# COVID 19 and Wage Polarization: A task based approach

# 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 migrant, 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 codes

J28 · J81 · H12 · I18

## Highlights

- Novel task-based data are used to analyse wage polarization during the pandemic.
- Applying Relative Distribution method, a general wage downgrading emerges.
- The polarization indices modify their sign during the Covid-19.
- Workers with low education, high proximity to customers suffered the hardest consequences
- Both individuals' characteristics and their tasks matter in wage polarization.

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## 1. Introduction

The Covid-19 emergency has affected every country in the world (Bloise and Tancioni, 2021; Caselli et al. 2022; Karabulut et al., 2021; Milani, 2021; Papageorge et al., 2021, Zimmermann et al. 2020), with major consequences for the labor market (Aina et al., 2021, 2023; Alon et al., 2020a; Biagetti et al. 2024; Botha et al., 2021, Baert et al., 2020, Esposito et al. 2024, Croce and Scicchitano, 2022). Governments have had to take drastic measures to combat the pandemic by shutting down non-essential services (Ascani et al., 2020; 2021; Brodeur et al., 2020a; Brodeur et al. 2020b; Caselli et al., 2020; Depalo, 2021; Qiu et al., 2020)[4]. Thus, "social distancing" has become the key public policy implemented globally during the COVID-19 pandemic, and shrinking the proximity between workers is an important dimension of this (Carbonero and Scicchitano, 2021). Among the different labor market outcomes affected by the COVID-19 crisis, the 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 the interviews (Adams-Prassl, et al, 2020, Hacıoğlu-Hokeet al. 2021, Gallo and Raitano, 2020).

The coronavirus crisis has shown that workers systematically differ across the types of occupations that were most likely to be hit by the pandemic and that workers with high personal proximity are the most economically vulnerable (Mongey et al. 2021, Barbieri et al. 2022). The COVID19 pandemic has added a "shadow cost" to labour due to the higher risk of proximity. More specifically, it increased the cost of physical contact between individuals and this is particularly clear in healthcare. Moreover, as lockdowns ease, activities intensive in physical proximity will likely be slower to recover in the medium to long run as people continue 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 of the workers (first with co-workers and then with 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 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 certain number of poles, not necessarily two (Esteban and Ray, 1994; Duclos, Esteban and Ray, 2004; Seshanna and Decornez, 2003; 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:

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

Esteban and Ray (1999) 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). Some articles have examined the impact of the Great Recession (GR) on income polarization (Jenkins et al., 2013; D'Errico et al., 2015; Adelino et al., 2016; Baiardo and Morana, 2018), but the empirical evidence of differentiated effects on population groups is still scarce. The key point is that if we limit the analysis to polarization across the entire distribution, without distinguishing on the 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 the processes of change in income distribution, which occur when there is a tendency to concentrate on the tails, rather than the middle, of the income distribution. Two different strands of research are observable within this field. The first assesses income polarization changes by developing quantitative measures called polarization indices. 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; 2023b; 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 across the whole distribution and 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?

We add to the current literature by investigating income polarization as a result out of the Covid-19 crisis between and within population groups, by physical proximity, gender, education, age, residential area. We employ the RD by group to evaluate what kinds of changes have occurred in the relative concentration of people at each income level over the period 2010-2020. This method combines the graphical tools of exploratory data analysis with statistical summaries, decomposition, and inference (Handcock and Morris, 1998).

We choose 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, on March 11 2020 (Barbieri et al., 2021; Bonacini et al. 2021). The COVID-19 has had significant effects on low wages and on poverty in Italy. Preliminary estimates of absolute poverty for the year 2020, released in March 2021 by the Italian National Institute of Statistics 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. Therefore,

during pandemic, absolute poverty in Italy reached its highest values since 2005 (i.e., since the time series for this indicator has been available[5]. Last estimates, report that in 2022, just over 2.18 million are in absolute poverty of families (8.3% of the total from 7.7% in 2021) and over 5.6 million individuals (9.7% up from 9.1% the previous year) The incidence of relative poverty 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 COVID-19 pandemic, by combining a task-based approach. The findings reveal a general strengthening wage polarization in the sub-period 2020-2019, guided by lowest deciles, after a reduction in the previous one (2019-10). Different groups have been also detected. Workers with low education, high proximity to customers job, such as the migrant, younger and female ones are the categories that more experienced the general downgrading of the Italian wages happened during the crisis.

