Heterogeneous income effects of the Covid-19 on Italian workers: the role played by jobs routinization and teleworkability

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Abstract

The Covid-19 pandemic is expected to engender heterogeneous effects on labour market prospects of individuals, according to workers' and jobs' characteristics. This paper focuses on two possible sources of a heterogeneous exposition to labour market risks associated with the pandemic outbreak: the routine task content of jobs and the telework ability. To evaluate whether these dimensions have played a crucial role in amplifying employment and wage gaps among workers, we focus on the case of Italy, the first EU countries hit by the first wave of Covid-19. By using a static microsimulation model based on IT-SILC data enriched with INPS monthly administrative data and aligned to monthly observed labour market dynamics by sector of activity and regions, this paper pursues two main aims. First, we simulate changes in the wage distribution in the whole 2020 using nowcasting techniques, before and after income support measures for workers to capture the effect of public redistribution. Second, we investigate whether income drops risks – both considering labour income only and adding income support measures – differed among workers whose job task are characterised by a different degree of routinization (as proxied by the RTI index) and teleworkability (as proxied by the TWA index). We find that the pandemic has largely increased wage inequality and low-pay risks, but the redistributive measures have been rather effective in cushioning the worsening of the income distribution. Furthermore, our data confirm that RTI and TWA are negatively and positively associated with lower wages, respectively, and they are also associated with significantly higher (resp. lower) risks of a large labour income drop due to the pandemic. However, differences in income drop risks for workers who differ by RTI and TWA disappear when income support measures are considered.

Keywords: Covid-19, wage distribution, inequality, income support measures, task routinization, telework ability

JEL codes: D31, H24, I38, J31, C15

1. Introduction

Some studies have recently inquired the immediate 'short-term' effect of the COVID-19 pandemic and the related emergency benefits introduced by the governments on workers' and households' income distribution. However, the capability to answer to this research question is strongly limited by data availability since, as known, representative surveys on population incomes and living conditions are usually delivered with about 2 years of delay from the moment of the interview.[1]

To overcome this limit, some studies used real time surveys (e.g., Adams-Prassl et al., 2020; Galasso, 2020) or big data on bank records (Aspachs et al. 2020), or also labour market outcomes (Berman, 2020, and Cortes and Forsythe, 2020). However, these kinds of data fail in being representative of the whole population, thus not allowing researchers to provide a thorough picture of changes in individuals' and households' income distribution.

Noteworthy, other studies have relied on existing microdata on income distribution, collected in past years and representative of the national population before the onset of the pandemic, to simulate counterfactual scenarios about the changes in the various income sources engendered by the spread of the new coronavirus, aligning past microdata with aggregate information on changes in labour market outcomes since the onset of the pandemic (see, e.g., Bronka et al., 2020, and Brewer and Tasseva, 2020, for the UK; Beirne et al., 2020, and O' Donoghue et al., 2020, for Ireland; Li et al., 2020, for Australia).[2]

All the above-mentioned studies, however, tend to focus on workers in general or on the pandemic effects on households. At the opposite, few is known on the characteristics of employees who have been more at risk of severe income losses due to the COVID-19 outbreak. Our paper has the main objective to provide some new insights on this regard looking at the Italian labour market as interesting case study.

<u>Brief debate on routinization:</u>

- During the past few decades we have assisted to the rapid digitization of the economy and technological transformation of work. Following the fast automation of work, an increasing number of tasks and occupations are becoming easily substitutable by machines.
- Which jobs?
  "The Routine Biased Technical Change (RBTC) hypothesis was put forth in the work by Autor et al. (2003) arguing that the unfolding of ICT is biased towards the replacement of routine tasks." […] *"The resilience of occupations to the threat of technological unemployment is contingent upon the share of routinary (i.e. repetitive and encodable) tasks characterizing each occupation. The larger the share of routinary tasks comprising a certain occupation, the greater the potential for a machine-driven substitution of human work associated to such occupation."* (Cirillo-Evangelista-Guarascio-Sostero 2020).
- This routine biased technological change explains the polarization of the labour market (both jobs and income):

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[1] The only exception regards the UK thanks to the release of an ad-hoc timely wave of the Understanding Society longitudinal survey. Among the studies which used this ad hoc survey, see Benzeval et al. (2020) and Witteveen (2020).

[2] Relying on past surveys on employees, other studies simulated, instead, labour market outcomes and individual wages making assumptions on the capacity of individuals to work under social distance measures (Duman, 2020, for Turkey; Bonacini et al., 2021, for Italy; Palomino et al., 2020, for 29 European countries).

In the face of automation, the demand for middle-skill jobs -that typically requires routine manual and cognitive skills- declines relatively to the rising demand in well-paid skilled jobs typically requiring non-routine cognitive skills and in low-paid less-skilled jobs requiring non-routine manual skills. Thus, in the short-term, digitization and automation of work produce occupational polarization, with medium-skilled routinary occupations hollowed out. Autor and Dorn (2013) provide a unified theory that shows how the RBTC hypothesis together with task offshoring (through the reallocation of low-skill labor to service occupations) explain job polarization. Goos, Manning, and Salomons (2009, 2014) provide evidence of job polarization across 16 Western European advanced economies over the period 1993–2010. "*By the same token, the progressive digitization and automation of work can affect also income dynamics: the role of technological change as one of the key drivers of wage polarization in both the US and Europe has been largely documented by the empirical literature (for an extensive review, see van Reenen 2011).*" (Cirillo-Evangelista-Guarascio-Sostero 2020).

