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Working from home and income inequality. Risks of a 'new normal' with COVID-19

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Abstract

In the current context of the COVID-19 pandemic, working from home (WFH) became of great importance for a large share of employees since it represents the only option to both continue working and minimize the risk of virus exposure. Uncertainty about the duration of the pandemic and future contagion waves even led companies to view WFH as a “new normal” way of working. Based on influence function regression methods, this paper explores the potential consequences in the labour income distribution related to a long-lasting increase in WFH feasibility among Italian employees. Results show that a positive shift in WFH feasibility would be associated with an increase in average labour income, but this potential benefit would be not equally distributed among employees. Specifically, an increase in the opportunity to WFH would favor male, older, high-educated, and high-paid employees. However, this “forced innovation” would benefit more employees living in provinces have been more affected by the novel coronavirus. WFH thus risks exacerbating pre-existing inequalities in the labour market, especially if it will not be adequately regulated. As a consequence, this study suggests that policies aimed at alleviating inequality, like income support measures (in the short run) and human capital interventions (in the long run), should play a more important compensating role in the future.

Keywords: COVID-19; working from home; inequality; unconditional quantile regressions.

JEL Classification: D31; J31; I24

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"That push [related to reopening decisions during the pandemic] *is likely to exacerbate longstanding inequalities, with workers who are college educated, relatively affluent and primarily white able to continue working from home and minimizing outdoor excursions to reduce the risk of contracting the virus"*
The New York Times, April 27 2020[2]

1. Introduction

The COVID-19 pandemic is raging worldwide and probably will not end in the short term, possibly resulting in structural effects on the labour market in many countries (Baert et al., 2020a). In order to limit the number of deaths and hospitalisations due to the novel coronavirus, most governments in developed countries decided to suspend many economic activities and restrict people's freedom of mobility (Brodeur et al., 2020a; Brodeur et al. 2020b; Qiu et al., 2020).

In this context, the opportunity to work from home (hereinafter called WFH) became of great importance (Acemoglu et al., 2020) since it allows employees to continue working and thus receiving wages, employers to keep producing services and revenues, and overall limits infection spread risk and pandemic recessive impacts. Recent estimates for the U.S. show that remote workers have quadrupled to 50% of U.S. workforce (Brynjolfsson et al., 2020). Due to uncertainty about the duration of the pandemic and future contagion waves, the role of WFH in the labour market is further emphasized by the fact that it might become a traditional (rather than unconventional) way of working in many economic sectors. According to Alon et al. (2020:17), "*Many businesses are currently adopting work-from-home and telecommuting options at a wide scale for the first time. It is likely that some of these changes persist, leading to more workplace flexibility in the future"*. Also, Baert et al. (2020b) recently found that the great majority of the employees believe that teleworking (85%) and digital conferencing (81%) will continue after the SARS-CoV-2 crisis. Facebook and a number of other companies, especially those dealing with IT (Information Technology), have already decided they will allow many employees to work from home permanently.[3]

Because of WFH's sudden prominence and growth, several studies recently investigated the WFH phenomenon, especially with the objective of identifying the number of jobs that can be done remotely (Adams-Prassl et al., 2020; Dingel and Neiman, 2020; Koren and Peto, 2020; Leibovici et al., 2020; Mongey at al., 2020). However, the literature neglects potential effects of WFH along the wage distribution and on income inequality in general. As we know, the causes of inequalities are heterogeneous and numerous, and these causes have been growing in prominence in policymakers' debates because inequality has increased in Western countries over the last decades (Atkison, 2015; Beckfield, 2019).

To the best of our knowledge, this study represents the first to show how a future increase in WFH would be related to changes in labour income levels and inequality, through the influence function regression method proposed by Firpo et al. (2009). In particular, we want to understand to what extent an increase in the number of employees who have the opportunity to WFH (or at least their professions are more likely to be performed from home) would influence the wage distribution under the hypothesis that this WFH feasibility shift is long lasting (as it seems it will happen because of the COVID-19 outbreak and its aftermath). Considering baseline feasibility levels across Italian

[2] See: https://www.nytimes.com/2020/04/27/business/economy/coronavirus-economic-inequality.html.
[3] Specifically, Mr. Zuckerberg stated: "*It's clear that Covid has changed a lot about our lives, and that certainly includes the way that most of us work. Coming out of this period, I expect that remote work is going to be a growing trend as well.*" (See: https://www.nytimes.com/2020/05/21/technology/facebook-remote-work-coronavirus.html).

employees as the counterfactual scenario, the Firpo et al. (2009)'s methodology allows us to estimate potential influences of this 'innovation' on labour income inequality moving toward a hypothetical distribution where shares of employees are swapped with others according to the reported WFH feasibility level. With respect to the (conventional) quantile regression method developed by Koenker and Bassett (1978), this methodology has also the merit of estimating the effects on a labour income distribution that is not conditioned by the set of covariates included in the model (Fortin et al. 2011).

To do that, we focus on Italy as an interesting case study because it was one of the countries most affected by the novel coronavirus and the first Western country to adopt a lockdown of economic activities (on March 11). Barbieri et al. (2020) estimated that at least 3 million employees (i.e. about 13% of the total) started to WFH because of lockdown measures, and another large number started even earlier due to the closure of schools and universities on March 5 (more details in Bonacini et al., 2021). Moreover, Italy was the European country with the lowest share of teleworkers before the crisis (Eurofound and ILO, 2017) and, as a result of the pandemic, it had to face a massive increase in WFH in a very short time without both precise legislation and adequate policies. Now that the country is steadily increasing the share of WFH, it is crucial to understand the possible effects on the labour market of such a structural change.

Our analysis relies on a uniquely detailed dataset relying on the merge of two sample surveys. The first one is the Survey on Labour Participation and Unemployment (INAPP-PLUS) for the year 2018, which contains information on incomes, skills, education level, and employment conditions of working-age Italians. The second sample survey is the Italian Survey of Professions (ICP) for the year 2013, which represents an Italian equivalent of the much more famous US O*NET. ICP provides detailed information on the task-content of occupations at the 5-digit ISCO classification level and allows to calculate the WFH index recently proposed by Barbieri et al. (2020). Different from other studies that analyse working from home in Italy through an elaborated matching between US O*NET data and Italian labour market information (e.g. Boeri et al., 2020), we use ICP data to avoid potential matching biases. In fact, being based on professions performed in the Italian labour market, ICP has the key advantage of being probably more able than the US O*NET to capture specific features (e.g. tasks, skills required, workplace characteristics) of the Italian economy.

To provide further insights on the relationship between a WFH shift and labour income inequality, we also estimate heterogeneous effects by gender, age group, and education level. The latter is particularly interesting because it allows us to test whether an increase in WFH among high-skilled and educated employees may be related to Skill Biased Technological Change (SBTC) (Acemoglu, 2002; Autor et al., 2003). In this context, the existing complementarity between new technologies and high-paid professions may be a key factor in wage polarization, which in turn is the key variable to understand, predict and manage some of the possible long-run consequences of COVID-19 in terms of working modality changes. Moreover, we merge our dataset with one provided by the Italian Civil Protection Department (2020) on COVID-19 infection spread at the provincial level (reference period February 24-May 5 2020) to investigate whether this potential increase in WFH would benefit more those areas of the country that have been affected the most by the novel coronavirus and thus will suffer worse economic consequences.

Finally, this study has relevant policy implications for tackling inequalities that will arise in the labour market because of the recent pandemic and the consequent (probably) increase in WFH. Our results are based on Italian data, but they may be useful to policymakers in other developed countries as well and, in general, where COVID-19 has forced governments to rethink production processes with a more intense and stable use of WFH.

The rest of the article is structured as follows. The next section presents the literature review on the topic and a brief chronicle of the COVID-19 outbreak in Italy. Section 3 describes the datasets, discusses the definition of our variables of interest and provides some descriptive statistics, while Section 4 reports the econometric methodology. Section 5 and 6 present results and robustness checks. Section 7 concludes with some policy implications.

2. Conceptual framework and existing evidence

2.1. Work from home and inequality: previous and current literature

Flexible work practices (Leslie, 2012) and WFH have already been studied in normal times (e.g. Blinder and Krueger, 2013; Bloom et al., 2015). Empirical economics literature suggests that there are theoretical reasons to associate both higher and lower wages to teleworkers with respect to “traditional workers”. As a result, the link between WFH and income inequality is still ambigous and under debate. On the one hand, lower wage levels may be due to a lower productivity of employees performing their occupation from home (Dutcher and Saral, 2012). A reduction of wage may be also due to a lower disutility of WFH as a consequence of attending child and elderly care, time flexibility, and lower commuting expenses (Bélanger, 1999). On the other hand, the adoption of telework may generate a costs reduction for firms which, in turn, may be translated in higher wages (Hill et al., 1998). Pabilonia and Vernon (2020) find that some teleworkers in the US earn a higher wage than the other workers, but results vary by occupation, gender, parental status, and teleworking intensity. Recent studies conducted in the US also find a high correlation between high income levels and high-speed Internet, thus meaning that WFH is easier for relatively rich people (Chiou and Tucker, 2020). As for Italy, to our knowledge, only Pigini and Staffolani (2019) deal with the average wage gap between teleworkers and employees making traditional jobs. Their study highlights that the small number of teleworkers in the labour market (1% of total), after accounting for observed individual and job-specific variables, enjoy an average wage premium ranging between 2.7 and 8 percent.

Even for the gender pay gap, although widely studied, there is not a clear evidence of the effect of WFH. Gariety and Shaer (2007), Bloom et al. (2014), Arntz et al. (2019) Angelici and Profeta (2020) point out that WFH may reduce (or at least not increase) wage differences between male and female workers. On the other hand, Weeden (2005), Goldin (2015) and Bertrand (2018) display results in the opposite direction.

The economic literature on COVID-19 is exploding daily: between March 2020 and June 2020 the Bureau of Economic Research (NBER) released more than 160 working papers on this topic and around 100 were the discussion papers published by the IZA Institute of Labor Economics (Brodeur et al .2020c). Similarly, the Global Labor Organization (GLO) Cluster Coronavirus published more than 30 discussion papers on the economics of COVID-19. A large number of articles investigated the consequences of the virus spread on the labour market in different countries (Béland et al., 2020a; Bennedsen et al., 2020; Bertocchi and Dimico, 2020; Duman, 2020; Greyling et al. 2020; Milani, 2021; Nikolova and Popova, 2020). Within this strand of increasing current literature, several studies recently analysed the WFH phenomenon because of its sudden growth of prominence.

Most of these studies (see, for instance, Béland, et al., 2020b; Dingel and Neiman, 2020; Gottlieb et al., 2020; Hensvik et al., 2020; Holgersen et al., 2020; Koren and Peto, 2020; Leibovici et al., 2020; Yasenov, 2020) aim to classify occupations according to their WFH feasibility in the US and some European countries (e.g. UK, Germany), as well as in Latin American and Caribbean countries (Delaporte and Pena, 2020). Papanikolaou and Schmidt (2020) examine differences in the opportunity of workers across industries to have WFH using data from the American Time Use Survey (ATUS). As for Italy, Boeri et al. (2020), relying on the US O*NET dataset, estimate that 24% of jobs can be carried out from home, while Barbieri et al. (2020) rank sectors and occupations according to the risk of contagion and propose an indicator of WFH feasibility to understand in which sectors this risk can be reduced without any interruction from working. However, they ignore the possible distributional consequences of a steady increase in working remotely. In this paper, we instead show the potential relationship between a positive shift in the WFH feasibility of employees and labour income inequality over the whole distribution, also distinguishing by individual characteristics.

2.2. *COVID-19 outbreak in Italy*

To expose the chronicle of the COVID-19 pandemic in Italy, we begin by Wuhan, a city in the Eastern China, where in the December 2019 several persons affected by a severe acute respiratory syndrome were reported. Scientists identified the cause of this pneumonia in a novel strain of Coronavirus, that World Health Organization named SARS-CoV-2. The disease, designated as COVID-19, caused more than 85 thousand confirmed deaths in China showing a great rate of spread.

To prevent the outbreak in Italy, on January 30, 2020 (i.e. the same day two Chinese tourists tested positive for COVID-19 and were hospitalised in Rome), the national government implemented the first restrictive measures: it declared the state of emergency and it blocked all flights to and from China. As a recent study by Zimmermann et al. (2020) highlighted, the contagion speed of the novel coronavirus seems to be also favoured by globalization and, despite measures adopted in Italy, on February 21 a cluster of cases was discovered in the Lombardy region. Despite the attempt of the Italian government to isolate the cluster declaring "red areas" all municipalities counting COVID-19 infected, the virus has spread throughout the country and on February 23, Italy became the European country with the highest number of registered positive cases.

The government reacted to the emergency implementing a series of increasingly stringent rules intended to prohibit the areas of aggregation and to avoid contacts between people. It has been the first European country to implement courageous acts to restrict citizens' mobility. On March 4, the Prime Minister signed a law forcing the closure of schools and universities and the stoppage of all sporting and social events from March 5, with the initial aim (and hope) of reopening in ten days. On March 8, the Italian government implemented another extraordinary restrictive measure declaring as "red areas" all the Lombardy region and other 14 northern provinces[4]. Due to the worsening situation, only three days after (i.e. March 11, the day-after World Health Organization declared the situation of global pandemic), the government compelled all commercial and retail businesses to close down, with the exception of those referred to basic necessities. Even food services (e.g. bars, restaurants) were forced to close and eventually provide takeaway services only. Around 2.7 million workers suspended their activity (Barbieri et al. 2020).

The last important containment measure adopted focused on the closure of all "non-essential" economic activities, but it followed a different path compared to the previous ones. A first version of the regulation was announced on March 21 and published on March 22, but it was modified on March 25 after the meeting between the Government, unions, and representation of the entrepreneurs. The final law tightened the measures in several ways, including: the suspension of every activity furnishing food, the closure of every professional activity or self-employment, and restrictions on people's mobility freedom. After these amendments, around 8 million workers (34% of total) were forced to stay home (Barbieri et al. 2020).

On May 4, "Phase 2" of coexistence with the COVID-19 virus began. It consisted of a progressive reduction of lockdown measures introduced during "Phase 1" (i.e. the epidemic phase), as well as those measures regarding the mobility freedom of population. The transition from the epidemic phase to Phase 2 was subordinated to the institutions' ability to diagnose, manage, and isolate COVID-19 cases and their contacts. Entrepreneurial and some other business activities could only reopen under precise conditions and much of normal life could resume with caution. For instance, physical distancing rules must be respected, collective demonstrations must be avoided, and concrete protection must be given to vulnerable subjects. Moreover, public hygiene must be radically improved and individual protection methods (e.g. masks) and systematic and routine cleaning of public spaces must be provided. The containment measures also concern: individual and collective limitations to mobility

[4] In this regard, recent accurate estimates have shown that one should be cautious before considering Lombardy as a "special" case (Depalo, 2021)

(local, medium and long distance); the supply and distribution of protective equipment (personal protective equipment); tracing infectious cases, with massive identification plans for primary and secondary infections; and the implementation of different levels of administrative and environmental engineering controls.

2.3. Working from home in Italy: before, during and after the COVID-19

During the pandemic period, many of measures regarding occupations and social distancing were linked to WFH. In fact, giving the opportunity of working remotely to employees limited their movements outside home and the risk of COVID-19 exposure in general, without interruptions (or at least small ones) on tasks generally performed and on consequent earnings. To easily allow the WFH for public sector employees, a momentary simplification of rules applied to public tenders for laptops purchases was even introduced. However, several income supports to quarantined employees who could not work from home was guaranteed, such as a replacement income (almost) totally financed by public resources (i.e. *Cassa Integrazione Guadagni*), a lump sum benefit of 600 euro for self-employed, seasonal and agricultural employees, an extension of unemployment benefits, and the suspension of dismissals for economic reasons.[5]

The opportunity to remain in a WFH status was confirmed in the Phase 2 for the majority of workers who have been involved in such condition during the lockdowns and nowadays this way of working is still strongly encouraged. Before the COVID-19 pandemic, however, the WFH practice in Italy was definitely not widespread and frequently the notions of teleworking and WFH (or smart working) were used interchangeably. The most representative Italian trade unions – the Italian General Confederation of Work (Confederazione Generale Italiana del Lavoro, CGIL), the Italian Confederation of Workers' Unions (Confederazione Italiana Sindacati Lavoratori, CISL) and the Union of Italian Workers (Unione Italiana del Lavoro, UIL) – usually call for the adoption of teleworking in order to improve the quality of work–life balance policies for workers whose residence is very far from the workplace or for those who have to provide care to young children or relatives with disabilities (Eurofound and ILO, 2017).

In the Italian regulation, the telework implies the indication of times and location outside the office (Ichino, 2020a). Instead, the Law n. 81/2017 (the so-called Jobs Act of self-employment), concerning "Measures for the protection of self-employed non-entrepreneurial work and measures aimed at promoting flexible articulation in the times and places of subordinate work", which officially introduced the smart working (or *Lavoro agile*) in the Italian regulation, defines the smart work as an activity that, although carried out in a subordinate regime, is characterized by the absence of constraints on where and when the same is performed. Therefore, the smart work of WFH substantially differs from the telework, but the recent regulation has been actually applied in very few cases. More specifically, it deals with Chapter II "Agile work" (articles 18-23). Company agreements that also include WFH are very few, although growing in recent years. Currently, collective agreements clearly dealing with WFH are only present in the food, energy and banking-insurance sectors. There are also unilateral initiatives of high-tech companies aimed above all at higher professional figures (Tiraboschi, 2017). Recent estimates report that, among EU-28 countries, Italy shows the lowest share of employed which have the opportunity of WFH (Eurofound and ILO, 2017).