The rest of the paper is structured as follows. Section 2 discusses the main literature on the topic. Section 3. describes the datasets, while Section 4 reports the methodology used in the empirical analysis. Sections 5 and 6 present main results and robustness checks. Section 7 concludes with some policy implications.

## 2. Theoretical framework

### 2.1 Previous literature on income polarization

Our paper is related to different lines of economic literature. First, we build on previous literature on income polarization. Beginning with the studies of Foster and Wolfson (1992), Esteban and Ray (1994), and Wolfson (1994, 1997), various measures of polarization have been defined (Chakravarty and Majumder, 2001; Duclos, Esteban and Ray, 2004; Esteban, Gradín and Ray, 2007; Chakravarty and D'Ambrosio, 2010).

In these studies, polarization is related to but distinct from inequality, as shown by Esteban (2002), Duclos, Esteban and Ray (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 due to the grouping of community members around more than one pole and their consequent distance from the center, according to specific characteristics.

The literature on polarization gives a number of sets of axioms. Many authors provide axioms for bipolarization indices, which consider polarization as the result of a distribution concentrated around two points at its tails. The approach proposed by Foster and Wolfson (1992) 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. The first is a movement away from the center, while the second is an increasing

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

concentration around each pole. With this tool it is possible to compare different pairs of curves, one for each population to be analyzed. If the estimated curves do not cross at any point, it is possible to obtain 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 like the Gini index. It reflects the fact that, on the one hand, an increment in inequality between the two groups increases polarization but, on the other hand, an increase in inequality in 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 the individuals in a group share similar 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.

Indices regarding the concept of income polarization as conflict among groups have been studied in other works (Gradín, 2000; 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 indices 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 indices 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 indices 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 (Nissanov and Pittau, 2015; Clementi and Schettino, 2013, 2015; Clementi et al., 2017, 2018, 2021; 2023a; 2023b). Some works have been specifically dedicated to Italy. Boeri and Brandolini (2004) investigatee 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, the latter reduced in the following nine years. Massari et al. (2009) employ the RD approach to Italian income data between 2002 and

2004: the work obtains a significant location effect, together with an 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) indices in Italy between 2002 and 2012. Results from polarization indices confirm a gradual decline between 2002 and 2006. The period from 2006 to 2012 reports an increase in polarization, which indicates a shirking of the middle-income group. Simonazzi and Barbieri (2016) show the erosion of the Italian middle class, displaying that while many typically middle-class jobs are progressively disappearing or becoming increasingly precarious, wages in the last few years have persisted substantially stable. The authors show that while polarization did not change from 1991 to 2006, it significantly raised afterwards. Bloise et al. (2018) study wage polarization in Italy between 1985 and 2014 and obtain a clear process of wage accumulation at the extremes of the distribution in the latter years. Likewise, Pianta (2020) shows a clear drop of labour incomes for the Italian population over the period of 1994–2016 for all income groups except the top 10% — such a stylized fact was amplified during the crisis. Brandolini et al. (2018) report the evolution of income inequality in Italy from 1989 to 2014: they depict 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.

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 show evidence by tasks, gender, , education, age and residential area.

## 2.2 Coronavirus emergency, task-based approach, and income inequality

The economic literature on COVID-19 is exploding on a daily basis. Our paper is related to two strands of this literature. A first line of this literature investigates the distributional conequences 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, obtain a decrease in relative inequality between January and September 2020. It was claimed that a possible explanation is that the policy responses to foght the pandemic have been converged to 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 increase 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 (2020), 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 current pandemic on the Canadian labor market and demonstrate that half of job losses are associated to workers in the bottom earnings quartile.

This strand of literature highlights that the ability to study this issue is highly dependent on the availability of timely and reliable data, as representative datasets on income and living conditions of the population are typically released long after the interviews (Aina et al. 2023). Two exceptions with real-time ad hoc surveys are represented by the United Kingdom (Benzeval et al. 2020; Witteveen 2020) and the United States (Berman 2020; Cortes & Forsythe 2020). To answer this problem, scholars have generally used real-time surveys (e.g., Adams-Prassl et al. 2020; Galasso 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 & Raitano 2020).