<u>Role of the pandemic shock in this context</u>

- It introduces a new dimension: remote work
- This has implications related to digital technologies and automation:
    - (i) technology can facilitate remote work but not to the same degree for all occupations. A vast recent literature has used occupation-level data to characterize jobs by their working-from-home feasibility and assess quantitavely the share of teleworable jobs (Dingel and Neiman (2020), Koren and Peto (2020), Leibovici et al. (2020), Yasenov (2020) for US; for Italy, Boeri et al. (2020) and Cetrulo et al. (2020b) for Italy, Sostero et al. 2020 for European labour force, Holgersen et al. 2020 for Norway, Alipour et al. 2020 for Germany)[3]. All studies report strong heterogeneity across sectors ad occupations: remote work applies primarily to the top quartile of higher-educated or high-skill workers, those that also face the fewest risks from automation and artificial intelligence, while routinary-non-cognitive tasks typically involve physical contact and cannot be performed from home. These low wage manual and routine workers are potentially disproportionally affected by the covid crisis.
    - (ii) if remote work displaces office time and reduces the need for business travel and personal interaction, demand for many non-college-educated low-paid low-skill workers will drop (Autor and Reynolds 2020)
- As argued by Autor and Reynolds (2020), telework, together with the three other major post-covid transformations, i.e. urban re-densification, employment concentration in large firms and further automation pushed by the social distancing requirements, is likely to shape the post-covid crisis trajectory in the direction of complementing the impact of technology in removing middle-skill routine jobs and extending this trend to the low-wage end of the bar.
- Empirical evidence on differential labour market impact of covid crisis for different categoris of workers:

[3] These studies measure telework "feasibility" rather than prevalence. The latter is measured for example in Alon et al. (2020), Hensvik et al. (2020) and Papanikolaou and Schmidt (2020) using the American Time Use Survey.

- Some studies analysed the early impact on the labour market of the restrictive measures introduced in response to the pandemic by means of real-time surveys and documented that, already in the first phase of the crisis, more fragile individuals, e.g., low educated/low-income service workesr, who were more likely to stop working and less likely to work from home, were more severely hit (Galasso 2020, Adams-Prassl et al. 2020, Bajos et al. 2021)
- Cetrulo et al. (2020a) document that, among Italian worker, the feasibility of working-from-home is a "privilege" of a minority (only thirty percent of Italian workers would be able to work remotely) of advantaged workers, i.e. better remunerated and employed with permanent contracts. In another paper the same authors use data from the Italian LFS waves 2016-2017 and show that those individuals who are not able to perform their work remotely are also more exposed to transition to unemployment, to earn low wages, and to safety and health risks (Cetrulo, et al. 2020b).
- Bonacini et al (2021) show that a positive shift in working-from-home feasibility would be associated with a rise of labour income inequality among employees, because it would tend to benefit more male, older, graduated, and high-paid employees.
- Using Italian LFS data from 2019q1 to 2010q2, Aina et al (2021) document that the pandemic negatively affected the wages of workers at the bottom of the wage distribution more severely, but this negative effect is mitigated by the possibility of WFH (actual working from home) to a larger extent for this group of workers.
- Montenovo (2020): using CPS data from the first months on the pandemic crisis they document that in US job loss was larger in occupations that require more interpersonal contact and that cannot be performed remotely.

<u>What we do</u>

- We cannot observe what will happen in the future, but we look at what happened in the first year of the pandemic, considering Italy as a case study and providing new insights on this topic by means of a microsimulation model application
- Why Italy is relevant: national context and data
    - National context: …
    - Data on occupations: The Italian Survey on Occupations is the only European survey replicating the structure of the American O*Net and represents a unique source of information on skills, tasks, and work content of approximately 800 occupations (5-digit CP2011 classification, the Italian equivalent of the ISCO-08 ILO classification). The availability of this information allows characterising occupations both along the dimension of telework feasibility and according to their level of routiness. We rely on the technical teleworkability index built by Sostero et al (2020) and the routine task index constructed by Cirillo et al (2020) (see data section for details).
    - Dati AD silc: …

- Why microsimulation is important in this type of phenomena: …
- Preview of findings: …
- The remainder of the paper is organised as follows. Section 2 describes the model, data and hypotheses. Sections 3 and 4 present and discuss the results (descriptive and regressions respectively). Section 5 concludes.

2. Data and model assumptions

- Data on teleworkability and routinization
  - The Survey on Occupations (Indagine Campionaria Professioni – ICP), carried out jointly by INAPP and the Italian Statistical Office (Istat), was last released in 2013 by INAPP. It collects information on the contents of work through a rich questionnaire composed of seven sections, including knowledge, skills, attitudes, generalized work activities, values, work styles, and working conditions.
  - RTI index: Cirillo et al. (2021) exploit the information in ICP to classify tasks in three groups, Routine Task, Non-Routine Cognitive and Non-Routine Manual tasks, and build an index of Routine Task Intensity close to the one used in Acemoglu and Autor (2011), i.e. computed as the difference between the routine and non-routine dimensions of occupations.
  - Technical teleworkability index: Based on the information on task contents, methods and tools of work present in the Italian ICP, Sostero et al. (2020) construct a binary technical teleworkability index for each 5-digits CP2011 occupation, which indicates as non-teleworkable occupation with at least one physical task reported as sufficiently important. We aggregate the index at 4-digits CP2011 using ISTS-LFS weights based on the relative share of employment in each 5-digit occupation among the 4-digit group, and classify each 4-digit occupation as teleworkable when the technical teleworkability index is above the threshold of 0.4 (following Sostero et al. 2020).

2.1. Model characteristics and data

We adopt a static tax-benefit microsimulation model which partially draws on Baldini et al. (2018) and Gallo (2021) to simulate the implementation of redistributive policies in Italy. As typical in this class of models (Beirne et al., 2020; Bronka et al., 2020; Figari and Fiorio, 2020), we simulate pandemic effects on the income distribution assuming, on the one hand, no individuals' behavioural changes and, on the other hand, no structural changes in the labour demand and in the wage structure.

The model relies on the 2017 wave of the Italian component of the EU-SILC survey (henceforth, IT-SILC), enriched by the monthly information on workers' activity sector, wage, and other occupation characteristics recorded in the administrative archives managed by INPS. The dataset thus developed is called AD-SILC 2017. Income variables in AD-SILC 2017, which refer to the year 2016, have been inflation-adjusted to 2020 using consumer price indexes provided by ISTAT.