[5] Beyond these measures and the existing minimum income scheme (i.e. the Citizenship Income or *Reddito di Cittadinanza*), a means-tested "emergency income" (*Reddito di Emergenza*) was introduced to deal with households with economic distress but not eligible to all other income support measures. Further employment and social initiatives introduced in Italy (and other developed countries) at the time of COVID-19 outbreak are available here: https://www.oecd.org/coronavirus/country-policy-tracker/.

Using the Italian Labour Force Survey (LFS) for the period 2008-13, Pigini and Staffolani (2019) find that only 1% of workers are 'teleworkers', defined as those who WFH at least twice per week.

Because WFH is not popular in Italy, it is difficult to provide reliable estimates on how and to what extent this phenomenon affects the labour market except through experimental studies (an interesting example is the one provided by Angelici and Profeta, 2020). For this reason, we decided to investigate the feasibility to WFH under the hypothesis that the recent crisis related to the COVID-19 outbreak has determined a structural change in the use of this tool. In fact, consequently to the pandemic, WFH became much more popular and could turn into one ordinary way of working after the crisis. The Budget Committee of the Italian Parliament has approved an amendment in June 2020 which obliges public administrations to plan WFH for at least 50 percent "of the activities that can be carried out in this way" by the end of this year, 60 percent thereafter. On June 17, the Minister of Public Administration declared that 90 percent of public sector employees were engaged in WFH during Phase 1, reporting on average an increase of productivity rates. Moreover, by the end of 2020, the same Minister intends to survey activities that can be carried out remotely, with the objective of moving forward a stable use of WFH in about 50% of them (Ichino, 2020b). In this article, we want to analyse effects that this "forced innovation" would have on the labour market of a developed country. In particular, this study aims to underscore whether the potential increase (decrease) in the average labour income related to a positive shift in the WFH feasibility levels (e.g. because of a change in productivity) would be equally distributed throughout the wage distribution and among groups of employees or not.

3. Data and descriptive statistics

Our analysis relies on an innovative dataset recently built by merging two Italian surveys, developed and provided by the Italian National Institute for the Analysis of Public Policies (INAPP). The first one is the Participation, Labour and Unemployment Survey (PLUS), which provides reliable statistics on labour market phenomena that are rare or marginally explored by the much more known Labour Force Survey (LFS) by Eurostat. The INAPP-PLUS survey also contains information on a wide range of standard individual characteristics, as well as numerous characteristics related to professions and firms, for approximately 45,000 individuals in each wave. We use the (last) eighth wave of the survey which was collected in 2018 and released in the first half of 2019. A dynamic computer-assisted telephone interview (CATI) approach was used to distribute the questionnaire to a sample of residents aged between 18 and 74 according to a stratified random sampling over the Italian population.[6] One of the key elements of this dataset is the absence of proxy interviews: in the survey, only survey respondents are reported, to reduce measurement errors and partial non-responses. However, the INAPP-PLUS survey provides individual weights to account for non-response and attrition issues which usually affect sample surveys. Similarly to other empirical studies relying on the same dataset (see, among others, Clementi and Giammatteo, 2014; Filippetti et al., 2019; Meliciani and Radicchia, 2011, 2016), all descriptive statistics and estimates reported in this analysis are weighted using those individual weights.[7]

The second survey composing our innovative dataset is the 2013 wave of the Italian Sample Survey on Professions (ICP), created in 2004 and currently performed by INAPP. The ICP integrates the traditional approach by focusing on nature and content of the work. It aims to describe with a high

[6] The stratification of the INAPP-PLUS survey sample is based on population strata by NUTS-2 region of residence, urbanisation degree (i.e., metropolitan or non-metropolitan area), age group, sex, and employment status (i.e., employed, unemployed, student, retired, or other inactive status).

[7] As a sensitivity analysis, we replicated all estimates in our main analysis without applying individual weights. Results of this check, presented in Section 6, overall confirm the robustness of our main results presented in Section 5.

analytical detail all existing professions in terms of, on the one hand, requirements and characteristics required to the worker and, on the other hand, activities and working conditions each profession implies. It was chosen to involve workers rather than experts, privileging the point of view of those who exercise daily professions analysed and have a direct and concrete assessment of the level of use of certain characteristics essential to accomplish the job. 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, from those operating in private companies to those present within public institutions and structures, up to those operating under autonomy.

The conceptual reference framework for the investigation and the taxonomies of variables used in the ICP survey are borrowed from the US model of the Occupational Information Network (O*Net), because it is the most complete in terms of the job description and the ablest to comprehensively respond to potential stakeholder questions. Following to the US O*Net conceptual model, ICP questions explore each profession as a multi-dimensional concept that can be described referring to these 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). Remarkably, Italy is one of few European countries to have a dictionary of occupations similar to the US O*NET. Taking advantage from this feature, as it is based on the Italian dictionary of occupations rather than the US one, ICP appears more reliable in capturing the production structure, technology and industrial relations characterizing the Italian economics. Since our analysis relies on ICP data, we should thus avoid potential biases arising when matching information linked to occupational structures (e.g. those contained in the US O*Net repertoire) and labour markets of different countries. To be noted, the existing literature on automation (Goos et al., 2014) and recent contributions on WFH in Italy (Boeri et al., 2020) use instead US O*Net data, making a sophisticated ‘bridge’ between US and European (and Italian in particular) occupations which possibly reflects US-specific technology and ways of working.

From the total INAPP-PLUS sample (45,000 observations), to develop our analysis, we drop 25,064 people with no occupation (e.g. students, retires, unemployed). Then, as usual in empirical studies focusing on labour market phenomena, we apply an age restriction to our sample, further excluding from the analysis individuals who are not aged 25-64 years old (1,220 observations). We also decided to drop self-employed from our sample (3,741 observations) for two main reasons.[8] First, because their strong within-heterogeneity, related to several aspects such as the application of different regulations, may overall affect our estimates. (To give a better idea, note that in our analysis sample the Gini index of the annual gross labour income is equal to 0.444 among self-employed and 0.280 among employed.) Second, the potential unclarity in the usage of working from home procedures by self-employed, as they tend to perform multiple different tasks and do not have a subordinate role, may make considerations coming out from this analysis overall less clear. We finally drop further 668 observations with missing values in relevant variables. Our analysis sample of employees therefore counts 14,307 observations.

3.1. *Definition of the feasibility to work from home*

The ICP survey includes questions that are helpful to evaluate the feasibility to work from home of Italian workers, which is particularly relevant in the current COVID-19 emergency. To this end, we adopt the same WFH feasibility index recently proposed by Barbieri et al. (2020), which is calculated

[8] As a sensitivity analysis, we however replicated our main analysis on a sample including self-employed individuals aged 25-64 years old and with no missing values in relevant variables. Results of this check, presented in Section 6, overall confirm the robustness of our main results presented in Section 5.

for each 5-digit profession and ranges from a 0 (WFH is not essentially possible) to 100 (WFH is very easily possible). As the feasibility of an occupation of being performed from home is related to multiple dimensions regarding the specific task, this index is computed by taking into account replies to the following seven questions: i) importance of working with computers; (ii) importance of performing general physical activities (which enters reversely); (iii) importance of manoeuvring vehicles, mechanical vehicles or equipment (reversely); (iv) requirement of face-to-face interactions (reversely); (v) dealing with external customers or with the public (reversely); (vi) physical proximity (reversely); (vii) time spent standing (reversely). For each item, replies of workers are overall standardized to an index with a 0-100 range. The WFH feasibility index proposed by Barbieri et al. (2020) is then calculated through a simple average of these seven indexes. In other words, the WFH feasibility index here adopted consists of a multidimensional index where all the seven dimensions are equally weighted. The index is finally aggregated at the ISCO 4-digits level to allow this information to be merged with INAPP-PLUS data.

Once the WFH feasibility index is included in our analysis sample, it ranges from 8.8 to 85.0 and presents a median value of 52.2 and a mean value of 52.4. Although this index is provided as continuous variable, we preferred not to use it in this specification but by feasibility levels. Two of the main drawbacks of using a multidimensional index are indeed that it tends to report a skewed distribution and its specific values can be hardly interpreted. Rather, beyond allowing to consider different aspects together, this type of index allows to rank individuals (in this case, workers by the WFH feasibility of their professions) giving more importance to their relative position in the distribution than the absolute distance between observations. For this reason, we decided to define our variable of interest as a dummy taking value 1 (i.e. high level of WFH feasibility) for employees reporting a value of the multidimensional index over the sample median, and 0 otherwise (i.e. low level of WFH feasibility).

As regards the specification of our variable of interest, we however developed in Section 6 several robustness checks on results of the main analysis. Specifically, we replaced the dummy specification of the WFH feasibility variable with a continuous one, as well as with a quintile, quartile or tertile groups specification. Also, keeping constant the dummy specification, we changed the definition of the WFH feasibility variable making it take value 1 over the sample mean (rather than the median) or 60 percent of the sample mean. Results of all these tests highlight essentially the same conclusions of our main analysis, thus confirming its robustness. Finally, as to provide further insights on the potential effect of a positive shift in the WFH feasibility of professions on the wage distribution, we replicate our main analysis using as variable of interest the single items composing the adopted multidimensional index. Results of this thorough investigation are presented in Section 5.3.

3.2. Descriptive statistics

Table 1 shows some preliminary statistics about the sample composition, values of mean and Gini index of annual gross labour income, mean value of the WFH feasibility index and share of employees with high feasibility level by group of employees. Detailed descriptions of variables used in the analysis are provided in Table A.1, while Table A.2 illustrates the same information of Table 1 by activity sector in which employees work.

Table 1 highlights that employees in our sample appear to be more often males, aged 36-50, with an upper secondary education, local, and married. They live in households with more than four members in 37% of cases and with at least one minor child in 34% of cases. They tend to be located in small municipalities (i.e. cities with 5,000-20,000 inhabitants) and in the North of Italy, have more frequently a full-time open-ended contract and work in the private sector.

Table 1 – Sample composition, mean and Gini index of annual labour income, mean value of the WFH feasibility index and share of employees with high feasibility level by group of employees

Variable	Sample composition		Annual labour income		WFH feasibility	
	Mean	**Std. Dev.**	**Mean**	**Gini index**	**Mean**	**% of employees with high feasibility**
Low WFH feasibility	0.518	0.500	24,731	0.261	40.5	0.0
High WFH feasibility	0.482	0.500	27,320	0.296	65.1	100.0
Male	0.537	0.499	29,321	0.283	52.3	45.3
Female	0.463	0.499	22,098	0.256	52.5	51.5
Ages 25-35	0.204	0.403	21,962	0.257	51.7	46.9
Ages 36-50	0.467	0.499	26,146	0.279	52.5	47.9
Ages 51-64	0.329	0.470	28,232	0.282	52.5	49.4
Lower secondary education (or lower)	0.313	0.464	23,500	0.284	46.7	27.4
Upper secondary education	0.464	0.499	25,670	0.267	54.6	54.7
Tertiary education	0.224	0.417	30,082	0.277	55.8	63.7
Local	0.882	0.322	25,912	0.276	52.4	48.4
Migrant within macro-region	0.031	0.173	28,434	0.360	53.2	52.1
Migrant within country	0.066	0.248	26,839	0.276	52.8	51.5
Foreign migrant	0.021	0.143	22,429	0.306	48.2	22.8
Unmarried	0.429	0.495	24,045	0.261	52.3	47.6
Married	0.571	0.495	27,432	0.290	52.4	48.6
Household size = 1	0.141	0.348	26,961	0.269	53.4	48.9
Household size = 2	0.202	0.401	25,973	0.284	52.1	48.1
Household size = 3	0.283	0.450	24,772	0.258	52.5	48.8
Household size = 4	0.291	0.454	26,574	0.289	52.6	49.0
Household size = 5 or more	0.083	0.276	26,349	0.325	50.1	42.3
Absence of minors	0.657	0.475	25,770	0.285	52.4	48.4
Presence of minors	0.343	0.475	26,378	0.270	52.4	47.7
Very small municipality	0.206	0.404	25,394	0.270	50.9	41.4
Small municipality	0.329	0.470	26,376	0.285	51.5	45.2
Medium municipality	0.159	0.366	25,668	0.269	52.3	48.1
Big municipality	0.167	0.373	26,196	0.300	53.1	52.6
Metropolitan city	0.139	0.346	25,998	0.269	55.9	60.3
North	0.538	0.499	26,666	0.267	52.4	47.1
Center	0.214	0.410	24,911	0.267	53.6	53.2
South	0.248	0.432	25,410	0.317	51.3	46.1
Full-time open-ended worker	0.695	0.461	29,225	0.240	53.0	48.9
Part-time open-ended worker	0.153	0.360	17,527	0.293	52.7	52.7
Temporary worker and other	0.152	0.359	19,659	0.310	49.4	40.3
Private sector employee	0.700	0.458	25,443	0.301	52.7	47.8
Public servant	0.300	0.458	27,228	0.228	51.5	49.1
Total sample	-	-	**25,979**	**0.280**	**52.4**	**48.2**

Notes: All descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the sample median (52.2).

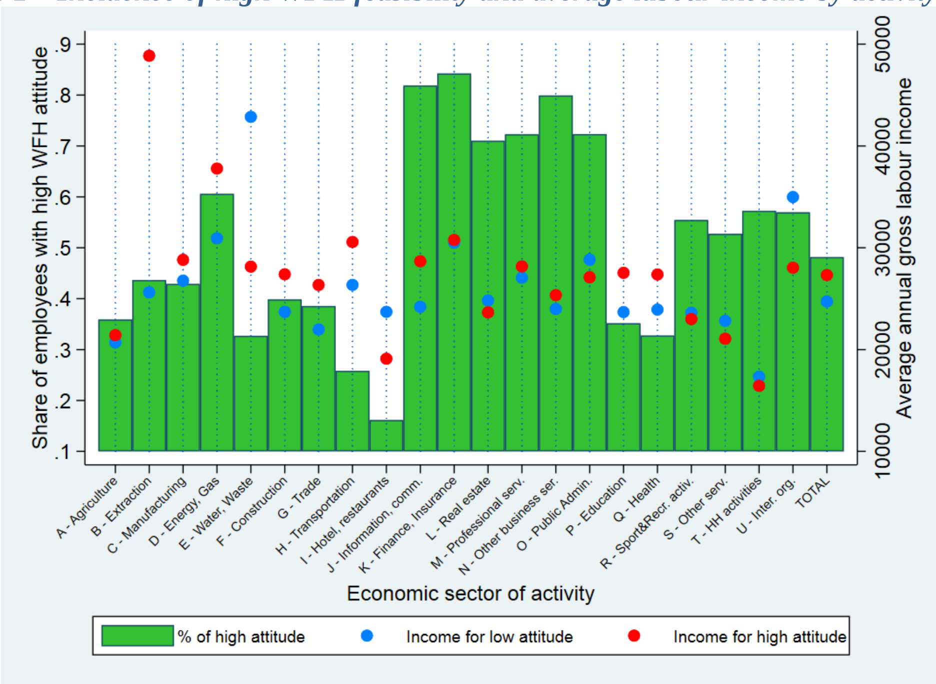
Focusing on labour income differences at five percent level only, Table 1 shows that employees with high WFH feasibility report on average a higher labour income than those doing an occupation with low feasibility levels. Also, employees appear to meanly receive a higher income if male, older (i.e. aged 51-64), graduated, married, live in northern regions, full-time open-ended worker, or public servant. At the opposite, employees living in households with three members tend to report a significantly lower labour income with respect to the others.[9]

Table 1 points out that groups of employees with higher labour income often report a greater within-level of income inequality too (i.e. higher values of Gini index), with few exceptions. For example, in this case, greater inequality levels are presented by employees with a lower secondary education (or lower), those living in bigger households or in the South of Italy, those having a temporary or other atypical job contracts, and those working in the private sectors.

Finally, it can be noted that employees with high WFH feasibility levels are more often female, older, high-educated, as well as among those living in metropolitan cities (Table 1). Interestingly, a higher level of WFH feasibility does not therefore imply a greater labour income on average as, for instance, employees living in metropolitan areas or female ones in particular are not the groups reporting highest income levels.

Figure 1 brings out that economic activity sectors being characterized by greater shares of employees with high WFH feasibility are: Finance and Insurance, Information and Communications, Professional Services, Other Business Services (e.g. car renting, travel agencies, employment agencies) and Public Administration. Figure 1 also highlights that employees working in sectors with high WFH feasibility receive, on average, a greater annual labour income than the others (€27,300 vs €24,700). Looking at differences between sectors, employees with high feasibility levels receive this "wage premium" in 13 out of 21 sectors, and sometimes – in B and E sectors - the wage premium is remarkable. At the opposite, employees with high WFH feasibility receive a lower labour income than the others especially in Hotel and Restaurants and Personal Services (i.e. R-U sectors).

Figure 1 – Incidence of high WFH feasibility and average labour income by activity sector

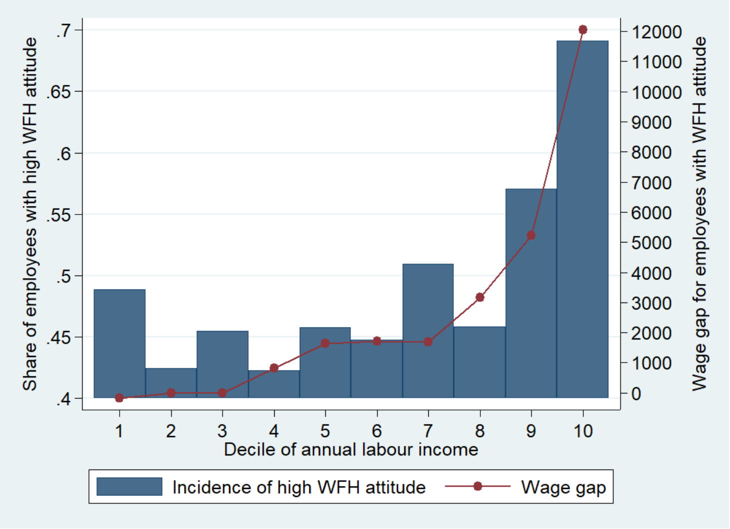


[9] Preliminary evidence confirms that differently from the US, where workers in high productivity areas tend to receive high salaries (see Hornbeck and Moretti, 2018), in Italy wage differentials between small and big cities are not significant. Recent estimates find that the urban wage premium is zero in nominal terms and even negative and non-negligible in real terms (Belloc et al., 2019).

Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.

As for potential differences across the labour income distribution, Figure 2 clearly shows that the wage gap between employees with high and low WFH feasibility is increasing along the distribution and reaches highest values in the last two decile groups, as well as the same incidence of high WFH feasibility among employees.

Figure 2 – Incidence of high WFH feasibility and wage gap in favor of employees with high feasibility levels by decile of annual income

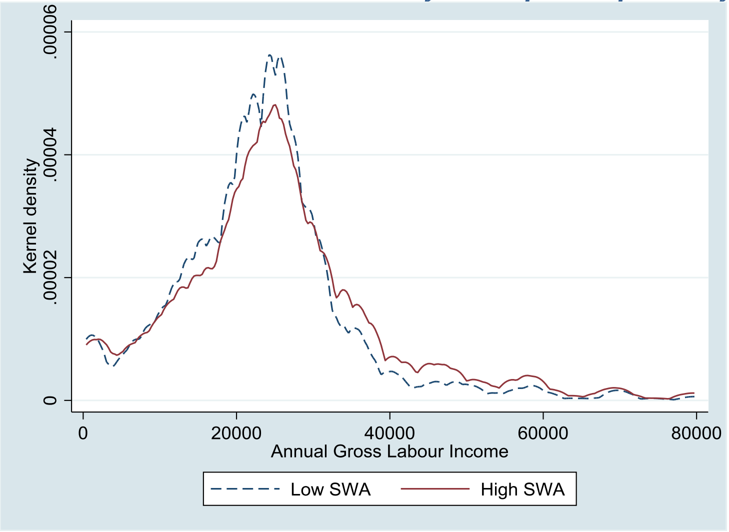


Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.

3.3. Kolmogorov-Smirnov test

In Figure 3 we plot the kernel estimates of the labour income density for both groups. It can be noted that the income distribution for employees with high WFH feasibility is clearly shifted to the right with respect to that of employees with low WFH feasibility.

Figure 3 – Labour income distribution by level of WFH feasibility



Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.

Researchers, not only in the economic literature, are often interested in evaluating the homogeneity of distributions across different samples and the Kolmogorov-Smirnov (K-S) statistic, which is obtained as the largest discrepancy of the empirical distribution functions by these samples, is probably the most used approach (Lehmann and Romano, 2005; Leonida et al., 2020; Otsu and Taniguchi, 2020). Therefore, in order to preliminarily test any difference in all moments between the two distributions, we develop the non-parametric K-S test based on the concept of stochastic dominance.[10]

Results of the K-S test for the first order stochastic dominance shown in Table 2 confirm that the annual gross labour incomes of employees with high WFH feasibility stochastically dominate, at the 1 percent level of significance, those reported by employees performing professions with low WFH feasibility.

Table 2 – Kolmogorov-Smirnov test for comparison between employees with high and low WFH feasibility

	Combined	Low WFH feasibility	High WFH feasibility
KS_2	0.0976 (0.000)		
KS_1		0.0976 (0.000)	-0.0059 (0.7333)

Note: p-values in parentheses. Descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.

4. Econometric methods

The merge of ICP and INAPP-PLUS data provides a representative snapshot on the levels of WFH feasibility of all professions in the Italian labour market and their relationship with labour incomes in 2018. However, restrictive measures introduced to cope with the recent COVID-19 pandemic forced many firms and institutions to innovate their work organization, workplaces (e.g. offices or plants), and procedures to be able continuing the goods production or services provision. The extra-ordinary situation and massive limitations to personal mobility led, in particular, to entitle employees in both the private and public sector to WFH, despite this way of working is not popular nor precisely regulated in the country (see Section 2.3). As a consequence, this event is expected to determine some long-lasting effects (or at least in the medium term) on the actual levels of WFH feasibility of a relevant number of professions.

The aim of this paper consists of estimating the potential influences related to a (persistent) positive shift in the WFH feasibility of employees on the overall labour income distribution. To this end, in the econometric analysis, we adopted the unconditional quantile regression method as

[10] The notion of first order stochastic dominance can establish a ranking for compared distributions. Let *F* and *G* denote the cumulative distribution functions of wages for two groups, e.g. workers with high and low WFH feasibility. First order stochastic dominance of *F* relative to *G* is defined as: $F(z) - G(z) \leq 0$ uniformly in $z \in$ R, with strict inequality for some *z*. To test whether there are statistically robust differences between distributions we adopt both the one-sided and two-sided K-S tests. The two-sided test (KS_2) permits one to determine whether both distributions are identical, while the one-sided test (KS_1) determines whether one distribution dominates the other. Thus, to state that *F* stochastically dominates *G*, a rejection of the null hypothesis for the two-sided test is required, while the null for the one-sided test cannot be rejected.

proposed by Firpo et al. (2009). With respect to the (conventional) quantile regression method developed by Koenker and Bassett (1978), this methodology has the merit to estimate the effects on an outcome variable distribution which is not conditioned by the set of covariates included in the model (Fortin et al. 2011). It allows, for instance, to directly compare results of income differences between groups of employees at different points of the distribution without imposing a path dependence in the gap estimation at different quantiles (Gaeta et al., 2018). Also, the method proposed by Firpo et al. (2009) allows to include additional covariates in the model without altering the interpretation of estimated coefficients on the distributional statistic, such as the mean or a quantile. This study does not represent the first application of this methodology with Italian data (see, amongst others, Gaeta et al., 2018; Regoli et al., 2019; Gallo and Pagliacci, 2020), but the first one analysing in this way the relationship between WFH and wage inequality.

The unconditional quantile regression method involves the calculation of the Recentered Influence Function (RIF) which is defined as

$$\mathrm{RIF}(y;v,F) = v(F) + \mathrm{IF}(y;v,F) = v(F) + \lim_{t\downarrow 0}\frac{v\big((1-t)F+t\Delta_y\big)-v(F)}{t} \quad (1)$$

where F is the distribution function of the outcome variable y (i.e. the gross labour income), $v(F)$ denotes a distributional statistic, and the $\mathrm{IF}(y;v,F)$ is the influence function initially introduced by Hampel (1974). According to Firpo et al. (2009), once the values of $\mathrm{RIF}(y;v,F)$ are computed for all observations, the effects of a marginal change in the distribution of the variable of interest (i.e. WFH feasibility) on the distributional statistic $v(F)$ can be correctly calculated through a simple OLS estimation. Following Choe and Van Kerm (2018), we both label this measure as 'unconditional effect' (UE) and determine a marginal change in the distribution of the WFH feasibility swapping a 10 percentage points share of employees from one feasibility level to the other one. In other words, considering the baseline feasibility levels across Italian employees as the counterfactual scenario, we estimate the UE of a WFH feasibility increase on labour income inequality moving toward a distribution composed of 10 percentage point less employees with a low level of WFH feasibility and 10 percentage point more employees with a high feasibility level. In this 'shares swap' scenario, within-groups income distributions remain constant.

The unconditional quantile regression method also allows for taking into account demographic and economic characteristics which may differ across employees, leading to potential biases on policy influences. We then regressed RIFs on the variable of interest and a vector Z of relevant covariates including demographic characteristics regarding the individual and her household (i.e. gender, age group, education level, migration status, marital status, household size, presence of minors, municipality size, and macro-region of residence) and job characteristics (i.e. job contract, public servant, and activity sector dummies). More details on variables included in the model are provided in Table A.1. The resulting effect on distributional statistics is labelled in this case as 'unconditional partial effect' (UPE) (Firpo et al., 2009; Choe and Van Kerm, 2018), but it is also named 'policy effect' or 'counterfactual effect' in the literature (Rothe, 2010; Chernozhukov et al., 2013; Gallo and Pagliacci, 2020). The main difference between UEs and UPEs relies on the fact that in the UEs calculation the WFH feasibility shift determines a consequent change in covariates in the vector Z according to the joint income distribution, whereas in the UPEs estimation these covariates are explicitly kept constant.

In this study, we estimate influences of a positive shift in the WFH feasibility on gross labour income distribution focusing on the following distributional statistics: the mean, the Gini index, and the nine deciles.[11] Sample values of first two statistics are reported in Section 3.2, while values of the

[11] For the sake of brevity, formulas to calculate the RIFs for the mean, the Gini index, and the quantiles are not replicated here, but they can be easily found in Choe and Van Kerm (2018).

nine deciles are presented in Figure A.1. Differently from the common choice to drop female employees to minimize selection issues, we decided not to restrict the sample to males only but to show separated results by males and females. To further explore the heterogeneous influences of an overall increase of WFH feasibility along labour income distribution, we also report main results distinguishing by age group and the attained education level (i.e. graduated rather than non-graduated). Finally, taking advantage by data provided by the Italian Civil Protection Department (2020) on the extent of COVID-19 infection at provincial (NUTS-3) level, we verify whether effects related to a WFH feasibility shift over time are expected to be greater in those areas more affected by the pandemic (i.e. overall COVID-19 cases represent more than 3.2‰ of total population).

As a sensitivity analysis, to control for the occupation skill heterogeneity among employees, we estimated our main results using a set of covariates including skill level dummies. In addition, given the potential endogeneity of job characteristics on the dependent variable, we also replicated UPE estimates adopting a set of covariates excluding these characteristics. As further robustness checks, we observed effects on different inequality indicators and controlled for potential endogeneity and selection issues related to the WFH feasibility. Results of all these checks are provided in Section 6 and overall confirm the robustness of our main considerations.

5. Results

5.1. Influences on labour income inequality

Table 3 highlights that a positive shift in WFH feasibility levels would significantly influence the labour income distribution and inequality. Specifically, RIF regression results suggest that swapping a 10 percentage points share of employees from the low feasibility level to the high one would be associated to an increase of both the mean labour income up to €259 (we refer to that as ‘premium’) and the Gini index for about 0.004 points. Considering that the mean labour income in our sample is equal to about €26,000 (see Table 1), a slight growth of WFH feasibility would be therefore linked to a 1% increase on the mean labour income. Taking advantage from the intrinsic functioning of the RIF regressions methodology, this estimated influence on the mean labour income (and Gini index) may be extended according to the assumption adopted on the employees shares swap. This means that, for instance, if the share of employees moving from low to high feasibility level is 20 (or 50) percentage points, then the increase on the mean labour income and Gini index will be 2% and 0.008 (or 5% and 0.02) respectively. As expected, UPE estimates (i.e. thus ones based on a model specification including relevant covariates) present reduced magnitudes, but effects remain overall positive and significant on the Gini index.

Disaggregating by employees’ characteristics, we find that the wage premium related to an increase of WFH feasibility mainly regards male – further enlarging the gender pay gap (see Table 1) –, graduated, younger and older employees. To this end, our results are in line with Goldin (2015) who reports that the gender wage gap may be also due to lack of flexibility in work arrangements, particularly in financial and business services, which we find being sectors with greater incidences of high WFH feasibility (Figure 1). Also, according to results in Table 3, a positive shift in WFH feasibility levels among Italian employees would increase the Gini index especially among female, younger, older, and graduated employees. As for the influences on incomes of a change of WFH feasibility by education level, however, when controlling for relevant covariates (i.e. UPE estimates) any significant difference appears among the two groups of employees.

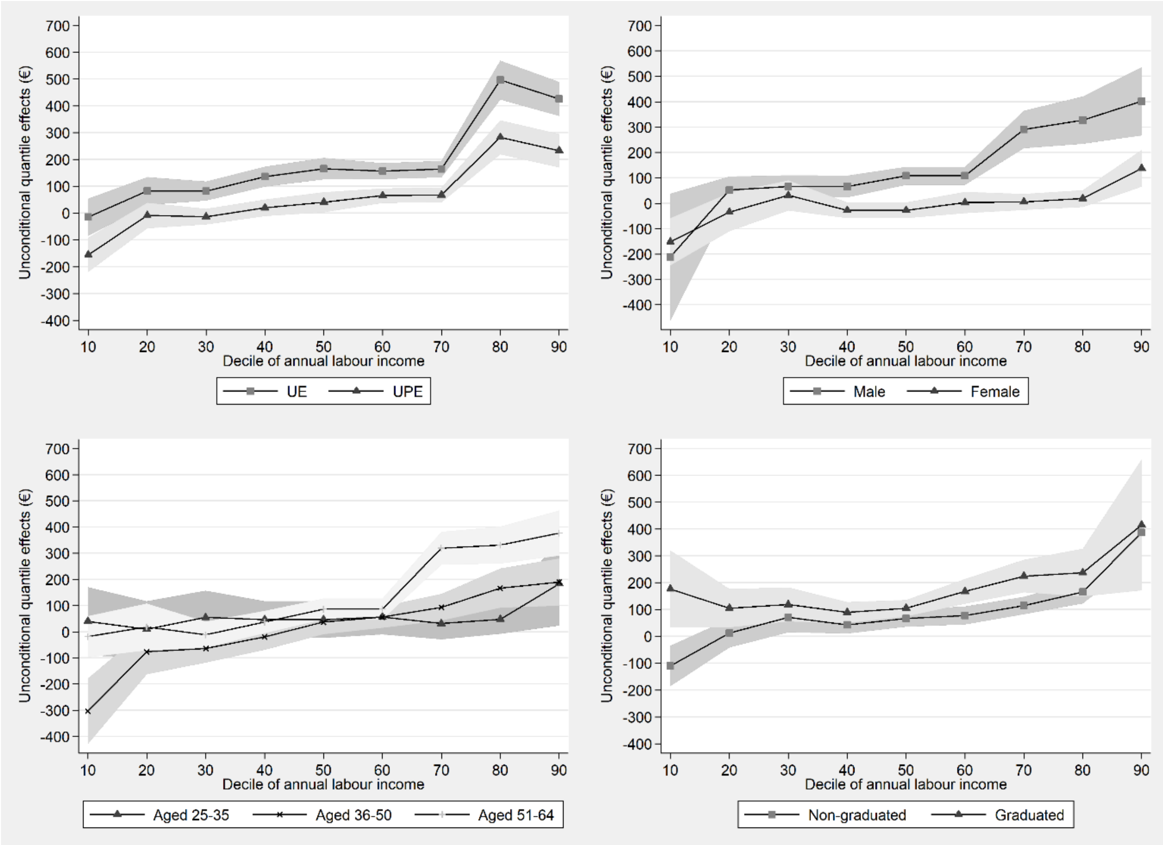
Table 3 – Unconditional effects of a positive shift in the WFH feasibility on the mean and Gini index

Group of employees	**Mean value**		**Gini index**	
	UE	**UPE**	**UE**	**UPE**
Total sample	258.86***	97.98	0.004**	0.004**
Male	473.03***	233.81**	0.004	0.004
Female	111.02**	-33.66	0.002**	0.001
Aged 25-35	375.75***	270.60*	0.005	0.008*
Aged 36-50	24.07	-82.64	0.001	0.001
Aged 51-64	496.39***	250.78**	0.007***	0.005*
Non-graduated	131.15	153.17*	0.003	0.003
Graduated	410.91***	167.95*	0.005***	0.000

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH feasibility) only. Complete estimates for the pooled sample are provided in Table A.3. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median. UE estimates are based on a model specification that only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Looking at the WFH feasibility influences along the labour income distribution (top-left panel of Figure 4), 10 percentage points swap of employees from low to high WFH feasibility appears to reward more high-paid employees, while it has no significant effects (or even negative when looking at UPE estimates) in the left-side of the distribution. In particular, the highest “wage premium” would be reached at the 8th decile where it amounts to about €500, thus leading to a 1.7% increase with respect to its baseline value (Figure A.2).

Figure 4 – Unconditional effects of a positive shift in the WFH feasibility along labour income distribution



Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median. UE estimates are based on a model specification that only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). Estimates by employees' characteristics refer to the UPE specification. Complete estimates for the pooled sample are provided in Tables A.4-A.5.

Top-right panel of Figure 4 points out that the wage premium deriving from a growth of WFH feasibility levels would be mainly in favor of male employees, whereas that would represent a penalty for female ones except for those in last decile group. (Note that the latter would receive a lower premium than males though.) A positive shift in WFH feasibility levels among employees aged 25-35 would have an overall stable but statistically insignificant effect along their whole distribution (bottom-left panel of Figure 4). At the opposite, swapping employees with low WFH feasibility levels with others with high feasibility levels would produce unequal influences along labour income distribution of older employees. In particular, employees aged 36-50 would report a wage penalty in the first three deciles and a relevant premium from the sixth decile onwards, while employees aged 51 or more would receive the highest rewards in the right-side of income distribution.

The bottom-right panel of Figure 4 points out a similar distributional pattern of UPEs among non-graduated and graduated employees related to a positive shift in WFH feasibility levels. This event would indeed be associated in both groups with a growth of labour income levels which is overall increasing along the distribution. Nevertheless, estimated UPE among graduated employees are slightly greater with respect to the ones reported by the other group (especially in the sixth and seventh deciles), in line with the SBTC explanation (amongst others, see Van Reenen, 1997; Berman et al., 1998; Autor et al. 1998; Acemoglu, 2002; Autor et al., 2002; Autor et al., 2003). In fact, technological innovations are not neutral and tend to increase the productivity of skilled labour, usually identified through a high level of education, compared to unskilled work, thus causing an increase in wage inequality levels. Our results show that the technological change would occur to determine the hypothesized shift in WFH feasibility levels is likely to strengthen existing wage inequalities between high and low educated employees. In this context, the existing relationship between new technologies and high paid jobs is a key factor of wage polarization, which in turn is fundamental to better understand and forecast possible long run consequences of the COVID-19 outbreak such as a persistent change in the ways of working.