The onset of the pandemic has led to another growing body of research characterizing occupations and sectors of economic activity along dimensions of risk and 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 labor market outcomes through the tasks performed by workers (Autor et al., 2003; Firpo et al., 2011; Autor and Dorn, 2013). In particular, many papers have defined job rankings according to the degree of physical proximity required (Koren and Peto, 2020; Leibovici et al., 2020; Mongey et al., 2020). Koren and Peto (2020) display that before the pandemic, 43 million U.S. workers were employed in occupations characterized by high physical proximity, and that job losses were clustered in these occupations. Montenovo et al. (2020) highlight that the hardest hit US workers were those in occupations that require physical proximity (Leibovici et al. (2020) show similar results at the state level). In addition, Beland et al. (2020) rank U.S. workers by degree of proximity and risk of illness and estimate the short-term effects of the pandemic on employment and wages. Their findings indicate that workers in occupations with a relatively high degree of proximity and a low risk of illness are more affected in terms of labor market outcomes. Mongey et al. (2020) investigate the socio-economic characteristics of workers more exposed to the risk of infections – since employed in jobs that involve a high degree of physical proximity. They further prove that these workers are also more vulnerable because have low levels of education, low level of income and low home ownership rates. Avdiu and Nayyar (2020) show that Activities intensive in face-to-face interactions with consumers are vulnerable beyond lockdowns. Regarding Italy, Barbieri et al. (2021) rank sectors and occupations in Italy according to the degree of 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, it seems to experience more than other countries from the effects of the pandemic due to its structural problems, especially in the labor market (Aina et al. 2021). A significant reduction in hiring and an increase in the termination of temporary contracts show from the beginning of March 2020 was found (Casarico and Lattanzio, 2020). They also demonstrate that young, temporary and low-skilled workers are

more at risk of unemployment due to COVID-19, while gender is not significant. Gallo and Raitano (2020) simulate the impact of the pandemic in Italy for the whole of 2020 under three different scenarios. They obtain that the crisis caused a relatively larger decline in labor 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. Carta and De Philippis (2021) investigate the impact of the pandemic on the distribution of labor income in Italy, using micro data referring to the fourth quarter of 2019, and obtain a possible clear increase in income inequality. Aina et al. (2023) study the effects of the crisis on the whole wages distribution in Italy using the quarterly LFS data and obtain that coronavirus pandemic positively affect the wages of the entire workforce, and that this result rises 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 showning how individuals' characteristics and their tasks contributed to the total polarization of wages in Italy during the Covid-19 crisis.

## 3. Data

Our analysis relies on an innovative dataset recently built by merging two Italian surveys. First, in order to calculate the *physical proximity* we use the data of ICP. It 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 directly asks workers to answer the questionnaire, rather than experts, to 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 use 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, 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 the European ones[6].

[6] It is relevant to note that Italy is the only country to have a dictionary of occupations which is similar to the US O*NET but it is based on the Italian dictionary of occupations rather than the US one. This allows us to avoid potential biases

Following to the US O*Net conceptual framework, ICP questions model each profession as a multi-dimensional concept that can be treated referring 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 and experience)[7]. The ICP survey includes questions that are particularly relevant to shed 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, based on the following 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 reports information also 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 examinate more precisely which measures should be adopted or reinforced to keep workers safe. Thus, in line with Barbieri et al. (2021) 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 with 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 with 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 the colleagues or with the public[8].

Second, we employ cross-sectional quarterly data (2019Q1-2020Q4) derived from the Italian Labour Force survey (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

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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.

7 A further description of the ICP survey is in Barbieri et al. (2021), Bonacini et al. (2021a, 2021b).

[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 high because requires a very high degree of interactions with colleagues, but mainly through the phone).