The microsimulation model includes all tax and benefit measures which existed before the pandemic and simulates entitlement conditions to the layoffs stoppage and to the new emergency benefits introduced from March 2020 onwards (see Section 2.2 for details). Microsimulations are aligned to aggregate data delivered by national institutions (updated up to July 2021) and to first descriptive evidence on the Italian Labour Force Survey data. In particular, we aligned our model to the spread of: the CIG allowance among the employees by NUTS-2 region, month, sector of activity, and occupation skill level.

To assess changes due to the occurrence of the pandemic, we refer to the inflation-adjusted income distribution observed in 2016 as the "No-Covid scenario". Hence, we use information on individuals' incomes and monthly occupational statuses recorded in INPS administrative data (or eventually declared during the IT-SILC interview if missing in INPS records) to simulate what would have been occurred in 2020 if the pandemic had not happened. In other words, we assume that no differences would have occurred in labour market outcomes of individuals from 2016 to 2020 in absence of pandemic.

The distributional analysis on workers assesses the effect of the pandemic on their gross incomes, also considering the role played by the different types of income support measures for workers. More in detail, the analysis is based on a subsample of 19,154 individuals aged 15-65 who had positive labour incomes and were not retired in 2016 (79% and 21% of sampled individuals work as an employee or a self-employed, respectively). We thus compare the 2016 distribution (henceforth, the No-Covid scenario) with the distribution in a simulated pandemic scenario of gross annual labour incomes (considering incomes from employment and self-employment) and workers total income. The latter is defined as the sum of labour incomes and the received amount of income support measures introduced or strengthened from March 2020 to help workers (namely, the CIG allowance, different types of UB, and Bonus-600). Therefore, comparing the effects on labour and total income, it is possible quantifying the cushioning effect of these benefits on workers' income loss due to the pandemic.

In order to simulate the effects of the COVID-19 pandemic on income distribution, the information on the activity sector available in our dataset and collected in administrative archives is crucial. Indeed, this information is recorded according to the 6-digit ATECO classification that is the classification used by the Italian government to establish essential and non-essential sectors. Thus, differently from other analyses about Italy (Figari and Fiorio, 2020; Brunori et al., 2020; MEF, 2020; Carta and De Philippis, 2021) which had data at the 2-digit ATECO level at most and had to randomly select 'essential' and 'non-essential' workers, our dataset allows us to exactly identify workers at risk of firm shutdown because of the social distancing measures introduced to stop pandemic.

2.2. Assumptions and simulated scenarios

In this article the effects of the pandemic are simulated in a scenario capturing the effects of pandemic during the whole 2020.

To simulate income distribution changes, we adopt several assumptions according to the occupational status of individuals. Specifically, we consider the following six categories of workers: i) open-ended employees in essential sectors; ii) open-ended employees in non-essential sectors; iii) temporary employees in essential sectors; iv) temporary employees in non-essential sectors; v) self-employed in essential sectors; vi) self-employed in non-essential sectors. In what follows we present in detail, for each category of workers, the COVID-19 effects on labour incomes and emergency policies simulated in our microsimulation model.

Although the stoppage of layoffs introduced by the national government was not limited to a specific typology of employment contract, we assume that this emergency policy is effective for open-ended employees only, since employers may merely not renew temporary contracts. To simulate the effect of the stoppage of layoffs, we use the information on the monthly employment in 2016 and, for those who were employed in February, we replace – for the whole duration of the layoff stoppage (i.e., March-December 2020) – the unemployment periods recorded in the following months (thus receiving zero incomes or UB/CIG) with the mean monthly wage (computed according to actual earnings in worked months).[4]

Since employers cannot fire their employees, all firms are allowed to take advantage of CIG. To simulate the CIG receipt, we rely on available data on the distribution of the CIG, for each NUTS-2 region and month, in essential and non-essential sectors. We thus identify the number of workers who received were suspended from their job and received this allowance (whose value amounts to 80% of previous wage until a ceiling) instead of their monthly wage through a monthly random selection. (Note that also temporary employees may receive the CIG until their contract does not expire.) Referring to elaborations of the authors on the available microdata from the Italian Labour Force Survey, we add a further dimension on this model assumption splitting up the CIG receipt also by occupation skill level (i.e. high level, thus first two levels of the 1-digit ISCO-08 classification, average level, thus ISCO-08 third and fourth level, and low level, thus from ISCO-08 fifth level onwards).

It has to be pointed out that the spread of CIG in non-essential sectors was below 100% during the lockdown period since some firms asked for derogation from the mandatory shutdown of their activity. Moreover, individuals who were able to work from home had the opportunity to continue their activity if their firm was not shut down. Likewise, CIG was also asked by firms in essential sectors which suffered from a reduction in their activity due to the pandemic.

As concerns fixed-term employees, our dataset does not provide information about the expected duration of the contract, thus preventing us from exactly considering the lack of a contract renewal. Consequently, we simulated unemployment spells from March to December for those temporary workers who changed firm or experienced some non-working month in the corresponding period in 2016. As usual in the nowcasting framework, this random procedure has been performed consistently with aggregated data on the monthly turnover for this category of workers for the year 2020. We assume that months spent in unemployment are covered by ordinary UB. Similarly, we extend the UB duration of those who were already UB recipients in February. Furthermore, some categories of seasonal temporary employees in non-essential sectors are also entitled to receive the monthly lump sum Bonus-600.

As the stoppage of layoffs, coupled with a deep recession, made very unlikely the worker re-employment until the end of the pandemic period, we also assume that part (randomly selected) of individuals unemployed in February and then working – according to the No-Covid scenario – as an employee or a self-employed in the following months have no labour income from March until the

[4] Consistently, we do not consider in the post-Covid scenarios UB and CIG received by open-ended employees in the No-Covid scenario during the months of application of the layoffs' stoppage.

end of 2020. Again, the extent of individuals remaining out of labour market is consistent with aggregated data on labour market transitions in 2020.