5.2. Estimates by incidence of COVID-19 infection

In this section we present some pieces of evidence on how a positive shift in the WFH feasibility levels would influence the labour income distribution characterizing local labour markets. Specifically, under the assumption that the structure of professions and their WFH feasibility remained unchanged from 2018 to 2020, we are interested to explore if this ‘forced innovation’ (potentially) regarding 10 percentage points of employees with a low feasibility level would affect more labour incomes in provinces which reported the highest numbers of COVID-19 cases from February 24 to May 5, 2020.[12] We distinguish between two areas (i.e. less/more COVID-19 infected area) according to the local infection incidence, thus the incidence of COVID-19 cases on total population at provincial level. We consider as ‘more COVID-19 infected area’ those provinces reporting an infection incidence over the sample median (i.e. 3.2‰). Figure A.3 provides COVID-19 infection incidences by province and overall shows that areas in the North of Italy are those more affected by the novel coronavirus, with the only exception of Marche (which belongs to the Centre of Italy). Given the adopted definition, our sample of employees are almost equally divided in the two areas (i.e. 52% of the sample lives in less COVID-19 infected provinces and 48% in more infected ones). No significant differences are revealed between these two groups of employees as regards our variable of interest (more details upon request), since they report similar values for both the average WFH feasibility level (52.2 in less infected areas and 52.5 in more infected areas) and the share of employees with a high feasibility level (48.7 and 47.6 respectively).

Table 4 highlights that employees living in more COVID-19 infected areas report a slightly higher labour income on average and lower levels of income inequality (in terms of Gini index) with respect to the ones living in less affected areas.

[12] Civil Protection Department. Repository of COVID-19 outbreak data for Italy. https://github.com/pcm-dpc/COVID-19. Accessed on May 5, 2020.

Table 4 – Unconditional effects of a positive shift in the WFH feasibility by COVID-19 infection incidence

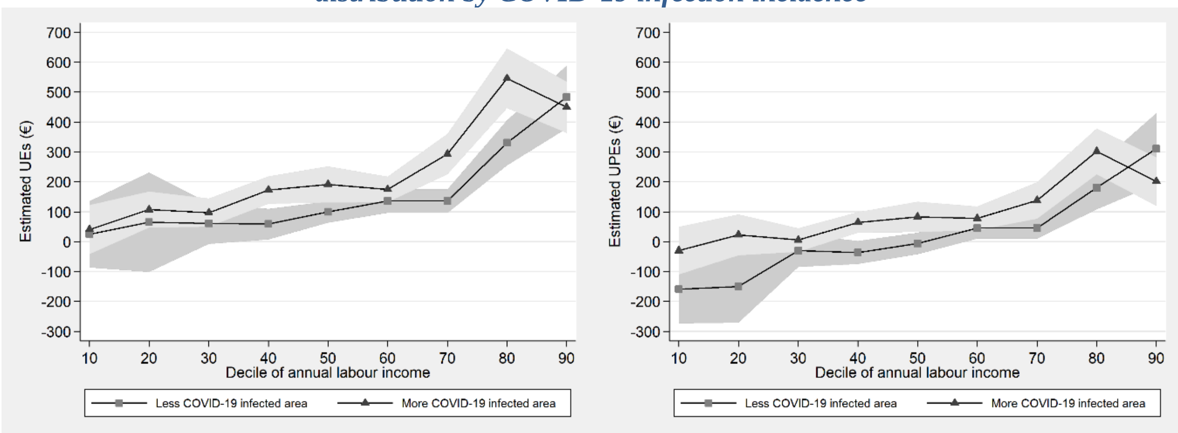
Group of employees	Statistic	Mean value		Gini index	
		UE	UPE	UE	UPE
Less COVID-19 infected area	Baseline value	25,624		0.297	
	Unconditional effect	193.36*	46.50	0.003	0.004
More COVID-19 infected area	Baseline value	26,356		0.262	
	Unconditional effect	330.43***	137.19**	0.005*	0.003*

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median. UE estimates are based on a model specification that only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

As for the UE and UPE estimates on the mean value of labour income, results show that the effects related to a positive shift in the WFH feasibility would be greater and more significant among employees being resident in provinces more affected by the pandemic (i.e. the Northern and more developed ones). The same consideration occurs when referring to unconditional effects on the Gini index of labour income, because they appear insignificant among employees living in areas reported a lower incidence of COVID-19 infection.

Results illustrated in Figure 5 overall confirms that employees in more COVID-19 infected area would benefit more from a marginal improvement in WFH feasibility levels of professions. The increase in income levels associated to a positive shift in feasibility levels would be indeed greater for this group of employees in both the central part (fourth and fifth deciles) and right side of distribution (seventh and eighth deciles). (The latter is less significant when we look at UPE estimates.)

Figure 5 – Unconditional effects of a positive shift in the WFH feasibility along labour income distribution by COVID-19 infection incidence



Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median. UE estimates (in the left panel) are based on a model specification that only includes the variable of interest, while for UPE estimates (in the right panel) additional covariates are included in the model (see Section 4).

This is an interesting and important evidence as these territories actually needed for this kind of policy, although its potential influence remains unequal along the labour income distribution as it would be more in favor of high-paid employees.

5.3. Estimates by single item of the WFH feasibility index

Our analysis relies on the multidimensional index recently proposed by Barbieri et al. (2020), which try to assess the WFH feasibility of each profession performed in the Italian labour market looking at seven different items or dimensions. For each of the seven items listed in Section 3.1, a standardized index with a 0-100 range is computed. Except for the item 'working with computers', the other six dimensions has to be considered reversely. The 'reverse indexes', used to obtain the multidimensional index, are then calculated through a raw difference between 100 and the initial indexes.

Using the WFH feasibility index as variable of interest allows us to assess influences that may emerge from a marginal shift in its distribution among employees on labour income levels without assuming any specific technological change. For instance, considering the adopted multidimensional index, an increase in the WFH feasibility levels (i.e. a swap of employees having a low WFH feasibility level with other employees having a high one) may be gained reducing the performance of physical activities, encouraging the use of computers or decreasing the need of face-to-face discussions at work. However, it may appear of some interest better understanding how a marginal change on single items composing the WFH feasibility index would eventually influence the labour income distribution.

To provide further insights on the potential effect of a change in the WFH feasibility of professions on the wage distribution, we therefore replicate in this section our main analysis using as variable of interest the indexes referring to single items of the adopted multidimensional index. Of course, reverse indexes are considered for those items acting reversely on the total index, so that if an employee presents a high value of the index regarding, for instance, 'spending time standing' then it actually means that she spends a small amount of time standing to do her job. Also in this case, variables of interest are defined as dummy variables taking value 1 if the employee reports a value of the specific index over the sample median, and 0 otherwise. The seven, say, 'threshold values' are reported in Table 5, together with the one used for our main variable (i.e. WFH feasibility index). The highest threshold values are reported by indexes referring to 'performing physical activities' and 'manoeuvring vehicles or machines', because only few employees need these activities to perform tasks related to their profession. At the opposite, the lowest sample median is the one associated to the 'face-to-face discussion' index as most of employees consider this activity important in their profession.

Table 5 shows UE and UPE estimates by item of the WFH feasibility index under the hypothesis of moving toward a distribution composed of 10 percentage point less employees with low values of a specific index and 10 percentage point more employees with high values of the same index. As regard to the 'working with computers' item, this change is interpreted as an increase in the number of employees using a computer to make their occupation. As for the other items, because they act reversely in the adopted multidimensional index, this change has to be interpreted as a decrease in the number of employees for which a specific activity (e.g. manoeuvring vehicles or machines) or profession feature (e.g. dealing with customers and public, physical proximity) is important to perform their job.[13]

[13] Some of the single indexes on which the WFH feasibility index is based, in their initial version (i.e. before being reversed) and in a 0-100 range, report value 0 for a number of employees. This happens when a specific dimension/activity is totally unrelated or necessary to develop a profession. This phenomenon mainly occurs in the index regarding 'performing physical activities' (value equals to 0 for 455 observations) and 'manoeuvring vehicles or machines' (0 for 2,594 observations). Because these 0 values may represent a potential issue for estimates referring to the two indexes, we also replicated the same analysis excluding employees who report this peculiarity. Results of this sensitivity analysis (Table A.6) overall confirm the

Table 5 – Unconditional effects on mean value and Gini index by item of the WFH feasibility index

Item of the multidimensional index	Threshold value	Mean value		Gini index	
		UE	UPE	UE	UPE
Performing physical activities (−)	82.9	388.07***	211.61***	0.000	0.002
Working with computers	49.5	507.49***	249.27***	0.001	0.002
Manoeuvring vehicles or machines (−)	96.0	5.48	128.62	0.002	0.004**
Face-to-face discussion (−)	22.0	-274.30***	-171.03	0.002	0.001
Dealing with customers and public (−)	46.0	-243.08***	-205.62***	-0.002	-0.003
Physical proximity (−)	63.8	-394.20***	-208.31***	-0.005***	-0.005***
Spending time standing (−)	47.0	469.31***	292.61***	0.002	0.003**
WFH feasibility (total)	52.2	258.86***	97.98	0.004**	0.004**

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High index value) only. Employees with high index value are defined, for each item, as those reporting a value of the single index over the threshold value illustrated in the table (i.e. the sample median). UE estimates are based on a model specification that only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). The symbol '(−)' means that the index referring to the specific item is considered reversely.*

Table 5 highlights that not all items composing the WFH feasibility index goes in the same direction revealed by the total (multidimensional) index in terms of unconditional effects on the mean value of labour income. In fact, only an increase in the employees' feasibility of working with computers, a reduction in their feasibility of performing physical activities, or a decline in the importance of spending time standing would be associated to positive and significant influences on the mean income. The highest 'wage premium' would come from a potential growth of employees working with computers confirms, once again, the role of technological change in wage levels and inequality highlighted in many OECD countries since the 1980s (Krueger, 1993; Freeman and Katz, 1995; Gottschalk and Smeeding, 1997; Autor et al., 1998; Berman et al., 1998; Acemoglu, 2003).

At the opposite, reducing the physical proximity to other colleagues in the workplace for a share of employees, as well as the need in performing their profession to deal with customers and public or to make face-to-face discussion, would significantly be related to an overall decrease of income levels. The main reason for this evidence is related to the fact that these activities/features of professions are positively correlated to the labour income,[14] even when controlling for relevant covariates (UPEs remain statistically significant for the item 'dealing with customers and public' and the one referring to physical proximity). Interestingly, the latter evidence on professions performed in Italy appears in contrast with results reported by Mongey et al. (2020) for the US labour market, which show that high physical-proximity workers tend to have lower incomes and their potential reduction would lead to an increase of the average income.

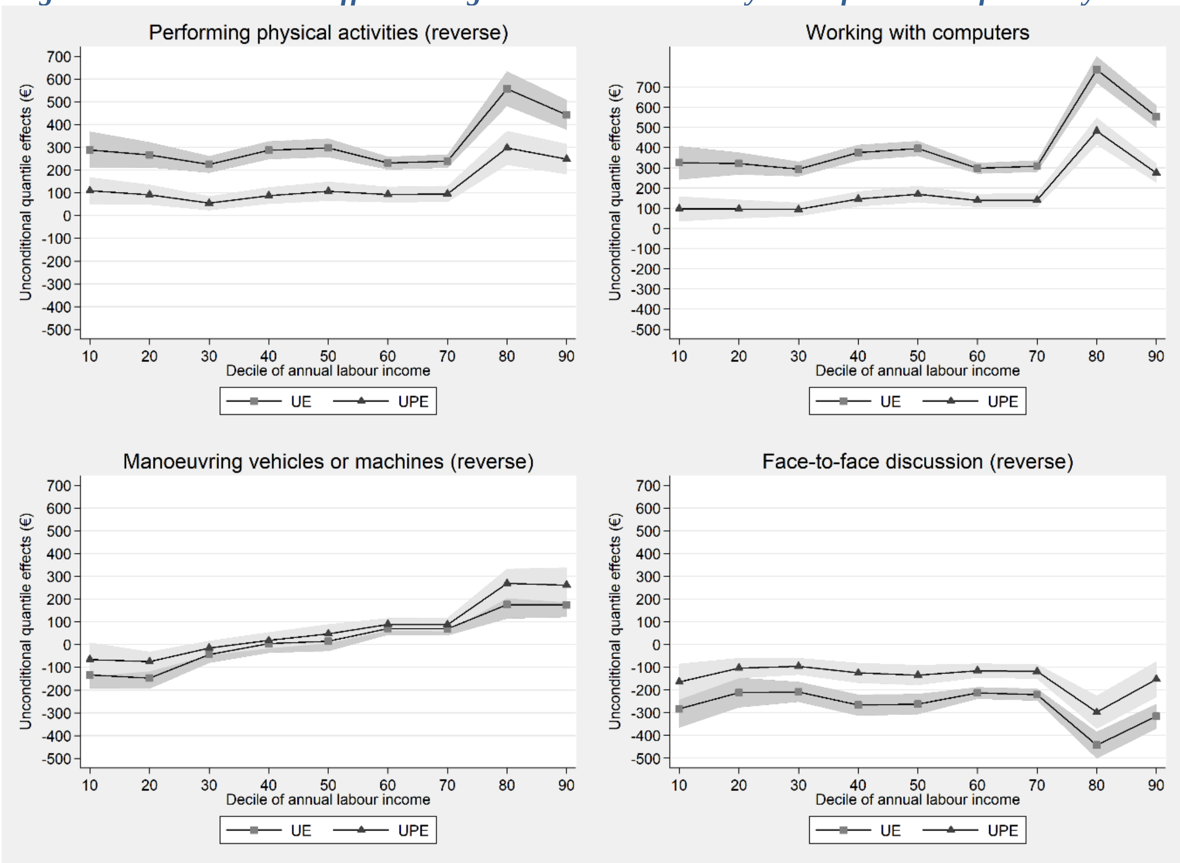
ones presented in Table 5, except for the fact that a reduction of employees for whom manoeuvring vehicles or machines is important does not significantly increase anymore the Gini index of labour income.

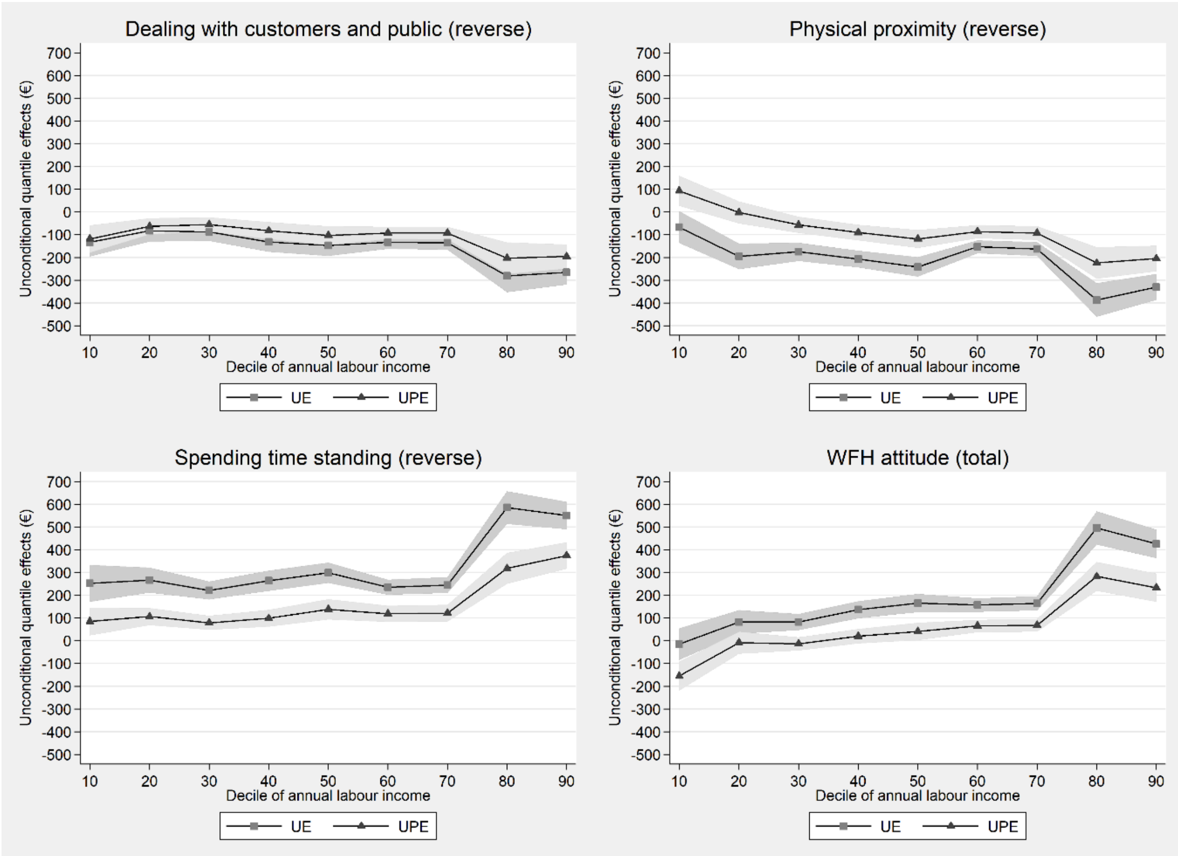
[14] As regards the physical proximity among colleagues at the workplace, additional elaborations of the authors show that employees reporting high levels of physical proximity present an annual gross labour income about 4,000€ greater on average than the others. This peculiarity of the Italian labour market – Mongey et al. (2020) show the opposite for the US – is related to the fact that high physical-proximity employees tend to be paid much more than low physical-proximity ones in Health, Public Administration, and Trade sectors. Also, 24% of high physical-proximity employees work in the highly profitable Manufacturing sector, while 30% of high physical-proximity employees work in the much less profitable Education and Trade sectors (see Table A.2 for average income levels by sector). More details are available upon request to the authors.