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 – Summary measures of wages distribution, inflation adjusted in 2013 euros (RCFL – Istat).

| | **Y2020** | Q201 | Q202 | Q203 | Q204 | **Y2019** | Q191 | Q192 | Q193 | Q194 | **Y2010** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Obs | **138368** | 34431 | 33110 | 34540 | 36287 | **149396** | 37473 | 37828 | 37098 | 36997 | **133986** |
| 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 | **14606** | 9737 | 11685 | 14606 | 10711 | **15534** | 11650 | 11650 | 15534 | 9951 | **15940** |
| 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** |

Table 1 contains the principal descriptive statistics of the three considered surveys. 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 GDP. The principal distributional parameters (such as the consumption shares) did not significantly move from the 2010. Therefore, both Gini and Theil index slightly reduced, while the Foster-Wolfson catch an important increase in wage polarization already in the 2019-2010 period. 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 ones. It is important to remark that all the indices of Table 1 are "relatives". In the next sections we propose a different methodology (RD, by Handcock and Morris, 1998) to the inquire on distributional changes that use a different point of view: the "absolute" one (for a wider debate on this item see Clementi et al., 2022).

## 4. Methodology: the relative distribution approach (RD)

We employ the Relative Distribution (RD) approach (Handcock and Morris, 1998), which combines the strengths of summary polarization indices 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; 2023b; Massari et al., 2009a; 2009b; 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 such as the income polarization, by also providing the possibility to decompose the overall effect into location and shape components. The first one can be considered as the "growth" effect (the location component). The second represents the "pure distributional" effect (the shape component). The RD methodology also allows to estimate the median relative polarization index (MRP) can range between -1 and 1, taking value equal to 0 when no changes in the distribution have happened. 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).

Let $Y_0$ be a continuous random variable for the reference population (e.g. income distribution in 2019) and $Y$ the comparison population (e.g. income 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 $R \in [0; 1]$. The CDF of the relative data R is $G(r) = F(F_0^{-1}(r))$ with $0 \leq r \leq 1$.

The corresponding PDF is

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

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 $[F_0^{-1}(r)]$. 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 to obtain 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.

Let $Y_{0L} = Y_0 + \rho$ be an *additive* location-adjusted population with the shape as the reference distribution and the median as the comparison distribution, where $\rho$ 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 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:

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

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:

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

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

and can be estimated in a similar way.

## 5. Results and Discussion

As described previously, probably the strongest features of the RD tools are represented by: 1) the capacity of capturing the dynamic evolution of distributional changes in two different points in time comparing not parametrically two Kernel densities; 2) the possibility of decomposing the overall effect into the location (that has to be considered as the "growth" component) and the shape (the "pure distributional" one) effect. Having data for three distinct waves (2010-2019-2020), we can exploit these characteristics deeply analyzing what

happened during the pandemic diffusion. In sum, our aim is to inquire mainly on to what extent the previous distributional trend has been modified by the COVID19 public restriction policies and their direct and indirect consequences. Therefore, we apply the RD method to three different subsequent periods: the first (2010-2019) one able to describe the distributional changes happened previously to the pandemic; the second (2010-2020) able to describe the potential changes that the pandemic has determined on the previous detected trend (2019-2020) ; the third (2020-2019) tries to specifically isolate the pandemic effect on the Italian wage distribution. The results, by indicator, are in Table 2.

Table 2 – 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

Figure 1 – The Relative Distribution analysis (Ref2010-Comp2019)

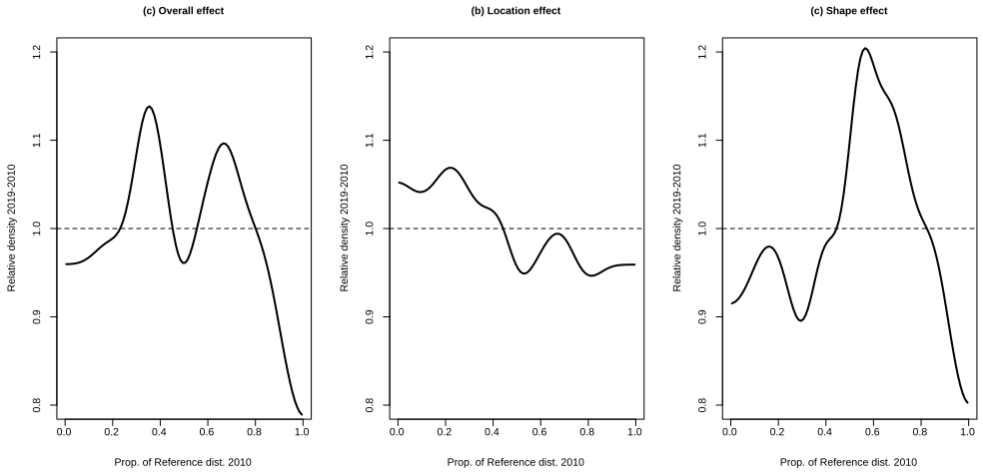


Figure 2 – The Relative Distribution analysis (Ref 2010 – Comp2020)