As concerns the self-employed, to better take into account changes in social distancing measures during 2020, we make different assumptions on their income loss by month and according to their sector of activity (essential or non-essential), their teleworkability, and their region of residence. Self-employed working in non-essential sectors and performing a non-teleworkable occupation are those to whom we simulate the highest income losses during the two waves of COVID-19 contagions, followed by self-employed working in non-essential sectors but performing a teleworkable occupation, self-employed working in essential sectors but performing a non-teleworkable occupation, and self-employed working in essential sectors and performing a teleworkable occupation. We however assume that the minimum decrease of self-employed incomes during the ‘lockdown months’ (from March to April 2020) and May 2020 is equal to 25%. As for the June-October period, we assume that all self-employed suffer a 25% decrease of their incomes except for those working in essential sectors and performing a teleworkable occupation. As for the November-December period, we further distinguish assumptions on self-employed income losses according to the number of days spent in the yellow area of restrictions, the orange area, or the red area.

Self-employed are entitled to receive the monthly lump sum Bonus-600 for the March-May period. For the sake of simplicity, we adopt a 100% take-up rate for Bonus-600 among self-employed with an annual labour income lower than €50,000, while the take-up rate becomes 0 for those with an income level higher than €50,000. On the basis of the outputs of our model, about 4.6 million of individuals received this benefit, consistently with aggregated data provided by INPS.

3. Pandemic effects on income distribution

Table 1. Loss from pandemic by RTI tertile group and income definition

Gross labour income								
Loss from pandemic	RTI tertile group = 1		RTI tertile group = 2		RTI tertile group = 3		Total	
No loss	3,172,477	45.4%	2,364,663	33.1%	1,834,394	27.3%	7,371,534	35.3%
Moderate loss	1,786,936	25.6%	1,595,231	22.3%	1,519,332	22.6%	4,901,499	23.5%
Great loss	2,029,661	29.0%	3,190,529	44.6%	3,377,562	50.2%	8,597,752	41.2%
Total	6,989,074	100.0%	7,150,423	100.0%	6,731,288	100.0%	20,870,785	100.0%
Gross individual income								
Loss from pandemic	RTI tertile group = 1		RTI tertile group = 2		RTI tertile group = 3		Total	
No loss	3,562,803	51.0%	2,739,761	38.3%	2,013,589	29.9%	8,316,153	39.8%
Moderate loss	1,908,967	27.3%	2,375,511	33.2%	3,075,396	45.7%	7,359,874	35.3%
Great loss	1,517,304	21.7%	2,035,151	28.5%	1,642,303	24.4%	5,194,758	24.9%
Total	6,989,074	100.0%	7,150,423	100.0%	6,731,288	100.0%	20,870,785	100.0%

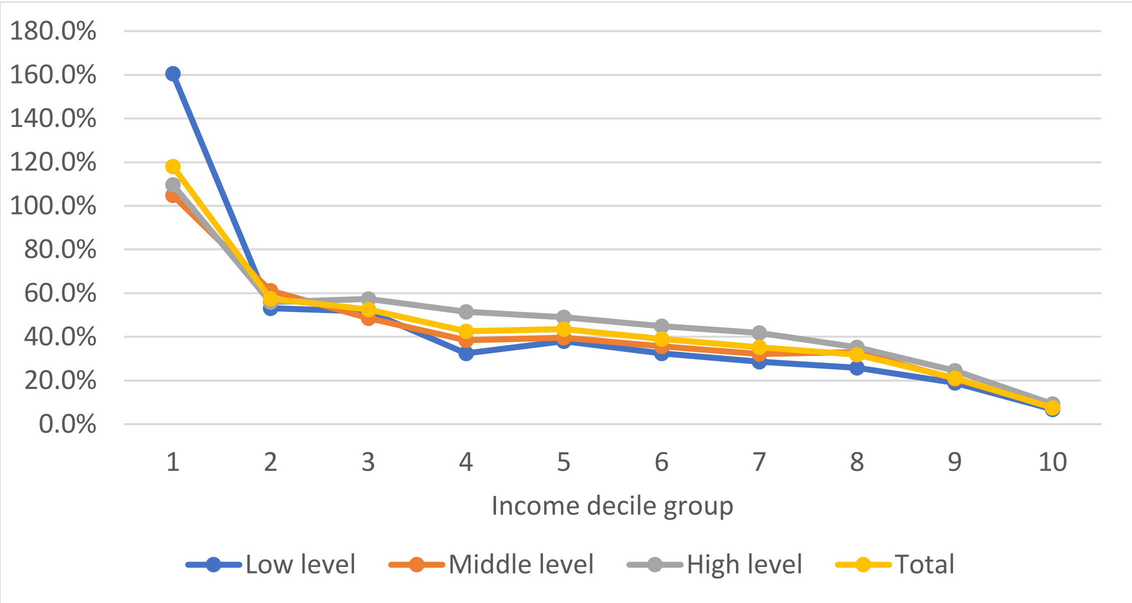
Notes: The income loss is ‘great’ if the relative decrease is more than 10%, it is ‘moderate’ otherwise. ‘No loss’ means that the income level remains unchanged or even increases after the pandemic.