A change in feasibility levels regarding manoeuvring vehicles or machines would instead have no significant effect on the mean value of labour income. As for the effects on the Gini index of labour income, results by single item are overall in line with those on the average income but with a lower statistical significance. Looking at UPE estimates, the effects on the Gini index are significant at five percent level only for three items: manoeuvring vehicles or machines, physical proximity, and spending time standing. More specifically, a reduction of physical proximity among employees would be associated with a decreasing income inequality, whereas a reduction of employees who spend a lot of time standing or manoeuvring vehicles or machines would increase the Gini index of labour income.

Figure 6 helps to better explain the role of a change in single items composing the adopted WFH feasibility index on the labour income inequality illustrating unconditional effects by income decile. Most of times present indeed insignificant effects on the Gini index, and thus on the income inequality, probably because estimated influences related to a marginal "low-to-high" change of employees are stable along the labour income distribution, except for the last two deciles. At the opposite, the negative effect of a reduction of physical proximity among employees would be clearly increasing (in absolute terms) along the distribution, so that high-paid employees would "pay" more this kind of change in professions.

Figure 6 – Unconditional effects along income distribution by item of the WFH feasibility index





Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High feasibility) only. Employees with high feasibility level are defined, for each item, as those reporting a value of the single index over the sample median. UE estimates are based on a model specification that only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).

Figure 6 also supports to understand why a reduction of employees manoeuvring vehicles or machines would have no effect on the mean value of labour income but increase its inequality levels. In fact, the employees' swapping would have a negative effect on the first two deciles of income distribution, then its effects appear insignificant in the central part of distribution (i.e. third-fifth deciles), and finally it would influence positively and increasingly incomes in the right-side of distribution.

6. Robustness checks

In this section, we briefly summarize several robustness checks of the main results presented in the paper, concerning sample restrictions, the specification of our variables of interest, the adoption of different income inequality indexes, the inclusion of endogenous or additional covariates in the regressions, the use of sample weights, and potential selection issues related to the WFH feasibility of professions. Results of robustness checks performed are illustrated in Appendix B and more details are available upon request to the authors.

First, as our analysis is based on a definition of labour income which is annual referred, we then need to verify that our results might be biased by the presence of part-time and temporary employees in the sample. So, in this robustness check, we drop from the sample all employees having these employment contracts. Results by including only full-time open-ended employees (9,812 observations) are presented in Table B.1 and the left panel of Figure B.1 and strongly corroborate our main conclusions. Similarly, to be sure the adopted sample restriction strategy (detailed described in Section 3) did not affect our results, we made a sensitivity analysis including in the sample self-employed individuals aged 25-64 years old and with no missing values in relevant variables. Also here, estimation results based on a sample of employed and self-employed (17,899 observations in total) and presented in Table B.2 and the right panel of Figure B.1 seem to overall confirm the robustness of our main results.

Second, as anticipated in Section 3.1, we developed several robustness checks on the specification of our variable of interest. Specifically, we replaced the dummy specification of the WFH feasibility variable with a continuous one, as well as with a quintile, quartile or tertile groups specification. Also, keeping constant the dummy specification, we changed the definition of the WFH feasibility variable making it take value 1 over the sample mean (rather than the median) or 60 percent of the sample mean. As for the continuous variable of interest (i.e. WFH feasibility index), in line with the methodology proposed by Firpo et al. (2009), unconditional effects are estimated assuming a one-unit increase on the average value of the same variable among employees. In other words, results of this sensitivity analysis provide potential influences on labour income levels and inequality related to an increase of the WFH feasibility index of all professions in the Italian labour market, so that its mean value in our sample moves from 52.4 to 53.4. As for the variables of interest with levels specification, UE and UPE estimates are still obtained through a 'employees shares swap', but in this case replacing employees in the first level (i.e. the first quintile/quartile/tertile group) with employees in another one. For instance, a shares swap scenario may be represented by a distribution composed of 10 percentage point less employees in the first quintile group of WFH feasibility and 10 percentage point more employees in the fourth quintile group.

Table B.3 and Figure B.2 report estimation results for the continuous specification of our variable of interest, while Figure B.3 shows UPE estimates for all the other specifications attempted (in comparison with those attained through the base specification in Panel A). When the counterfactual scenario of a WFH feasibility increase is based on a positive shift of the WFH feasibility index (in its continuous specification), unconditional effects on the mean and Gini index of labour income are pretty similar to those reported in Tables 3 and 4, but less significant on the income inequality and when relevant covariates are included in the model (Table B.3). However, Figure B.2 confirms that an increase of the average WFH feasibility would be related to a 'wage premium' which is greater among high-paid, male, and aged 51-64 employees (differences in the premium between non-graduated and graduated employees are instead less sharp). Results illustrated in Figure B.3 overall validate our main conclusions too, showing that a swap of employees with low values of the WFH feasibility index and others reporting high values would increase income levels especially in the right side of the labour income distribution. Since single items composing the adopted multidimensional index may be used as continuous variables, as a further sensitivity analysis, we replicated estimates provided in Table 5 using as variable of interest the single indexes in their standard (continuous) specification. Table B.4 shows that our main results hold also when considering single items as continuous variables.

Third, we run RIF estimates on two different income inequality indexes with respect to the one we adopted (i.e. the Gini index): the mean log deviation and the Atkinson index with e=1. Results of these tests, presented in Table B.5 for the pooled sample and by group of employees, overall confirm the robustness of our main conclusions. The only exception regards the fact that a positive shift of WFH feasibility seems not to influence anymore income inequality indexes in areas more affected by the recent COVID-19 pandemic (despite influences are clearly increasing along the labour income distribution, see Figure 5).

Fourth, we tried to change the set of covariates adopted for UPE estimates to assess two different issues: potential endogeneity of covariates related to job characteristics and skill heterogeneity among employees. As for the potential endogeneity of job characteristics on the dependent variable, we define a new vector of covariates (UPE2) which includes only demographic characteristics regarding the individual and her household. Estimates based on the UPE2 specification, reported in Table B.6 for the effects on mean value and inequality indexes of labour income and in both Table B.7 and Figure B.4 for the effects along the income distribution, show that our main results hold. As for the skill heterogeneity among employees, we enlarge the set of covariates used for UPE estimates including other three (probably endogenous) variables to solve this issue. Specifically, we add the occupation skill level of employees to control for skill heterogeneity as suggested by Picchio and Mussida (2011) and Leonida et al. (2020). The occupation skill level is included through a set of dummy variables representing different levels of the ISCO classification of occupations. In particular, we define as: 'Medium skill level', employees in the fourth ISCO level (i.e. clerical support workers); 'High skill level', employees in the third one (i.e. technicians and associate professionals); 'Very high skill level', employees in the first two ISCO levels (i.e. managers and professionals). The reference category is 'Low skill level'. We label estimates based on this model specification as UPE3 and we present them for the total sample in Tables B.6 and B.8. Outcomes of these robustness checks overall confirm that our main results hold even considering these additional relevant covariates. In particular, the wage inequality would result from a potential increase in the WFH feasibility of some professions existing in the labour market is fully compatible with the SBTC theory (Acemoglu, 2002).

Fifth, we replicated all estimates in our main analysis without applying individual weights. Indeed, although the application of individual weights ensures the representativeness of our sample to the total population, non-response biases these weights have the objective to solve may be somehow related to the probability to perform a profession with a lower (or higher) level of WFH feasibility. Table B.9 and Figure B.5 show that results of this further sensitivity analysis overall confirm our main conclusions.

6.1. Controlling for selection bias: the IPW methodology

Finally, in order to control for selection bias in the WFH feasibility for the two groups of employees, we also estimate the influence of the WFH feasibility on the logarithm of the labour income distribution by adopting a non-parametric framework allowing for flexibly control for potential confounders. Specifically, we implement an inverse probability weighting (IPW) estimator as proposed by Di Nardo et al. (1996) and Firpo (2007). This method estimates quantiles for two counterfactual distributions, one if every employee had a high WFH feasibility, the other if they had all a low WFH feasibility, where in the first stage the conditional probability of performing an profession with a low(high) WFH feasibility is estimated by using a Probit model, given a set of characteristics. In other words, the counterfactual density can be determined by a "reweighting" function that estimates the probability of having a WFH feasibility as a function of all the other characteristics to be kept constant (Leonida et al., 2020, Scicchitano et al., 2020).

The definition of the set of observable conditioning variables is crucial to ensure the unconfoundedness assumption (Albanese and Gallo, 2020), i.e. the potential increase in the labour income of employees in different levels of WFH feasibility is independent of the actual feasibility level. In this robustness check, we adopt the same set of covariates defined in Section 4 to estimate UPEs as we believe it considerably reduces the role of unobserved heterogeneity between the two groups of employees. Nonetheless, even though controlling for a large number of relevant characteristics that may affect both outcome and treatment selection, we cannot avoid that other unobservable confounding factors may be still in place.

Table 6 reports estimated coefficients on the mean and nine decile values from the IPW approach. The effect of having a high WFH feasibility on the average income is equal to +3.5%, while it is equal to +5.0% at the median and to +16.3% at the last decile of labour income.

Table 6 – Estimated effect of performing a profession with high WFH feasibility on the mean and along the labour income distribution (IPW estimation method)

Group of employees	Mean value	p10	p20	p30	p40	p50	p60	p70	p80	p90
Total sample	0.035**	-0.025	0.000	0.000	0.039***	0.050***	0.000	0.072***	0.065***	0.163***
Male	0.093***	0.000	0.083***	0.077***	0.071	0.067***	0.107***	0.120***	0.057***	0.183***
Female	-0.013	-0.074	0.000	0.000	0.000	-0.039***	-0.015	0.000	-0.037**	0.000
Aged 25-35	0.033	0.000	0.118***	0.100**	0.000	0.041**	0.000	0.035**	0.067***	0.000
Aged 36-50	-0.008	-0.065**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.112***
Aged 51-64	0.077***	-0.057	0.000	0.077***	0.035**	0.067***	0.072***	0.102***	0.061**	0.191**
Non-graduated	-0.009	-0.111***	0.000	0.000	-0.041***	-0.005	0.000	0.026**	0.035***	0.000
Graduated	0.093***	0.118**	0.091*	0.039**	0.057***	0.000	0.105***	0.069***	0.106***	0.147**
Less COVID-19 infected area	0.027	-0.042	0.000	0.000	0.000	0.000	0.000	0.072***	0.000	0.112***
More COVID-19 infected area	0.045**	0.000	0.000	0.042**	0.077***	0.071***	0.040***	0.072***	0.122***	0.212***

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** <0.05, * <0.1. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median (52.2).*

Looking at estimates by group of employees, results illustrated in Table 6 seem to be overall in line with conclusions stated in Section 5.1. In fact, high levels of WFH feasibility would go in mainly favor of male, aged 51-64, and graduated employees, as well as those living in the areas have been more affected by the recent COVID-19 pandemic (i.e. northern provinces of the country). In conclusion, results based on the IPW estimation approach indicate that the estimated influence of the WFH feasibility on income distribution is not substantially distorted by a selection bias, thus strengthening the evidence obtained through the RIF method.

7. Conclusions

Working from home (WFH) is considered an important solution in developed societies for the coexistence with the COVID-19 virus, because it allows to work while keeping the social distancing. Besides, since the absence of herd immunity against COVID-19 suggests that a second wave of the virus transmission is possible (Leung et al., 2020), the WFH may become a long-lasting solution. The current crisis has forced many companies to a massive use of WFH and, for some of them, to think about a “new normal”[15] way of working as a future challenge. As a result, the study of the potential socio-economic outcomes related to the WFH spread is becoming a more and more relevant topic for researchers worldwide.

Based on unconditional quantile regression methods, this paper represents the first contribute showing how a future increase in the WFH feasibility would be related to changes in labour income levels and inequality. To do that, we focus on Italy as an interesting case study, because both it has been one of the countries most affected by the novel coronavirus and it was the European country with the lowest share of teleworkers before the crisis (Eurofound and ILO, 2017). Our analysis relies on a unique dataset merging the INAPP-PLUS survey and Italian equivalent of the US O*NET repertoire, thus the Italian Survey of Professions (ICP).

[15] Link: https://www.upwork.com/resources/how-to-adjust-to-the-new-normal-of-remote-work.

Assuming a long-lasting increase in the WFH feasibility levels (i.e. swapping 10% of employees with a low level of WFH feasibility with other employees with a high one), our results show that this marginal change would have potential 'collateral effects' on income inequality among employees that should not be underestimated. An increase of the WFH feasibility levels of professions would be associated to a growth of the average labour income, probably because of their higher productivity. However, it would also 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. It also has to be reported that a positive shift in the WFH feasibility levels would be more in favor of employees living in provinces have been affected the most by COVID-19 infections, thus those areas will probably suffer more demographic and economic effects of the pandemic. Our results hold after a number of robustness checks, regarding different definitions of interest variables, income inequality indexes, model specifications, and controls for skill heterogeneity and selection bias.

Given that the shares of professions can be performed from home may clearly differ by country (Dingel and Neiman, 2020; Boeri et al., 2020), the intrinsic functioning of the RIF regressions methodology provides the relevant advantage to be easily extended according to the specific assumptions adopted on the employees shares swap (related to, e.g., economics structure, innovation spread, type of technological change, political decisions). In other words, the flexible methodology here adopted allows to researchers and (of course) policymakers to somehow "forecast" potential consequences on income levels related to their decisions on the increase of WFH opportunities.

In conclusion, WFH risks to exacerbate pre-existing inequalities in the labour market, especially if it will not be adequately regulated. In this respect, during a health emergency, ex-post policies aimed at alleviating inequality in the short run, like income support measures broad enough to cover most vulnerable employees, should be implemented.

Unemployment insurance (UI), for example, is playing a critical role in many western countries during the pandemic. In the US, by late June, 36 million individuals either were receiving or had applied for unemployment benefits (Shierholz, 2020) and the general idea is that expanded UI should remain in the US, with adjustments made according to unemployment rate changes (Furman, 2020). Also in Italy and other European countries multiple employment and social initiatives where implemented as reported by the OECD.[16] The problematic aspect is that, while UI has a large, positive effect on the demand side by supporting consumption and thus all the economy, it may also negatively affect labour supply, suggesting that the amount and the duration should be well tailored among countries. The effect of unemployment benefit on unemployment spell duration have been largely investigated (Card and Levine, 2000; Lalive et al., 2006; van Ours and Vodopivec, 2006) and results usually show that the higher the benefit the higher the unemployment duration is. This can lead to an opportunistic behaviour while searching for a job. As for Italy, according to recent results, the unemployment benefit eligibility was proved to affect worker layoffs, particularly for jobs started after the onset of the Great Recession and in the South (Albanese et al., 2020).

This crisis given a boost to WFH forcing companies to invest and reorganize work even remotely. This push has to be transformed into something structural in a new way of producing and managing flexible work practices within companies, but not all firms are able to do that (Dosi et al., 2019; Cetrulo et al., 2019). We need a massive reorganization of work (Cetrulo et al., 2020), particularly in the field of re-engineering of production processes based on new digital technologies and on the possibility offered in terms of work from home. This requires new skills not only for workers but also for managers and entrepreneurs. As Brynjolfsson et al. (2020) explain, once companies and workers will incur significant fixed costs for remote work due to technologies, changes in production processes

[16] OECD (2020), Tackling coronavirus (COVID-19): Contributing to a global effort. Link: https://www.oecd.org/coronavirus/country-policy-tracker/.

and updating of human capital, it is likely that they will no longer want to go back (or at least not exactly to the same starting point) and therefore the WFH is intended to be extended over time. If it will be the case, temporary income support measures will not be sufficient anymore to compensate potentially increasing wage differentials.

Long-term interventions filling potential knowledge gaps are going to be therefore necessary to prevent the rise of inequalities in the labour market. First, childcare facilities and financial support to households with children, are required to facilitate the adoption of WFH especially for female employees with young children (Pouliakas, 2020). In the same direction, Checchi (2006) suggests that a higher average educational attainment is correlated with lower differences in educational achievement among the population, leading to reduced income inequality. Second, not surprising, two set of education policies may be suggested: increasing the school enrolment rate and improving the training courses. The latter would play an important role in reducing unequal distribution of benefits related to an increase of WFH opportunities, by increasing human capital and favouring its complementarities with technology (Acemoglu, 1997).

The most important issue that several developed countries has to solve in this period concerns how to restart the national economy avoiding, at the same time, a rise of the contagion risk in the so-called "Phase 2", thus the one on which people live with the virus under control (Favero et al., 2020). While many countries are designing exit strategies by also increasing the share of people working remotely, the evidence we provide in this paper can inform policymakers on the potential effects of such a decision and "forced innovation" in terms of wage inequality. Our analysis may therefore represent a useful starting point to select policies that would assist, especially in developed countries, a possible structural re-organization of the WFH and the labour market in general.