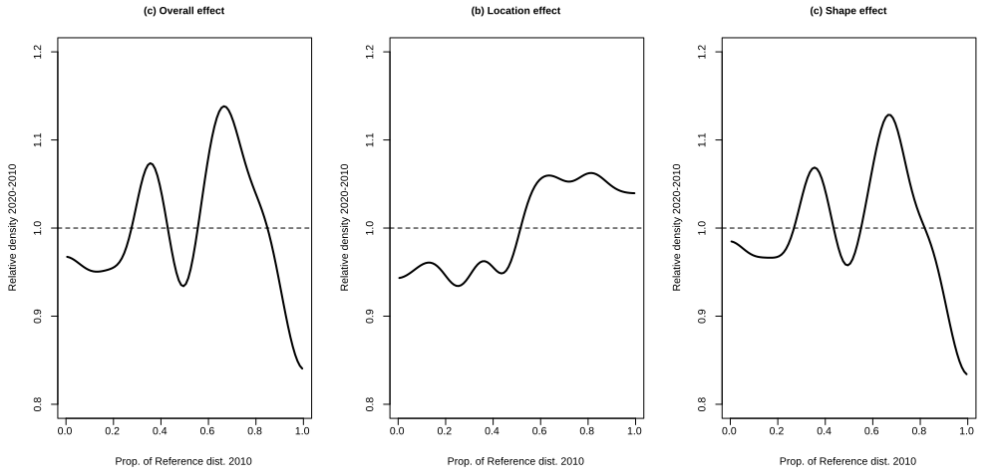


Figure 3 – The Relative Distribution analysis (Ref2019 – Comp2020)

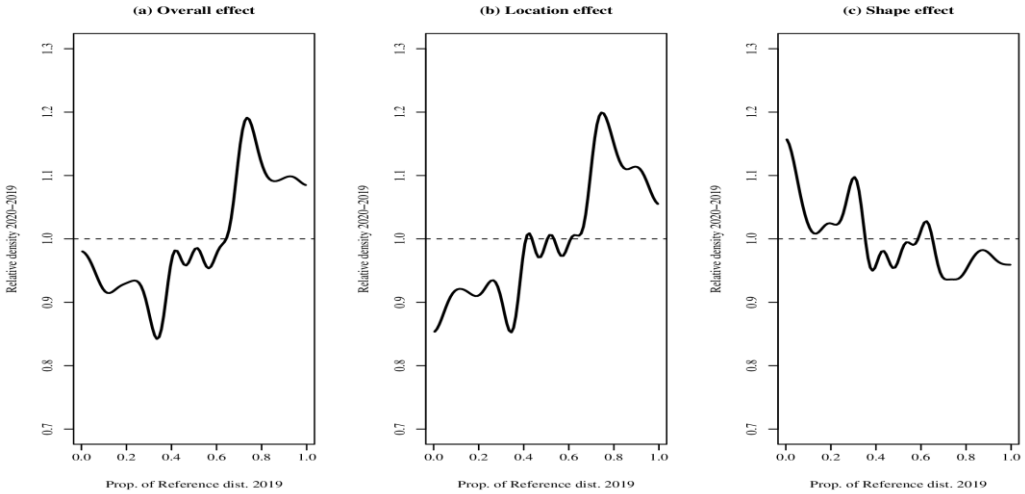


Figure 1-3 provides the results of RD analysis showing the overall (panel a), the location (panel b) and shape effect (panel c) for the three selected subperiods.