Table 2. Loss from pandemic by teleworkability and income definition

Gross labour income						
Loss from pandemic	Not teleworkable		Teleworkable		Total	
No loss	2,310,185	26.4%	5,061,349	41.7%	7,371,534	35.3%
Moderate loss	1,955,542	22.4%	2,945,957	24.3%	4,901,499	23.5%
Great loss	4,471,465	51.2%	4,126,287	34.0%	8,597,752	41.2%
Total	8,737,192	100.0%	12,133,593	100.0%	20,870,785	100.0%
Gross individual income						
Loss from pandemic	Not teleworkable		Teleworkable		Total	
No loss	2,736,568	31.3%	5,579,585	46.0%	7,371,534	35.3%
Moderate loss	3,530,073	40.4%	3,829,801	31.6%	4,901,499	23.5%
Great loss	2,470,551	28.3%	2,724,207	22.5%	8,597,752	41.2%
Total	8,737,192	100.0%	12,133,593	100.0%	20,870,785	100.0%

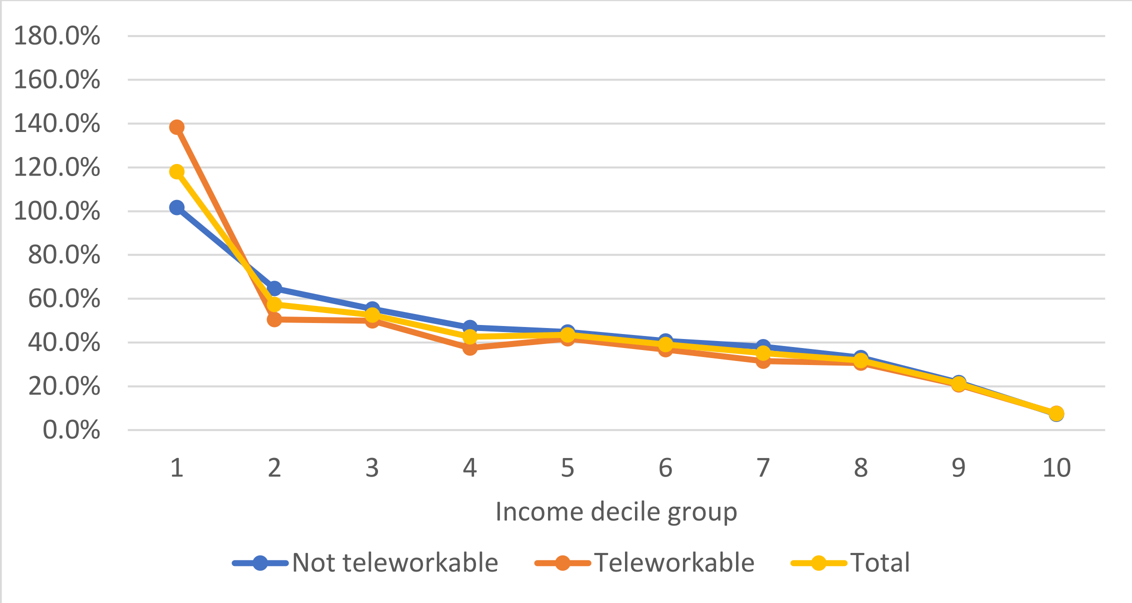
Notes: The income loss is 'great' if the relative decrease is more than 10%, it is 'moderate' otherwise. 'No loss' means that the income level remains unchanged or even increases after the pandemic.

Figure 1. Benefits coverage of income loss by RTI tertile group



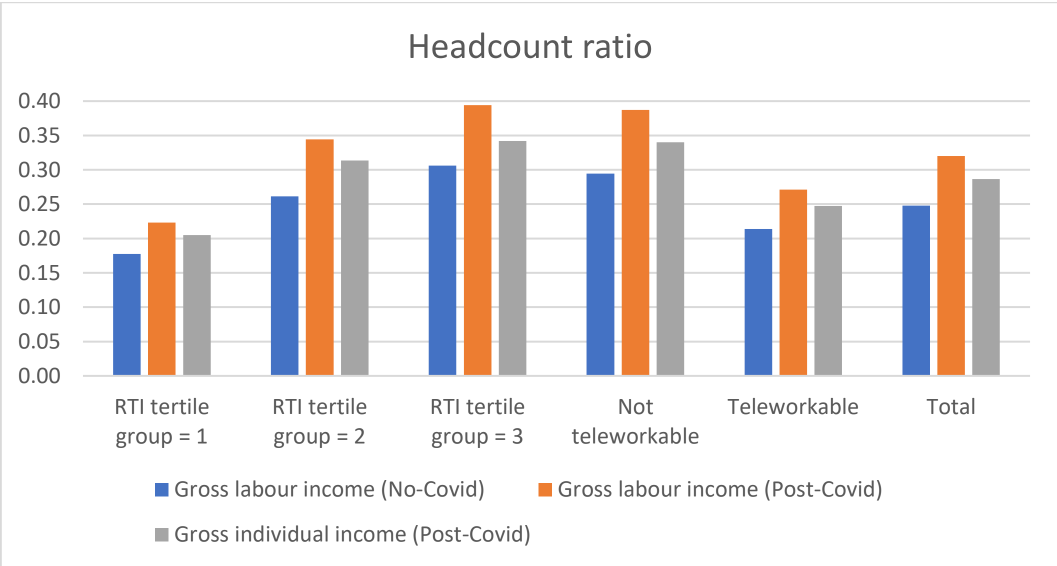
Source: Elaborations on AD-SILC 2017 data.

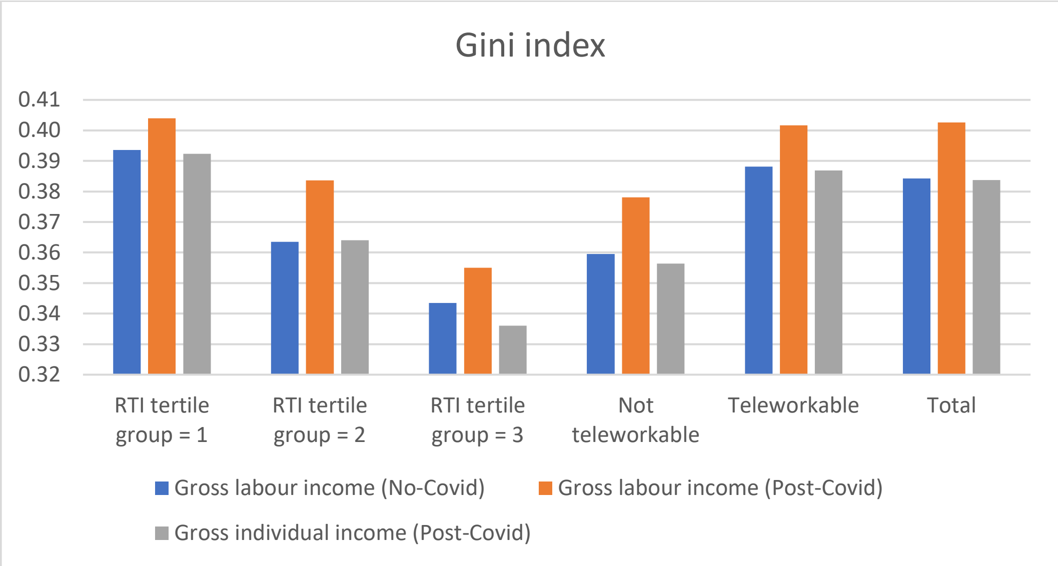
Figure 2. Benefits coverage of income loss by level of teleworkability