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Appendix A. Descriptive statistics and additional estimates

Table A.1 – Variable description

Variable	Description
Annual gross labour income	Continuous variable representing the annual gross labour income. All recentered influence functions on distributional statistics are based on this variable.
High working from home (WFH) feasibility	Binary variable reporting the level of WFH feasibility. The WFH feasibility is measured, for each occupation at 5-digit ISCO classification level, through a composite index recently introduced by Barbieri et al. (2020). This index relies on replies to seven questions in the ICP 2013 survey questionnaire regarding: i) the importance of performing general physical activities (which enters reversely); (ii) the importance of working with computers; (iii) the importance of manoeuvring vehicles, mechanical vehicles or equipment (reversely); (iv) the requirement of face-to-face interactions (reversely); (v) the dealing with external customers or with the public (reversely); (vi) the physical proximity (reversely); and (vii) the time spent standing (reversely). The WFH feasibility is calculated as average of the listed seven items and ranges from 0 to 100. Binary variable is equal to 1 for those having an index value over the sample mean (i.e. 52.2), and 0 otherwise.
Female	Binary variable taking value 1 for female, 0 for male.
Aged 36-50 Aged 51-64	Binary variables representing the age group of individuals. The reference category is Aged 25-35.
Upper secondary education Tertiary education	Binary variables representing the highest education level achieved. The reference category is composed by Lower secondary education (or lower education level).
Migrant within macro-region Migrant within country Foreign migrant	Binary variables representing the migration status. An individual is 'Migrant within macro-region' if her region of birth and her region of residence belong to the same macro-region (i.e. North, Center, or South). An individual is 'Migrant within country' if her region of birth belongs to a different macro-region with respect to her region of residence. An individual is 'Foreign migrant' if she moves from outside Italy. The reference category is Local.
Married	Binary variable taking value 1 for married people, and 0 otherwise.
Household size = 2 Household size = 3 Household size = 4 Household size = 5 or more	Binary variables representing the household size. The reference category is Single person (or Household size = 1).
Presence of minors	Binary variable taking value 1 for people living in households with at least one minor child, and 0 otherwise.
Small municipality Medium municipality Big municipality Metropolitan city	Binary variables representing the size of the municipality of residence. Small municipality has a number of inhabitants between 5,000 and 20,000, Medium municipality has 20,000 - 50,000 inhabitants, Big municipality counts 50,000 - 250,000 inhabitants, and Metropolitan city has 250,000 or more inhabitants. The reference category is Very small municipality (number of inhabitants lower than 5,000).
Centre South	Binary variables representing the macro-region of residence. The reference category is North.
Part-time open-ended worker Temporary worker and other	Binary variables representing the type of job contract. The reference category is Full-time open-ended worker.
Public servant	Binary variable taking value 1 for employees working in the public sector, and 0 otherwise.
Less COVID-19 infected area More COVID-19 infected area	Variable representing the degree of COVID-19 infection at provincial level. The infection degree is measured as the incidence of COVID-19 cases on total population at provincial level. People live in a 'more COVID-19 infected' area if their province of residence reports an infection incidence over the sample median (i.e. 3.2‰). Alternatively, they live in a 'less COVID-19 infected' area. Data on the overall COVID-19 cases at provincial level are provided by the Italian Civil Protection Department (2020) and refers to the period between February 24 and May 5, 2020.

Table A.2 – Sample composition, mean and Gini index of annual labour income, mean value of the WFH feasibility index and share of employees with high feasibility level by economic sector of activity

Economic sector of activity	Sample composition		Annual labour income		WFH feasibility	
	Mean	**Std. Dev.**	**Mean**	**Gini index**	**Mean**	**% of employees with high feasibility**
A - Agriculture	0.024	0.153	20,960	0.270	49.8	35.9
B - Extraction	0.006	0.077	35,770	0.380	54.3	43.7
C - Manufacturing	0.168	0.374	27,650	0.252	52.4	42.9
D - Energy, Gas	0.016	0.127	35,084	0.356	56.5	60.6
E - Water, Waste	0.005	0.068	38,049	0.424	51.0	32.7
F - Construction	0.029	0.167	25,176	0.242	49.6	39.8
G - Trade	0.098	0.298	23,662	0.305	48.4	38.6
H - Transportation	0.049	0.216	27,445	0.262	49.6	25.8
I - Hotel, restaurants	0.035	0.184	22,965	0.366	39.0	16.2
J - Information, comm.	0.040	0.196	27,866	0.275	63.8	81.9
K - Finance, Insurance	0.038	0.191	30,730	0.277	64.6	84.2
L - Real estate	0.003	0.053	23,995	0.236	58.2	71.0
M - Professional services	0.062	0.241	27,863	0.341	59.9	72.3
N - Other business services	0.040	0.196	25,076	0.222	62.6	79.9
O - Public Administration	0.070	0.254	27,581	0.254	59.8	72.3
P - Education	0.124	0.329	25,040	0.194	47.9	35.2
Q - Health	0.105	0.307	25,060	0.281	44.6	32.8
R - Sport, recreational activ.	0.012	0.109	23,277	0.302	52.6	55.5
S - Other services	0.068	0.252	21,895	0.316	53.3	52.7
T - Household Activities	0.008	0.087	16,822	0.232	53.6	57.3
U - International organizations	0.002	0.046	31,033	0.339	58.9	57.0
Total sample	**-**	**-**	**25,979**	**0.280**	**52.4**	**48.2**

Notes: All descriptive statistics are computed with individual sample weights. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.

Table A.3 – Unconditional effects on the mean and Gini index in the total sample

Variable	Mean value		Gini index	
	UE	**UPE**	**UE**	**UPE**
High WFH feasibility	258.86***	97.98	0.004**	0.004**
Female		-609.03***		-0.005***
Aged 36-50		350.56***		0.004**
Aged 51-64		508.34***		0.005*
Upper secondary education		369.68***		-0.001
Tertiary education		967.14***		0.005**
Migrant within macro-region		215.77		0.008
Migrant within country		-10.81		0.001
Foreign migrant		-61.27		0.005
Married		290.77***		0.005*
Household size = 2		-102.24		-0.001
Household size = 3		-198.23*		-0.003
Household size = 4		-75.66		-0.000
Household size = 5 or more		48.40		0.004
Presence of minors		-63.58		-0.004
Small municipality		84.14		0.001
Medium municipality		-46.48		-0.001
Big municipality		27.54		0.002
Metropolitan city		-22.35		-0.000
Center		-186.27***		-0.000
South		-154.14*		0.005**
Part-time open-ended worker		-838.13***		0.014***
Temporary worker and other		-650.36***		0.010***
Public servant		12.68		-0.005**
Constant	2,473.14***	2,080.79***	0.026***	0.017***
Activity sector dummies	No	Yes	No	Yes
Observations	14,307	14,307	14,307	14,307
R-squared	0.002	0.061	0.001	0.016

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.*

Table A.4 – Unconditional effects of WFH feasibility along the wage distribution (UE estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH feasibility	-15.26	82.82***	82.03***	136.35***	166.01***	157.13***	164.51***	496.49***	426.11***
Constant	1,177.16***	1,563.81***	1,878.03***	2,024.41***	2,190.42***	2,353.40***	2,616.42***	2,666.40***	3,232.28***
Activity sector dummies	No	No	No	No	No	No	No	No	No
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.000	0.001	0.002	0.004	0.006	0.010	0.010	0.017	0.014

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median.*

Table A.5 – Unconditional effects of WFH feasibility along the wage distribution (UPE estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH feasibility	-155.43***	-8.49	-13.21	19.95	40.63*	65.24***	67.72***	282.86***	233.28***
Female	-254.63***	-313.18***	-330.98***	-398.77***	-439.50***	-287.69***	-302.34***	-728.77***	-512.24***
Aged 36-50	56.43	149.21***	187.60***	204.82***	248.88***	203.22***	208.61***	434.14***	293.09***
Aged 51-64	93.92	267.50***	268.12***	320.70***	395.24***	334.28***	347.94***	735.91***	515.99***
Upper secondary education	293.65***	246.12***	263.21***	297.27***	312.74***	271.72***	283.31***	526.40***	396.87***
Tertiary education	464.93***	470.40***	532.49***	651.74***	707.50***	551.68***	577.58***	1,300.18**	1,093.69**
Migrant within macro-region	-287.65**	-24.49	84.23*	155.12**	114.78*	45.57	27.77	119.35	147.57
Migrant within country	-86.55	-95.39**	-2.08	-9.60	-7.15	11.93	13.37	66.65	-71.15
Foreign migrant	-260.42	-449.85***	-168.57**	-114.72	-122.31	-47.38	-44.49	5.86	49.81
Married	109.3**	40.44	54.28**	78.62***	105.38***	103.06***	114.45***	307.91***	232.60***
Household size = 2	-126.23*	-6.01	-17.41	-16.31	-56.43	-50.32	-61.60*	-47.15	-30.88
Household size = 3	-93.98	-33.33	-49.42	-45.75	-95.02**	-87.73***	-101.72***	-142.13*	-44.43
Household size = 4	-106.13	-27.96	-29.08	-29.53	-46.60	-46.07	-54.56	0.040	37.22
Household size = 5 or more	-128.12	-61.44	-14.98	0.74	-13.17	23.21	15.20	146.74	151.16
Presence of minors	46.14	108.63***	69.01**	98.24***	80.05***	49.03**	60.51***	52.29	22.33
Small municipality	38.21	9.99	49.51	4.19	-4.63	-8.30	-1.00	-46.15	-28.09
Medium municipality	-29.94	-11.87	26.65	2.61	-2.41	-19.54	-22.25	-98.07*	-62.39
Big municipality	-69.83	-30.65	22.79	-16.03	3.82	-22.62	-15.88	-70.99	1.79
Metropolitan city	-46.62	-43.18	32.88	41.05	56.68	4.40	10.70	65.51	93.59**
Center	-123.49***	-174.31***	-114.23***	-105.19***	-106.86***	-79.42***	-79.37***	-215.23***	-125.35***
South	-446.04***	-313.09***	-159.68***	-152.85***	-144.43***	-85.74***	-86.23***	-157.85***	-101.13**
Part-time open-ended worker	-1,085.10***	-1,540.70***	-937.75***	-871.29***	-770.87***	-423.05***	-436.96***	-676.02***	-321.68***
Temporary worker and other	-979.34***	-912.85***	-585.93***	-605.05***	-560.87***	-292.67***	-301.95***	-433.00***	-202.83***
Public servant	233.99***	209.01***	142.71***	134.17***	99.34**	22.55	19.46	-104.21*	-104.12**
Constant	1,403.34***	1,477.30***	1,724.32***	1,871.21***	2,044.65***	2,154.48***	2,413.92***	2,146.75***	2,848.82***
Activity sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.161	0.344	0.322	0.289	0.248	0.208	0.206	0.170	0.101

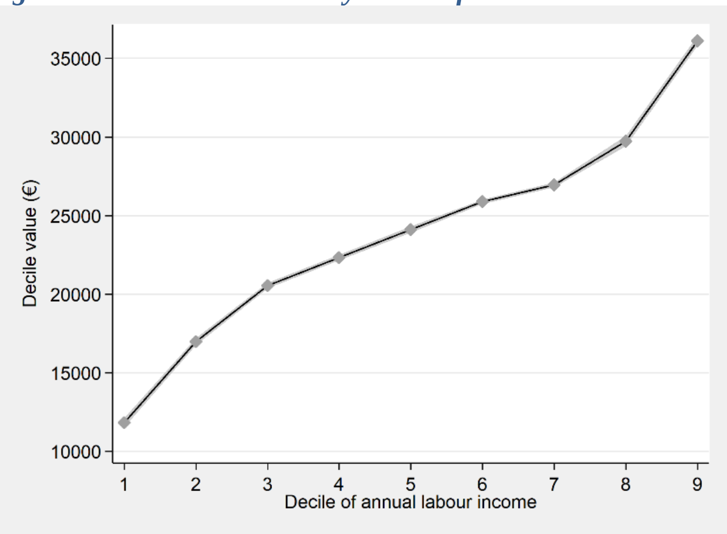
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median .*

Table A.6 – Unconditional effects on mean value and Gini index by item of the WFH feasibility index (excluding employees with index value equals to 0)

Item of the multidimensional index	Threshold value	Mean value		Gini index	
		UE	UPE	UE	UPE
Performing physical activities (−)	82.5	383.22***	217.80***	-0.000	0.002
Working with computers	50.0	459.96***	202.18***	0.000	0.000
Manoeuvring vehicles or machines (−)	95.6	-101.23	-78.13	-0.002	-0.003
Face-to-face discussion (−)	22.0	-274.30***	-171.03	0.002	0.001
Dealing with customers and public (−)	46.0	-243.08***	-205.62***	-0.002	-0.003
Physical proximity (−)	63.8	-394.14***	-208.15***	-0.005***	-0.005***
Spending time standing (−)	47.0	469.31***	292.61***	0.002	0.003**
WFH feasibility (total)	52.2	258.86***	97.98	0.004**	0.004**

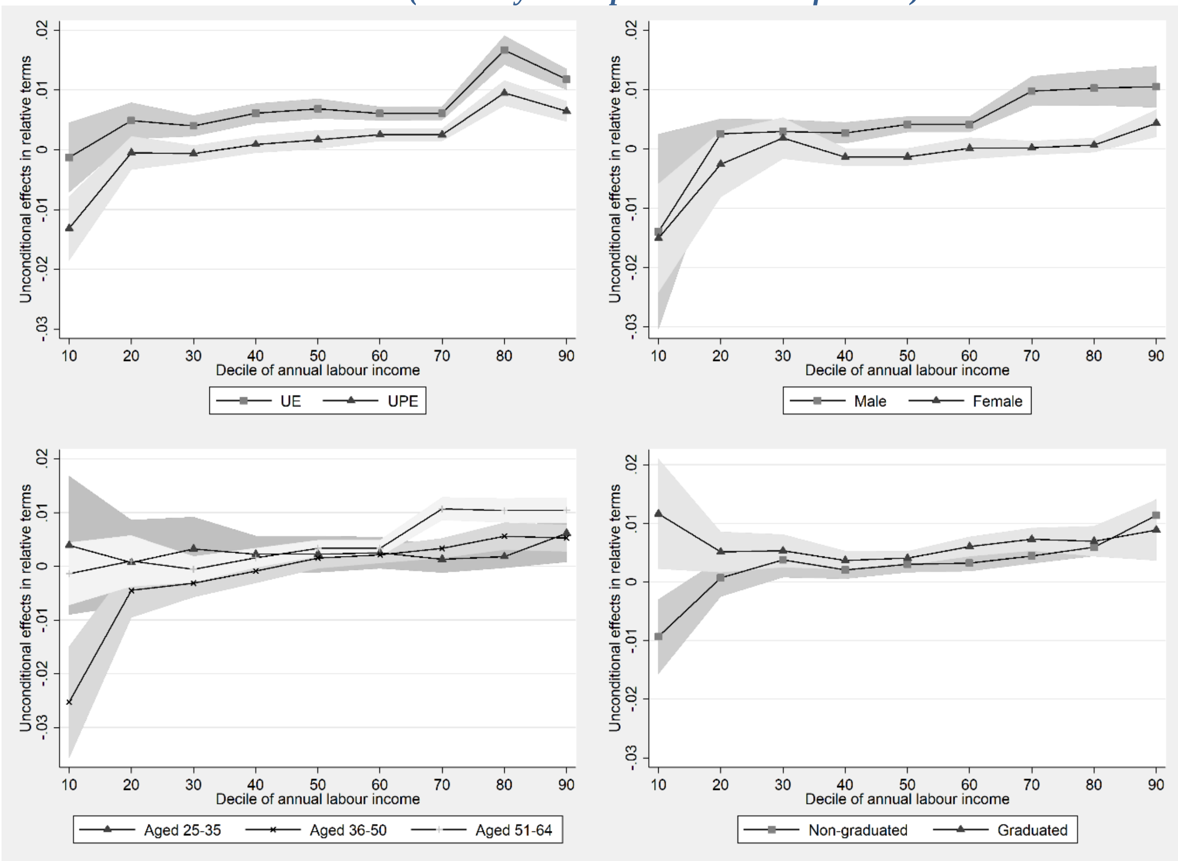
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High index value) only. Employees with high index value are defined, for each item, as those reporting a value of the single index over the threshold value illustrated in the table (i.e. the sample median). UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). The symbol '(−)' means that the index referring to the specific item is considered reversely.*

Figure A.1 – Income values by decile of annual labour income



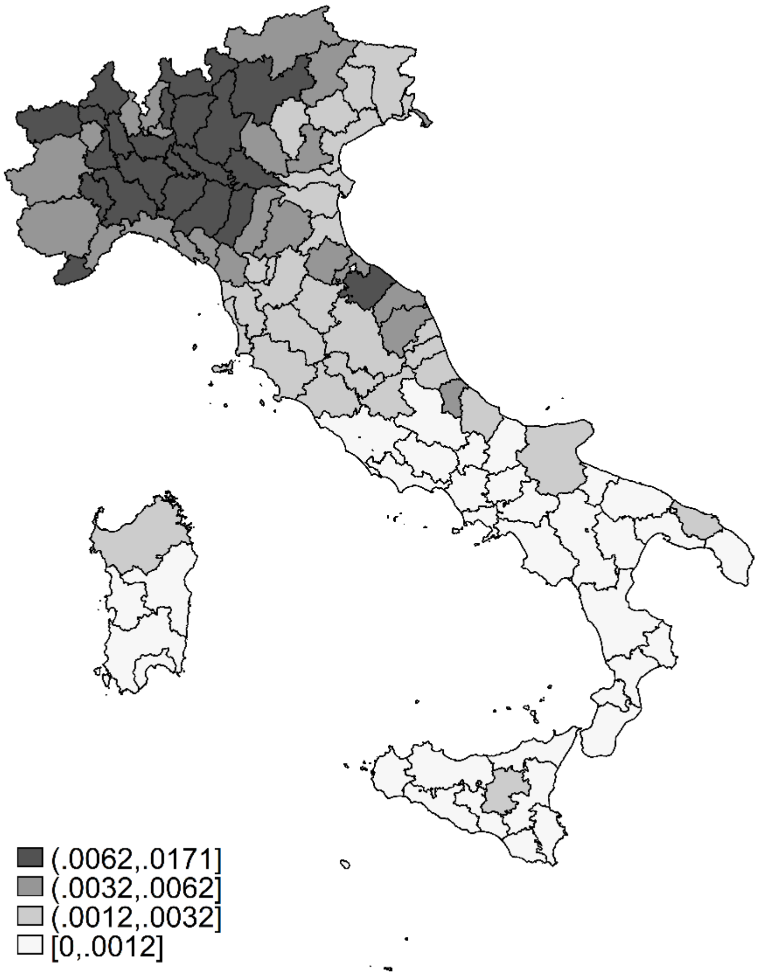
Notes: All descriptive statistics are computed with individual sample weights.