In the period before the COVID19 diffusion (2019-2010), a more equal wage distribution appears to have happened only looking at MRP value. Anyway, observing the sign of the indicators, such as the panel c of the Figure 1, emerges that relative "fattening" of the deciles close to the median is mainly due to the downgrading of the highest deciles (URP<0) while the bottom part of the distribution is also "fattening". In other words, the general downgrading of the top deciles is not completely counterbalanced by the fattening of the bottom ones, determining a negative value of MRP. This confirms the recent widespread worsening tendency of the Italian wages as discussed previously. This medium-period trend is confirmed by using the 2020 as the comparison distribution (column 2, Table 2 and Figure 2). Isolating the 2020/2019 subperiod (panel c, Figure 3 and column 2, Table 2) a strong general downgrading emerges in the whole distribution. Notwithstanding a slight increase of the median real wage (panel b, Figure 3), the fattening of the bottom deciles has not counterbalanced by the hollowing out of the top deciles, giving to the MRP a positive sign. These results could be interpreted as a *downgrading* of the wage earners during the COVID-19 first wave. Differently than the analysis employed on the whole distribution, in our case – that does not consider profits or rents earners – the negative score of the URP index must be interpreted as a convergence through the middle\lower class by the workers previously belonging the higher middle class.

Table 3 – Median relative polarization indices by employee characteristics (2020-2019-2010).

| Charcteristics | 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 *** | 138368 | 149396 | 133986 |
| SOUTHISL = 1 | -0.0352 *** | 0.0027 | 0.0247 ** | -0.0193 * | 36455 | 39552 | 37415 |
| SOUTHISL = 0 | -0.0279 *** | 0.0176 *** | 0.0734 *** | -0.0381 *** | 101913 | 109844 | 96571 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| CITITA = 1 | -0.0315 *** | 0.0132 *** | 0.0685 *** | -0.0421 *** | 123565 | 131989 | 120943 |
| CITITA = 0 | -0.0076 | 0.0761 *** | 0.0686 *** | 0.0833 *** | 14803 | 17407 | 13043 |
| FEMALE = 1 | -0.0547 *** | 0.0567 *** | 0.1013 *** | 0.0194 ** | 66202 | 71177 | 62197 |
| FEMALE = 0 | -0.0443 *** | 0.0476 *** | 0.1377 *** | -0.0279 *** | 72166 | 78219 | 71789 |
| Age1534 = 1 | -0.0073 . | 0.0621 *** | 0.0372 *** | 0.0852 *** | 28233 | 32020 | 36054 |
| Age1534 = 0 | -0.0566 *** | 0.0507 *** | 0.0577 *** | 0.0439 *** | 110135 | 117376 | 97932 |
| LowEDU = 1 | -0.0187 *** | 0.0467 *** | 0.1277 *** | -0.0216 ** | 39903 | 45914 | 45006 |
| LowEDU = 0 | -0.0606 *** | 0.0485 *** | 0.0564 *** | 0.0413 *** | 98465 | 103482 | 88980 |
| proximity = 1 | -0.0562 *** | 0.0144 *** | 0.0604 *** | -0.0316 *** | 39757 | 43321 | 36366 |
| proximity = 0 | -0.015 *** | 0.015 *** | 0.0641 *** | -0.0341 *** | 98611 | 106075 | 97620 |
| proximityColl = 1 | -0.0605 *** | 0.0009 | 0.0502 *** | -0.0454 *** | 40656 | 44277 | 40934 |
| proximityColl = 0 | -0.0271 *** | 0.0465 *** | 0.0028 | 0.0933 *** | 97712 | 105119 | 93052 |
| proximityPub = 1 | -0.0269 *** | 0.0179 *** | 0.0681 *** | -0.0322 *** | 34287 | 37698 | 37502 |
| proximityPub = 0 | -0.0217 *** | 0.0502 *** | 0.0539 *** | 0.0467 *** | 104081 | 111698 | 96484 |
| FEMALE=0:proximity=0 | -0.016 *** | 0.0216 *** | 0.0829 *** | -0.0398 *** | 61086 | 66110 | 61288 |
| FEMALE=0:proximity=1 | -0.0535 *** | 0.0509 *** | 0.0137 | 0.0905 *** | 11080 | 12109 | 10501 |
| FEMALE=1:proximity=0 | -0.0272 *** | 0.045 *** | 0.1308 *** | -0.0231 ** | 37525 | 39965 | 36332 |
| FEMALE=1:proximity=1 | -0.0597 *** | 0.0704 *** | 0.0604 *** | 0.0794 *** | 28677 | 31212 | 25865 |
| Age1534=0:proximity=0 | -0.0626 *** | 0.0467 *** | 0.114 *** | -0.0121 * | 79931 | 85257 | 71933 |
| Age1534=0:proximity=1 | -0.0544 *** | 0.0577 *** | 0.0078 | 0.1092 *** | 30204 | 32119 | 25999 |
| Age1534=1:proximity=0 | -0.0168 *** | 0.0152 ** | 0.0609 *** | -0.0306 ** | 18680 | 20818 | 25687 |
| Age1534=1:proximity=1 | -0.0111 . | 0.0255 *** | 0.0708 *** | -0.0197 | 9553 | 11202 | 10367 |
| LowEDU=0:proximity=0 | -0.0812 *** | 0.0206 *** | 0.0733 *** | -0.0321 *** | 67456 | 70474 | 60821 |
| LowEDU=0:proximity=1 | -0.0514 *** | 0.0527 *** | -0.037 *** | 0.1515 *** | 31009 | 33008 | 28159 |
| LowEDU=1:proximity=0 | 0.0016 | 0.0115 ** | -0.0338 *** | 0.0568 *** | 31155 | 35601 | 36799 |
| LowEDU=1:proximity=1 | -0.0435 *** | 0.0231 ** | 0.0955 *** | -0.0492 ** | 8748 | 10313 | 8207 |