Source: Elaborations on AD-SILC 2017 data.

Figure 3. Effects of pandemic on the low income risk (headcount ratio) and income inequality (Gini index) of employees by RTI tertile group and level of teleworkability





Notes: The low income threshold is defined as 60% of the median of the distribution of labour or total income in the No-Covid scenario. Source: Elaborations on AD-SILC 2017 data.

4. Econometric results

Regressions on the probability to suffer a great income loss during the pandemic (pre and post emergency benefits).

Table 3. Determinants of the log annual gross labour income in No-Covid scenario

Variables	m1 - Base	m2 - RTI	m3 - RTI and TWA	m3b - RTI and TWA	m4 - dummies for RTI	m5 - dummies for RTI and TWA	m5b - dummies for RTI and TWA
Female	-0.400***	-0.398***	-0.413***	-0.355***	-0.397***	-0.411***	-0.354***
Foreign	-0.369***	-0.344***	-0.332***	-0.258***	-0.337***	-0.328***	-0.257***
Age	0.057***	0.055***	0.055***	0.050***	0.054***	0.054***	0.050***
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
Medium education	0.245***	0.213***	0.196***	0.158***	0.209***	0.194***	0.157***
High education	0.507***	0.433***	0.411***	0.272***	0.422***	0.404***	0.271***
Center	-0.166***	-0.166***	-0.164***	-0.148***	-0.164***	-0.163***	-0.147***
South	-0.347***	-0.346***	-0.347***	-0.312***	-0.347***	-0.348***	-0.313***
Mid populated area	-0.019	-0.014	-0.010	-0.020	-0.014	-0.010	-0.020
Low populated area	-0.067***	-0.060***	-0.053**	-0.046**	-0.061***	-0.054**	-0.047**
Private, fixed-term employee	-0.389***	-0.382***	-0.371***	-0.232***	-0.382***	-0.372***	-0.231***
Public, open-ended employee	0.162***	0.127***	0.135***	0.238***	0.128***	0.137***	0.238***
Public, fixed-term employee	-0.237***	-0.277***	-0.268***	-0.157*	-0.275***	-0.266***	-0.157**
Self-employed	-0.396***	-0.424***	-0.417***	-0.365***	-0.422***	-0.416***	-0.366***
RTI		-0.496***	-0.387***	-0.194***			
TWA index			0.100***	0.028			
Medium RTI					-0.111***	-0.082***	-0.012
High RTI					-0.201***	-0.159***	-0.075***
High TWA						0.089***	0.027
Constant	8.484***	8.799***	8.717***	8.660***	8.691***	8.632***	8.589***
Fixed effects for sector and skill level	No	No	No	Yes	No	No	Yes
Observations	17,133	17,133	17,133	17,133	17,133	17,133	17,133
R-squared	0.247	0.253	0.255	0.295	0.253	0.255	0.295

*Notes: Standard errors are clustered by NUTS-3 region level and individual sample weights are included. *** p<0.01, ** p<0.05, * p<0.1. Additional covariates included in the model: household composition dummies (in all models), fixed effects for 2-digit NACE sector and occupation skill level dummies (in models m3b and m5b). Private, open-ended employee is the reference category for occupational status. Big city is the reference category for the area of living.*

Table 4. Marginal effects on the probability of reporting a great labour income drop

	m1 - Base	m2 - RTI	m3 - RTI and TWA	m4 - dummies for RTI	m5 - dummies for RTI and TWA
Log annual earnings before Covid-19	-0.007	-0.004	-0.002	-0.002	-0.000
Female	-0.028***	-0.029***	-0.017**	-0.029***	-0.020**
Foreign	0.049***	0.040***	0.032***	0.032***	0.027**
Age	-0.002	-0.002	-0.001	-0.001	-0.001
Age^2	0.000	-0.000	-0.000	-0.000	-0.000
Medium education	-0.071***	-0.059***	-0.047***	-0.051***	-0.042***
High education	-0.232***	-0.205***	-0.191***	-0.185***	-0.175***
Center	-0.026***	-0.026**	-0.027***	-0.027***	-0.028***
South	-0.099***	-0.098***	-0.097***	-0.097***	-0.096***
Mid populated area	0.042***	0.040***	0.037***	0.038***	0.037***
Low populated area	0.045***	0.043***	0.037***	0.042***	0.038***
Private, fixed-term employee	0.077***	0.074***	0.067***	0.073***	0.068***
Public, open-ended employee	-0.309***	-0.300***	-0.303***	-0.296***	-0.298***
Public, fixed-term employee	-0.166***	-0.148***	-0.153***	-0.141***	-0.145***
Self-employed	0.439***	0.451***	0.447***	0.455***	0.453***
RTI		0.200***	0.123***		
TWA index			-0.066***		
Medium RTI				0.069***	0.052***
High RTI				0.119***	0.093***
High TWA					-0.051***
Observations	17,133	17,133	17,133	17,133	17,133

