consequences.

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Table 8 Factors of Inequality (decomposition and changes)

Categories	Y2010	Y2019	Y2020	Values relative change 2010–2019	Quantity relative change 2010–2019	Values relative change 2019–2020	Quantity relative change 2019–2020
SOUTHISL	1.05%***	2.66%***	2.05%***	27.82%	2.48%	– 15.21%	– 1.33%
Immigrant	3.39%***	3.17%***	3.1%***	– 16.28%	8.52%	6.94%	– 5.85%
FEMALE	10.03%***	8.83%***	7.73%***	– 23.48%	– 9.86%	– 23.86%	– 1.56%
Age1534	4.13%***	3.71%***	3.15%***	0.81%	– 13.14%	– 6.53%	– 7.37%
LowEDU	5.1%***	4.54%***	4.75%***	– 19.25%	3.37%	14.16%	– 3.26%
proximity	0.65%***	2.6%***	2.54%***	32.74%	4.56%	3.42%	– 2.69%
SOUTHISL:proximity	– 0.23%***	– 0.6%***	– 0.56%***	– 5.41%	– 1.56%	– 0.23%	0.82%
Immigrant:proximity	– 0.27%***	– 0.42%***	– 0.42%***	3.82%	– 6.61%	– 1.66%	1.34%
FEMALE:proximity	– 1.19%***	– 1.87%***	– 1.68%***	– 6.66%	– 0.14%	2.07%	2.12%
Age1534:proximity	0.93%***	0.75%***	0.73%***	– 4.4%	– 4.62%	1.83%	– 1.75%
LowEDU:proximity	0.19%***	– 0.17%***	– 0.1%*	– 7.75%	0.55%	1.71%	0.4%
Residuals	76.21%	76.8%	78.72%		– 64.73%		136.5%

Significance levels ‘***’ < 0.001, ‘**’ < 0.01, ‘*’ < 0.05, ‘. < 0.1’

Declarations

Conflict of interest The authors have not disclosed any competing interests.

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