Figure A.2 – Unconditional effects of a positive shift in the WFH feasibility along labour income distribution (relatively to the point estimates of deciles)



Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients reported in Figure 4 divided by the point estimation value for the specific decile in the specific subgroup of employees. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median . UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). Estimates by employees' characteristics refer to the UPE specification.

Figure A.3 – COVID-19 infection incidence by province



Notes: All descriptive statistics are computed with individual sample weights. The choropleth map is based on a quantile method, so that class breaks coincides with quartiles of COVID-19 infection incidence at provincial level in the analysis sample. Source: Elaboration of the authors on data by the Italian Civil Protection Department (2020). Accessed on May 5, 2020.

Appendix B. Robustness checks

Table B.1 – Unconditional effects on the mean and Gini index of labour income considering only full-time open-ended employees

Group of employees	Mean value		Gini index	
	UE	UPE	UE	UPE
Total sample	390.45***	209.16**	0.004*	0.003
Male	544.90***	329.72**	0.005	0.004
Female	193.42***	36.94	0.003*	0.001
Aged 25-35	488.21***	541.49**	0.007	0.012
Aged 36-50	205.19	30.96	0.001	0.000
Aged 51-64	595.26***	315.36**	0.007***	0.005
Non-graduated	281.71**	287.87***	0.003	0.004
Graduated	473.55***	254.05**	0.006***	0.001
Less COVID-19 infected area	361.24***	219.28	0.004	0.004
More COVID-19 infected area	421.96***	201.77**	0.004	0.003

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median . UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Table B.2 – Unconditional effects on the mean and Gini index of labour income (self-employees included in the sample)

Group of employees	Mean value		Gini index	
	UE	UPE	UE	UPE
Total sample	206.56***	58.59	0.002*	0.002*
Male	360.05***	178.31*	0.002	0.002
Female	109.58***	-61.77	0.003*	0.001
Aged 25-35	226.40***	129.92	0.003	0.005
Aged 36-50	37.39	-68.21	0.001	0.001
Aged 51-64	435.29***	183.19*	0.004**	0.004
Non-graduated	95.32	104.15	0.001	0.002
Graduated	310.01***	166.63**	0.005***	0.001
Less COVID-19 infected area	159.80*	33.68	0.001	0.002
More COVID-19 infected area	262.78***	77.97	0.003*	0.003**

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median . UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Table B.3 – Unconditional effects on the mean and Gini index of labour income (variable of interest with continuous specification)

Group of employees	Mean value		Gini index	
	UE	**UPE**	**UE**	**UPE**
Total sample	90.22***	16.03	0.000	0.000
Male	151.03***	61.74	0.001	0.001
Female	40.55**	-16.57	-0.000	-0.001
Aged 25-35	111.76***	69.50**	0.001	0.002
Aged 36-50	30.51	-32.03	-0.000	-0.000
Aged 51-64	151.52***	41.02	0.001**	0.001
Non-graduated	61.58**	35.96	0.000	0.000
Graduated	121.99***	50.39	0.002***	0.000
Less COVID-19 infected area	55.41	-11.74	-0.000	-0.000
More COVID-19 infected area	128.89***	45.24***	0.001	0.001

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. WFH feasibility index) only. The WFH feasibility index is a multidimensional index ranging from 0 to 100. UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Table B.4 – Unconditional effects on mean value and Gini index by item of the WFH feasibility index (variable of interest with continuous specification)

Item of the multidimensional index	Mean value		Gini index	
	UE	**UPE**	**UE**	**UPE**
Performing physical activities (−)	120.66***	55.35***	-0.0003	-0.0001
Working with computers	108.46***	41.14***	-0.0003	-0.0003
Manoeuvring vehicles or machines (−)	-13.52	7.55	0.0004	0.0009*
Face-to-face discussion (−)	-189.91***	-149.25***	0.0007	-0.0002
Dealing with customers and public (−)	-61.80***	-61.91***	-0.0008*	-0.0008
Physical proximity (−)	-165.26***	-85.74***	-0.0012***	-0.0013***
Spending time standing (−)	102.98***	60.60***	0.0003	0.0006
WFH feasibility (total)	90.22***	16.03	0.0004	0.0004

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. single index value) only. Each index considered ranges from 0 to 100. UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). The symbol '(−)' means that the index referring to the specific item is considered reversely.*

Table B.5 – Unconditional effects on the mean log deviation and Atkinson index (e=1)

Group of employees	Mean log deviation		Atkinson index (e=1)	
	UE	**UPE**	**UE**	**UPE**
Total sample	0.003	0.004*	0.003	0.003*
Male	0.002	0.004	0.002	0.003
Female	0.003**	0.002	0.003**	0.002
Aged 25-35	0.005	0.008*	0.004	0.007*
Aged 36-50	0.000	0.002	0.000	0.002
Aged 51-64	0.006**	0.004	0.005**	0.004
Non-graduated	0.002	0.003	0.002	0.003
Graduated	0.005**	0.000	0.004**	0.000
Less COVID-19 infected area	0.002	0.004	0.002	0.003
More COVID-19 infected area	0.004	0.003	0.003	0.003

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median . UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Table B.6 – Unconditional effects on the mean and inequality indicators in the total sample (UPE2 and UPE3 estimates)

Variable	Mean value		Gini index		Mean log deviation		Atkinson index (e=1)	
	UPE2	UPE3	UPE2	UPE3	UPE2	UPE3	UPE2	UPE3
High WFH feasibility	129.05**	24.31	0.004***	0.005***	0.004**	0.007**	0.004**	0.006***
Female	-887.05***	-583.24***	-0.002	-0.004**	-0.003	-0.004*	-0.002	-0.003*
Aged 36-50	414.99***	346.10***	0.001	0.004**	0.001	0.004*	0.001	0.003*
Aged 51-64	598.46***	493.09***	-0.000	0.004*	-0.001	0.005	-0.000	0.004
Upper secondary education	384.32***	280.57***	-0.003	-0.000	-0.005*	-0.001	-0.004*	-0.001
Tertiary education	993.80***	673.39***	-0.001	0.003	-0.004	0.001	-0.003	0.001
Migrant within macro-region	133.09	194.85	0.009	0.007	0.011*	0.010	0.010*	0.008
Migrant within country	1.83	-31.34	0.001	0.001	0.001	0.001	0.001	0.001
Foreign migrant	-76.14	-28.99	0.006**	0.004	0.004	0.002	0.003	0.002
Married	348.63***	279.49***	0.003	0.005*	0.003	0.004	0.003	0.004
Household size = 2	-165.16	-94.73	0.000	-0.001	0.000	-0.001	0.000	-0.001
Household size = 3	-303.45***	-195.10*	-0.002	-0.003	-0.003	-0.004	-0.002	-0.003
Household size = 4	-184.45*	-68.73	0.001	-0.000	0.001	-0.001	0.001	-0.001
Household size = 5 or more	-108.91	37.53	0.005	0.003	0.006	0.004	0.005	0.004
Presence of minors	-41.76	-64.03	-0.004	-0.004	-0.005	-0.005	-0.004	-0.004
Small municipality	81.19	90.30	0.001	0.002	0.001	0.002	0.001	0.001
Medium municipality	-37.13	-47.20	-0.000	-0.000	0.000	0.000	0.000	0.000
Big municipality	5.55	32.96	0.002	0.002	0.004	0.004	0.003	0.003
Metropolitan city	-59.61	-29.51	0.000	-0.000	0.000	0.000	0.000	0.000
Center	-217.19***	-176.72***	0.000	-0.000	0.000	-0.000	0.000	-0.000
South	-243.20***	-153.30*	0.005**	0.005**	0.006**	0.006**	0.005**	0.005**
Part-time open-ended worker		-781.41***		0.015***		0.012***		0.010***
Temporary worker and other		-629.84***		0.009***		0.010***		0.008***
Public servant		-50.51		-0.006***		-0.007***		-0.006***
Average skill level		46.36		-0.007***		-0.009***		-0.008***
High skill level		224.07**		-0.004*		-0.005*		-0.004*
Very high skill level		693.10***		0.005*		0.003		0.003
Constant	2,243.14***	2,083.66***	0.025***	0.017***	0.017***	0.007	0.015***	0.007*
Activity sector dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.043	0.066	0.004	0.018	0.004	0.013	0.004	0.013

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median .*

Table B.7 – Unconditional effects of WFH feasibility along the wage distribution (UPE2 estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH feasibility	-138.38***	-27.85	-28.42	6.67	35.57	60.03***	63.58***	311.11***	279.52***
Female	-559.0.5***	-723.48***	-582.05***	-630.85***	-655.43***	-408.95***	-428.71***	-962.83***	-644.20***
Aged 36-50	235.02***	317.16***	296.38***	311.97***	339.82***	242.73***	247.54***	459.70***	269.93***
Aged 51-64	389.15***	549.84***	450.24***	502,39***	545.40***	396.95***	409.05***	747.82***	460.51***
Upper secondary education	409.61***	341.07***	325.27***	361.75***	356.70***	289.04***	300.03***	514.72***	362.47***
Tertiary education	726.81***	761.42***	718.35***	838.55***	844.88***	606.87***	630.72***	1,265.35***	973.99***
Migrant within macro-region	-410.87***	-160.71**	-2.21	69.12	37.41	5.86	-12.93	54.27	131.74
Migrant within country	-50.90	-43.71	28.36	18.48	17.12	24.41	26.03	78.95	-73.51
Foreign migrant	-362.54*	-506.32***	-219.14***	-161.30*	-148.21	-49.69	-45.69	32.86	84.15
Married	214.11***	134.50***	116.32***	141.30***	159.50***	129.08***	141.33***	345.47***	244.40***
Household size = 2	-221.85***	-99.22*	-76.50*	-77.87*	-108.19**	-76.48**	-88.92***	-80.00	-47.85
Household size = 3	-246.60***	-190.29***	-148.52***	-146.88***	-183.57***	-136.41***	-152.78***	-211.43***	-86.98
Household size = 4	-271.48***	-203.74***	-139.94***	-140.49**	-143.75**	-98.81**	-109.59***	-73.99	-2.36
Household size = 5 or more	-345.67***	-280.33***	-151.47***	-138.47**	-139.33**	-46.76	-58.03	33.45	83.12
Presence of minors	64.74	109.51***	70.20***	102.28***	86.82***	54.22***	66.42***	63.24	40.23
Small municipality	46.77	12.00	49.04*	2.99	-6.46	-8.26	-0.81	-45.95	-32.99
Medium municipality	-21.68	-9.86	26.49	4.62	-1.29	-13.70	-15.70	-86.61	-58.65
Big municipality	-97.00	-71.98	-2.41	-40.21	-19.56	-32.74	-25.95	-80.98	-7.21
Metropolitan city	-88.22*	-100.64**	-5.05	3.79	19.60	-12.20	-5.87	49.85	73.60*
Center	-163.46***	-214.55***	-140.67***	-133.14***	-135.44***	-94.78***	-94.85***	-245.76***	-144.00***
South	-502.99***	-366.10***	-193.85***	-190.90***	-188.93***	-115.88***	-118.03***	-237.07***	-169.87***
Constant	1,182.89***	1,515.56***	1,684.71***	1,786.98***	1,950.13***	2,130.55***	2,384.74***	2,234.23***	2,895.55***
Activity sector dummies	No	No	No	No	No	No	No	No	No
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.067	0.132	0.166	0.171	0.165	0.157	0.157	0.140	0.081

*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median .*

Table B.8 – Unconditional effects of WFH feasibility along the wage distribution (UPE3 estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH feasibility	-301.67***	-104.40***	-90.47***	-58.05***	-33.22	23.54	27.92	232.08***	193.29***
Female	-270.28***	-314.91***	-322.28***	-382.47***	-417.30***	-269.46***	-283.19***	-689.75***	-483.29***
Aged 36-50	57.90	152.08***	189.94***	207.61***	252.08***	203.62***	208.89***	431.76***	285.14***
Aged 51-64	87.84	266.02***	266.01***	318.63***	393.62***	330.39***	343.88***	724.59***	496.70***
Upper secondary education	195.12***	171.24***	190.93***	215.35***	227.12***	216.72***	228.76***	439.76***	331.23***
Tertiary education	327.52***	353.69***	385.96***	468.73***	504.19***	393.87***	416.87***	993.28***	804.22***
Migrant within macro-region	-284.88**	-24.19	79.81	147.73**	105.36	35.79	17.50	95.94	122.17
Migrant within country	-82.57	-93.50**	-4.87	-14.97	-14.27	3.28	4.19	44.42	-97.29
Foreign migrant	-220.28	-416.31***	-135.91*	-76.99	-82.09	-23.30	-20.67	40.82	68.52
Married	101.98**	34.60	47.73*	70.75***	96.85***	96.80***	108.14***	296.43***	222.22***
Household size = 2	-119.98	-2.09	-13.57	-12.10	-52.20	-46.98	-58.26*	-40.79	-23.58
Household size = 3	-92.54	-32.13	-47.91	-43.87	-92.93**	-86.09***	-100.05***	-138.90*	-41.30
Household size = 4	-101.39	-25.25	-26.3	-26.48	-43.57	-43.35	-51.81	5.76	44.55
Household size = 5 or more	-126.05	-64.72	-21.99	-9.80	-26.36	14.01	5.72	129.73	141.59
Presence of minors	46.45	108.46***	68.57**	97.54***	79.1598***	48.46**	59.92***	51.31	22.04
Small municipality	36.37	8.57	49.51*	4.78	-3.65	6.21	1.26	-39.89	-19.58
Medium municipality	-37.58	-15.90	24.42	1.15	-3.08	-19.42	-21.96	-96.38*	-61.58
Big municipality	-74.92	-32.42	23.53	-13.72	7.38	-19.18	-12.20	-62.77	8.73
Metropolitan city	-62.31	-51.33	27.48	36.74	53.72	2.54	9.06	63.43	88.08**
Center	-109.95***	-164.38***	-105.24***	-95.34***	-96.80***	-73.33***	-73.40***	-206.50***	-119.32***
South	-436.65***	-305.15***	-153.10***	-145.70***	-137.07***	-82.69***	-83.38***	-156.33***	-105.18**
Part-time open-ended worker	-107.55***	-1,525.58***	-912.03***	-835.85***	-729.01***	-389.93***	-402.87***	-609.42***	-263.61***
Temporary worker and other	-963.48***	-898.00***	-569.58***	-585.11***	-538.84***	-278.31***	-287.54***	-409.38***	-187.41***
Public servant	208.96***	187.40***	113.87***	97.54***	58.30	-10.45	-14.26	-170.31***	-168.52***
Average skill level	377.45***	216.56***	134.03***	105.90***	74.12**	16.60	8.65	-52.05	-44.17
High skill level	257.39***	253.70***	262.45***	316.27***	348.75***	203.02***	201.81***	288.90***	102.53**
Very high skill level	313.99***	255.09***	323.69***	403.30***	446.36***	356.81***	363.86***	709.10***	700.19***
Constant	1,432.74***	1,487.35***	1,725.81***	1,866.97***	2,035.16***	2,148.10***	2,406.90***	2,133.58***	2,851.29***
Activity sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.165	0.347	0.330	0.301	0.263	0.226	0.223	0.184	0.115

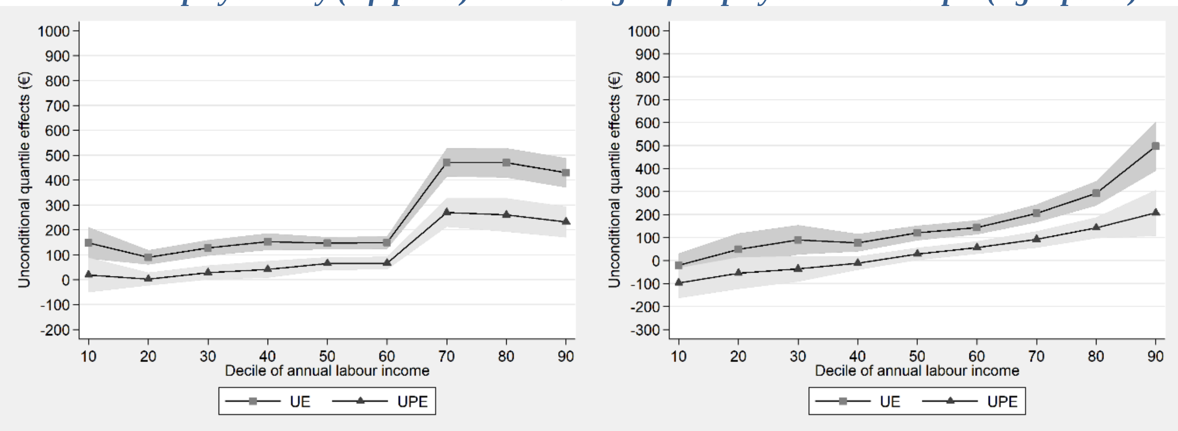
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median .*

Table B.9 – Unconditional effects on the mean and Gini index of labour income (with no sample weights)

Group of employees	Mean value		Gini index	
	UE	UPE	UE	UPE
Total sample	337.14***	149.77***	0.005***	0.002*
Male	558.23***	264.70***	0.004**	0.002
Female	92.61	54.98	0.003**	0.000
Aged 25-35	268.87***	66.28	0.002	0.002
Aged 36-50	231.24***	67.97	0.003	0.001
Aged 51-64	515.37***	320.36***	0.007***	0.004
Non-graduated	243.20***	173.89**	0.002	0.002
Graduated	421.00***	221.09*	0.008***	0.002
Less COVID-19 infected area	220.27***	36.95	0.003*	0.000
More COVID-19 infected area	461.43***	268.42***	0.006***	0.004**