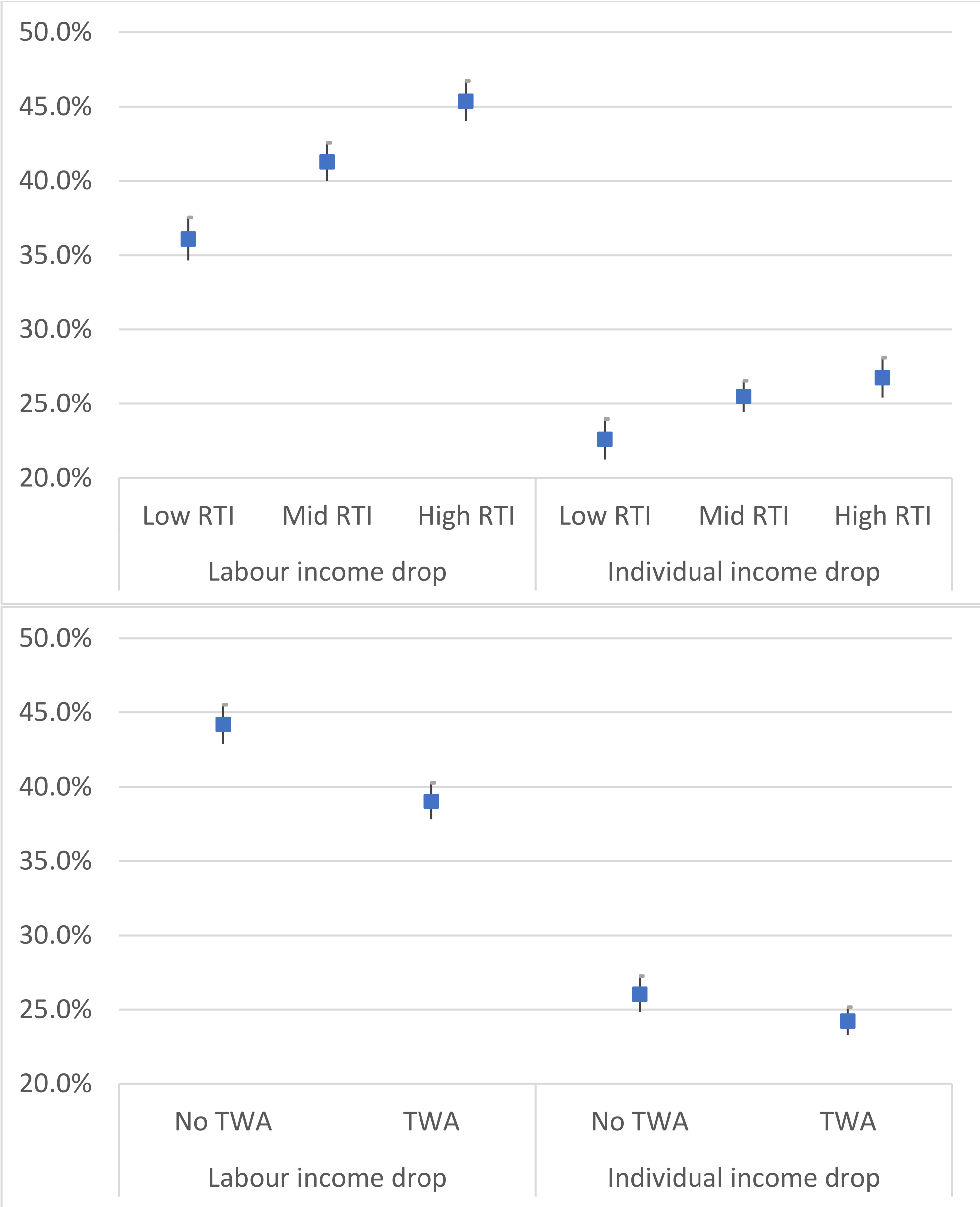
*Notes: Standard errors are clustered by NUTS-3 region level and individual sample weights are included. *** p<0.01, ** p<0.05, * p<0.1. Additional covariates included in all models: household composition dummies. Private, open-ended employee is the reference category for occupational status. Big city is the reference category for the area of living.*

Table 5. Marginal effects on the probability of reporting a great individual income drop

	m1 - Base	m2 - RTI	m3 - RTI and TWA	m4 - dummies for RTI	m5 - dummies for RTI and TWA
Log annual earnings before Covid-19	0.066***	0.066***	0.067***	0.068***	0.068***
Female	-0.043***	-0.043***	-0.039***	-0.043***	-0.040***
Foreign	0.004	0.002	-0.001	-0.003	-0.004
Age	0.003	0.003	0.003	0.003	0.003
Age^2	-0.000	-0.000	-0.000	-0.000	-0.000
Medium education	-0.028***	-0.024**	-0.019*	-0.018*	-0.015
High education	-0.129***	-0.123***	-0.117***	-0.109***	-0.106***
Center	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
South	-0.046***	-0.045***	-0.045***	-0.045***	-0.045***
Mid populated area	0.021*	0.020*	0.019*	0.020*	0.019
Low populated area	0.022*	0.022*	0.019	0.021*	0.019
Private, fixed-term employee	0.007	0.006	0.004	0.006	0.005
Public, open-ended employee	-0.126***	-0.124***	-0.125***	-0.121***	-0.122***
Public, fixed-term employee	-0.027	-0.023	-0.026	-0.018	-0.020
Self-employed	0.524***	0.528***	0.527***	0.533***	0.532***
RTI		0.050	0.014		
TWA index			-0.030***		
Medium RTI				0.035***	0.029***
High RTI				0.051***	0.042***
High TWA					-0.018**
Observations	17,133	17,133	17,133	17,133	17,133

*Notes: Standard errors are clustered by NUTS-3 region level and individual sample weights are included. *** p<0.01, ** p<0.05, * p<0.1. Additional covariates included in all models: household composition dummies. Private, open-ended employee is the reference category for occupational status. Big city is the reference category for the area of living.*

Figure 4. Predicted probability of reporting a great labour or individual income drop by RTI tertile group and level of teleworkability



Notes: The income loss is 'great' if the relative decrease is more than 10%. Estimates are based on the Logit model regression of model 'm5' in Table 4 (labour income drop) and Table 5 (individual income drop).