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

Source: Authors' elaboration using IFLS-ICPdata

In Table 3 the results have been presented splitting the sample by subperiod and employee characteristic and task. First, the simple comparison between the second and the third column clearly confirms that, during the first months of pandemic, the (only apparent) improve of Italian distribution happened during the 2010-2019 subperiod has been completely subverted, independently than the subsamples feature. MRP is also higher for employees living in Central\North Italian region, confirming the higher pandemic impact on the areas more dedicated to manufacturing activities. Moreover, the results of Table 3 highlight that not Italian, female, and young workers suffered more in terms of overall downgrading. From a structural point of view, the mere higher degree of physical proximity in the workplace does not imply a clear effect on relative polarization measures.

This is probably due to the very different jobs present the same level of "indistinct" proximity (i.e. University professors and Bartenders). To overcome this problem, we considered two separate variables, giving different weight to the proximity with colleagues (*ProximityColl*) or with customers (*ProximityPub*). As expected, the employees whose job has a higher proximity with customers higher suffered in terms of earnings the effect of pandemic (Table 3).

To provide robustness check to the results summarized in Table 3 an unconditional (RIFREG) quantile regression approach (Firpo et al. 2009) has been adopted (see also Clementi et al., 2018)[9]. 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):

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

where r∈[0,1] is the realization of wages relative distribution. *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 *y*, for any statistical measure ν on the distribution of y the general expression of the RIF is:

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

where the value of ν depends on *G* and IF is the influence function. In such 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

$$Y_i = \boldsymbol{X}_i \boldsymbol{\beta} + \epsilon_i$$

with the stochastic term $\epsilon_i$and *k* parameters $\beta_j$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 indices (MRP, LRP and URP), calculated for the period 2020-2019, following the methodology suggested by Rios-Avila (2020), Jann (2021), Clementi and Fabiani (2023). Table 4 presents the results confirming substantially what yet analysed and commented in previous sections. In sum, the features of high proximity to the public, of being not Italian (*strange*), resident in a Northern region, Young, Female having Low education increased the probability of suffer wage downgrade during the COVID-19.

[9] In Appendix A another test for robustness is provided.