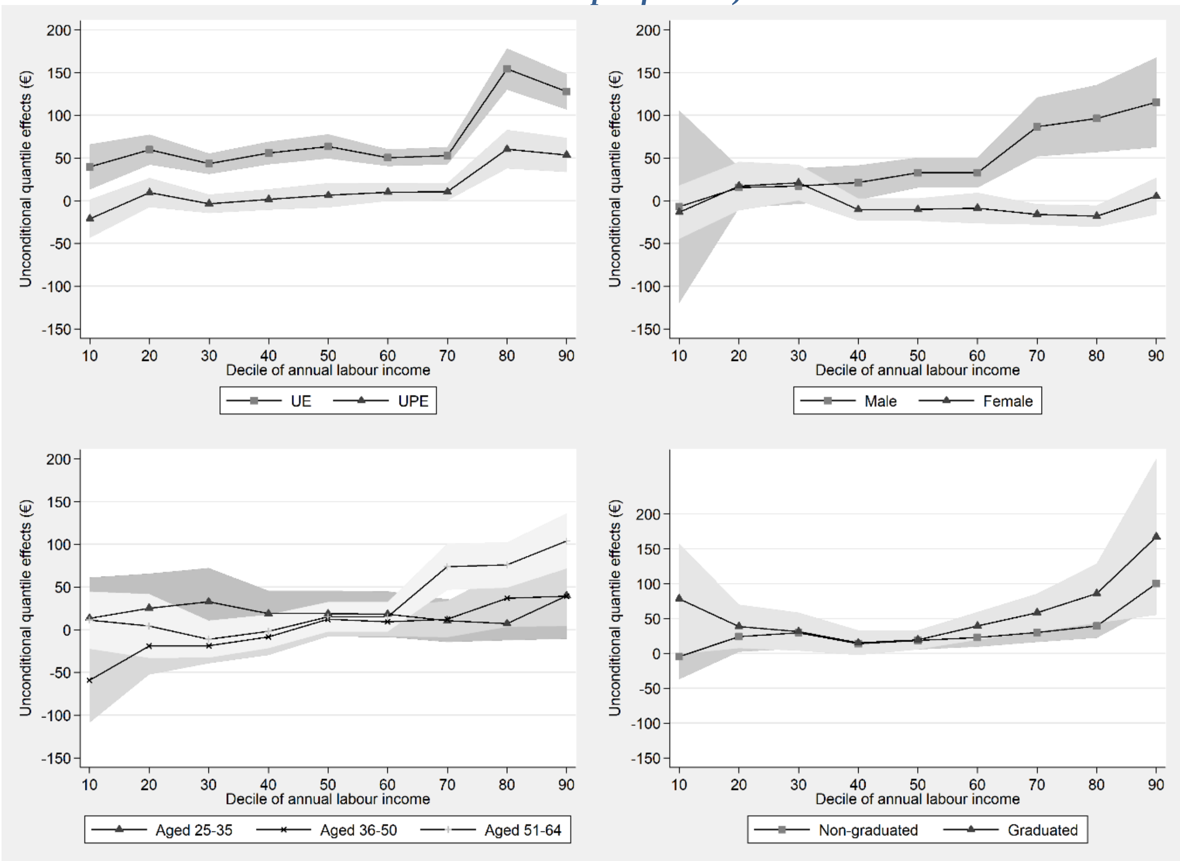
*Notes: Standard errors are clustered by NUTS-3 region; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index over the (non-weighted) sample median (i.e. 53.4). UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).*

Figure B.1 – Unconditional effects along the labour income distribution considering full-time open-ended employees only (left panel) or including self-employees in the sample (right panel)



Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index over the sample median (i.e. 52.2 for both samples of workers). UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).

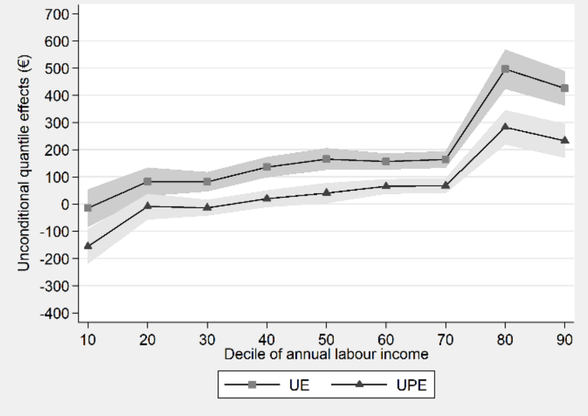
Figure B.2 – Unconditional effects along the labour income distribution (variable of interest with continuous specification)



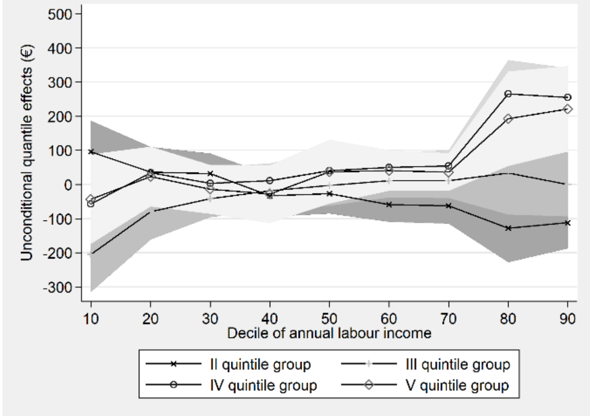
Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. WFH feasibility index) only. The WFH feasibility index is a multidimensional index ranging from 0 to 100. UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). Estimates by employees' characteristics refer to the UPE specification.

Figure B.3 – Unconditional effects along the labour income distribution (variable of interest with other specifications)

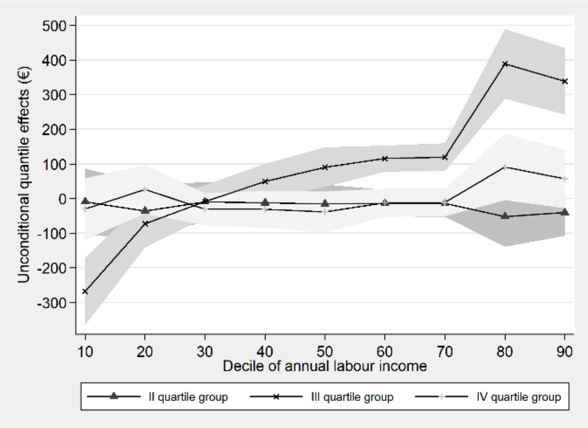
Panel A. Median of the WFH feasibility index (base)



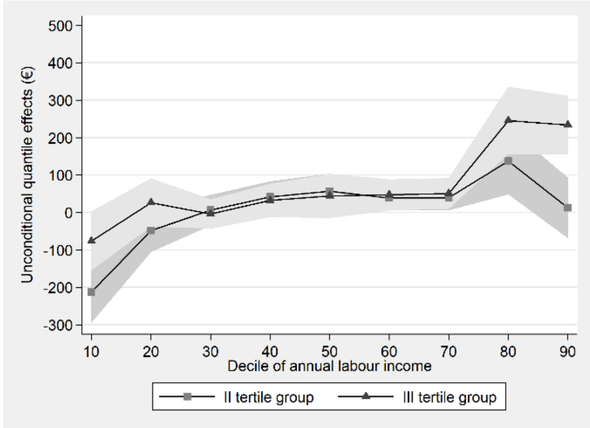
Panel B. Quintile groups of the WFH feasibility index



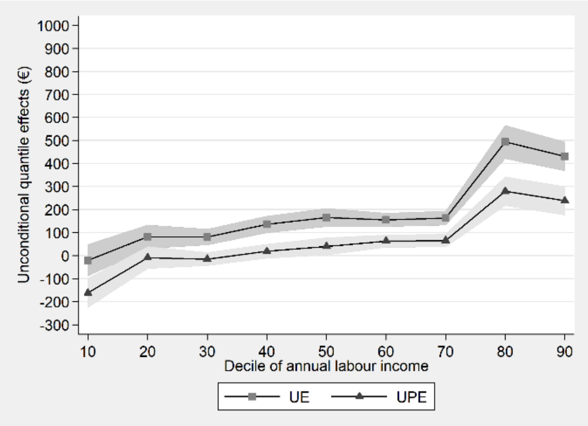
Panel C. Quartile groups of the WFH feasibility index



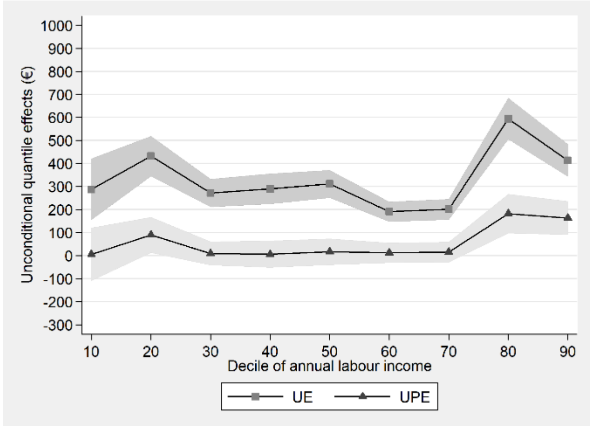
Panel D. Tertile groups of the WFH feasibility index



Panel E. Mean of the WFH feasibility index

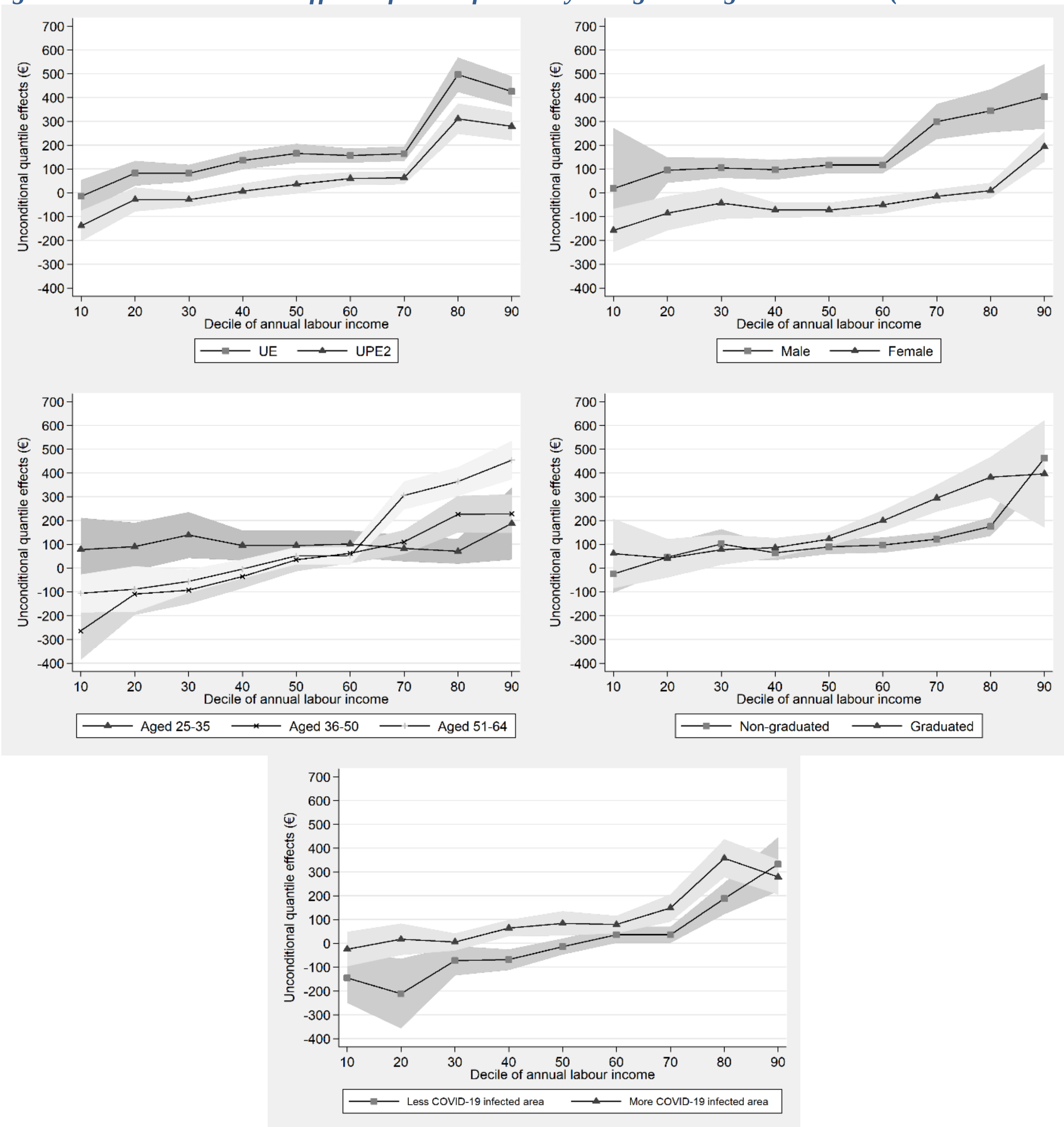


Panel F. 60% of mean of the WFH feasibility index



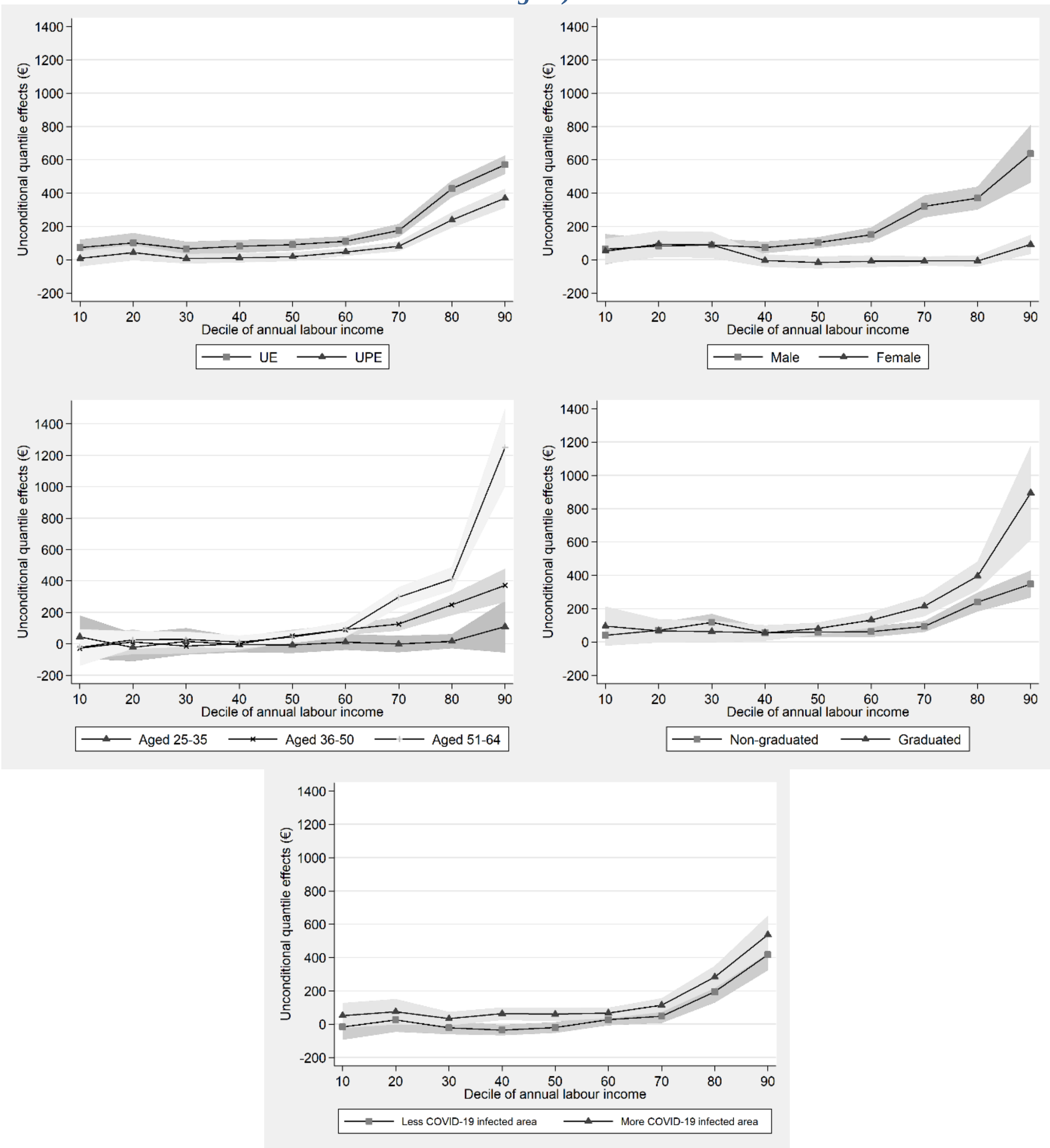
Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest only, which is defined through different specifications (expressed in Panel labels) of the same WFH feasibility index. UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). Estimates in Panels B, C and D refer to the UPE specification.

Figure B.4 – Unconditional effects of WFH feasibility along the wage distribution (UPE2 estimates)



Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index above the relevant sample median . UE estimates are based on a model specification which only includes the variable of interest, while for UPE2 estimates additional covariates demographic characteristics regarding individuals and their households are included in the model (see Section 6). Estimates by employees' characteristics refer to the UPE2 specification. Complete estimates for the pooled sample are provided in Table B.7.

Figure B.5 – Unconditional effects of WFH feasibility along the wage distribution (with no sample weights)



Notes: Standard errors are clustered by NUTS-3 region. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. High WFH feasibility) only. Employees with high WFH feasibility level are defined as those reporting a value of the WFH feasibility index over the (non-weighted) sample median (i.e. 53.4). UE estimates are based on a model specification which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4). Estimates by employees' characteristics refer to the UPE specification.