5. Conclusions

References

Adams-Prassl A., Boneva T., Golin M., Rauh C. (2020), "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys", Journal of Public Economics, 189, 104245.

Aina, Carmen & Brunetti, Irene & Mussida, Chiara & Scicchitano, Sergio, 2021. "Who lost the most? Distributive effects of COVID-19 pandemic," GLO Discussion Paper Series 829, Global Labor Organization (GLO).

Aspachs O., Durante R. García Montalvo J. Graziano A., Mestres J., Reynal-Querol M. (2020), "Real-Time Inequality and the Welfare State in Motion: Evidence from COVID-19 in Spain", CEPR Discussion Paper, n. 15118.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US Labor Market. American Economic Review, 103(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Alipour, J.-V., O. Falck, and S. Schuller (2020). Germany's capacities to work from home. CESifoWorking Paper.

Baldini M., Casabianca E.J., Giarda E., Lusignoli L. (2018). "The impact of REI on Italian households' income: A micro and macro evaluation" Politica Economica, 32(2), pp. 103–134.

Beirne, K., Doorley, K., Regan, M., Roantree, B., and Tuda, D. (2020), "The potential costs and distributional effect of COVID-19 related unemployment in Ireland", EUROMOD Working Paper Series, n. 05/20.

Berman J. (2020), "The Distributional Short-Term Impact of the COVID-19 Crisis on Wages in the United States", MPRA Paper, n. 100466.

Boeri T, Caiumi A, Paccagnella M (2020) Mitigating the work-security trade-off. CEPR Press. Covid Economics No 2:60–66

Bonacini, L., Gallo, G., & Scicchitano, S. (2021). Working from home and income inequality: risks of a 'new normal' with COVID-19. Journal of Population Economics, 34(1), 303–360. https://doi.org/10.1007/s00148-020-00800-7

Brewer M., Tasseva I. (2020), "Did the UK policy response to Covid-19 protect household incomes?", EUROMOD Working Paper Series, n. 12/20.

Bronka P., Collado D., Richiardi M. (2020), "The Covid-19 crisis response helps the poor: The distributional and budgetary consequences of the UK lockdown", Covid Economics, n. 26, pp. 96-104.

Brunori P., Maitino M.L., Ravagli L., Sciclone N. (2020), "Distant and Unequal. Lockdown and Inequalities in Italy", Università degli Studi di Firenze, Dipartimento di Scienze per l'Economia e l'Impresa, Working Paper n. 13.

Carta F., De Philippis M. (2021), The impact of the COVID-19 shock on labour income inequality: evidence from Italy, Bank of Italy Occasional Papers, n. 606.

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

Cetrulo, V., Guarascio, D., Virgilito, M.E. (2020b) Working from home and the explosion of enduring divides: income, employment and safety risks. LEM Working Paper Series

Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digitalization, routineness and employment: An exploration on Italian task-based data. Research Policy, 50(7), 104079. https://doi.org/10.1016/j.respol.2020.104079

Cortes G.M., Forsythe E., "Impacts of the COVID-19 Pandemic and the CARES Act on Earnings and Inequality", IZA Discussion Papers, n. 13643.

Figari F., Fiorio C. V. (2020), "Welfare resilience in the immediate aftermath of the COVID-19 outbreak in Italy", EUROMOD Working Paper Series, n. 06/20.

Galasso V. (2020), "Covid: not a great equialiser", Covid Economics, vol. 19, pp. 241-255.

Gallo G. (2021), "Regional Support for the National Government: Joint Effects of Minimum Income Schemes in Italy", Italian Economic Journal, https://doi.org/10.1007/s40797-019-00118-8.

Hensvik L, Le Barbanchon T, Rathelot R (2020) Which jobs are done from home? evidence from the American time use survey. IZA Discussion Paper 13138

Holgersen H, Zhiyang J, Svenkerud S (2020) Who and how many can work from home? Evidence from task descriptions and Norwegian job advertisements. (April 20, 2020). Available at SSRN: https://ssrn.com/abstract = 3580674 or. https://doi.org/10.2139/ssrn.3580674

Koren M, Peto R (2020) Business disruptions from social distancing. In: Covid Economics, (2) 13-31. Press, CEPR

Leibovici F, Santacrue AM, Famiglietti M (2020) Social distancing and contact-intensive occupations. St. Louis Federal Reserve Bank - On the Economy Blog, March

Li J., Vidyattama Y., Anh H., Miranti R., Sologon D. (2020), "The Impact of COVID-19 and Policy Responses on Australian Income Distribution and Poverty," Papers 2009.04037, arXiv.org.

Ministry of Economy and Finance – MEF (2020), "L'impatto del Covid-19 e degli interventi del Governo sulla situazione socio-economica delle famiglie italiane nei primi tre mesi della pandemia", Nota Tematica n. 3.

Montenovo, L., Jiang, X., Rojas, F., Schmutte, I.M., Simon, K., Weinberg, B.A., and Wing, C. (2020) Determinats of Disparities in Covid-19 Job Losses. NBER Working Paper Series 27132 doi: 10.3386/w27132

O' Donoghue C., Sologon D.M., Kyzyma I., McHale J. (2020), "Modelling the Distributional Impact of the COVID-19 Crisis", Fiscal Studies, 41(2), pp. 321-336.

Palomino J., Rodríguez J., Sebastian R. (2020), "Wage inequality and poverty effects of lockdown and social distancing in Europe", European Economic Review, https://doi.org/10.1016/j.euroecorev.2020.103564.

Sostero, M., S. Milasi, J. Hurley, E. Fernandez-Macías, and M. Bisello (2020). Teleworkability and the covid-19 crisis: a new digital divide? JRC working papers series on labour, education and technology

Yasenov V (2020) Who can work from home?, IZA DP No. 13197, April 2020.