Table 4 – MRP RIF-REG results by RP indicator (2020-2019)

| | MRP | LRP | URP |
|---|---|---|---|
| Proximitypub | 0.0001041 | 0.0004019 | -0.000194 |
| Strangers | 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 |

## Conclusions

This paper aims to present an original estimation of the distributional movements inside the wage earners, before and during the COVID-19. Notwithstanding it is well known that in the last decades the Italian wages did not significantly grow, in this paper we inquire on the distributional movements inside the wage earners class. The traditional tools used to measure these changes substantially don't present significant modifications in the considered period, but the Foster Wolfson polarization index. Anyway, applying a non-parametric method (RD, Handcock and Morris, 1998) to two dataset ICP and IFLS/ISTAT, we detect a general increasing wage polarization in the sub-period 2020-2019, driven by lowest deciles that counterbalanced the slight reduction of the previous decades. The economic consequences of COVID-19 in the labour market have been severe across countries in the world, but obviously workers that use to spend their activity near other people have been more at risk than the others. This paper aims also to inquire on how and to what extent individuals' characteristics and their tasks contributed to the total polarization of wages in Italy during the COVID-19 pandemic. Indeed, different groups have been isolated: workers with low education, high proximity to customers job, such as the migrant, younger and female ones are the categories that more suffered the general downgrading of the Italian wages happened during the COVID-19 crisis.

Income polarization can be seen as a warning sign that requires targeted corrective action for specific subgroups of the population (Schettino, 2020). Evidently, some classes have suffered more than others during the COVID-19 crisis: from this point of view, polarization indicators can be act as predictors able to suggest policies useful to reestablish a higher harmony degree in the society. Evaluating and calculating the polarization of income at a given moment, or in each period, is in fact 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 indices by population groups and task content is indeed provided to give specific policy indications, tailored to groups' needs. Inequalities popular perception is at utmost: indeed, the long-lasting absence of strong and effective public interventions can further exacerbate the yet scarce social cohesion of Italian society, with consequent risk of social conflicts.

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**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):[10]

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

$$y_{it} = \beta_{0t} + \sum \beta_{kt}\, x_{ikt} + e_{it}, \forall i \in \{1,2,\dots,N\} \qquad [B1]$$

where $y_{it}$ is the log of individuals wage at time $t$, $x_{ikt}$ are $K$ individual characteristics, $\beta_{kt}$ 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 A1 and A2 presents measures of inequality (the Gini index, the Mean log deviation, the Theil index and the variance of logs): consistently with Table 3, they slightly decrease from the year 2010 to the year 2019. From 2019 to 2020, they suddenly raise. Table A3 shows in the first three columns, the contribution of each explanatory factors (and for 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 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 2019-2020 some subgroups of workers suffered much more than others the sanitary public policies anti-COVID19 and their consequences.

Table A1 – 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 A2 – 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 |

Table A3 – 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% | *** | 2.9% | 27.39% | -0.95% | -15.59% |
| STRANGE | 3.39% | *** | 3.17% | *** | 3.1% | *** | 11.29% | -19.05% | -5.7% | 6.78% |
| FEMALE | 10.03% | *** | 8.83% | *** | 7.73% | *** | -4.81% | -28.54% | -0.82% | -24.59% |
| Age1534 | 4.13% | *** | 3.71% | *** | 3.15% | *** | -11.08% | -1.25% | -6.76% | -7.14% |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| LowEDU | 5.1% | *** | 4.54% | *** | 4.75% | *** | 4.67% | -20.55% | -3.09% | 13.99% |
| proximity | 0.65% | *** | 2.6% | *** | 2.54% | *** | 9.38% | 27.92% | -2.62% | 3.35% |
| SOUTHISL:proximity | -0.23% | *** | -0.6% | *** | -0.56% | *** | -1.47% | -5.5% | 0.84% | -0.25% |
| FOREIG:proximity | -0.27% | *** | -0.42% | *** | -0.42% | *** | -4.6% | 1.8% | 1.45% | -1.78% |
| FEMALE:proximity | -1.19% | *** | -1.87% | *** | -1.68% | *** | -5.8% | -6.23% | 1.9% | 2.29% |
| Age1534:proximity | 0.93% | *** | 0.75% | *** | 0.73% | *** | 0.08% | -4.62% | -1.83% | 1.91% |
| LowEDU:proximity | 0.19% | *** | -0.17% | *** | -0.1% | * | -0.5% | -6.7% | 0.24% | 1.87% |
| Residuals | 76.21% | | 76.8% | | 78.72% | | | -64.73% | | 136.5% |

Significance levels '***' < 0.001, '**' < 0.01, '*' < 0.05, '.' < 0.1