# WORKING FROM HOME AND THE EXPLOSION OF ENDURING DIVIDES:

# INCOME, EMPLOYMENT AND SAFETY RISKS.

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## **Abstract**

Why are there so many non-teleworkable occupations? Is teleworking only a matter of ICT usage or does it also reflect the division of labour and the underlying hierarchical layers inside organizations? What does it happen to those workers not able to telework in terms of socio-economic risks, and how does the gender dimension interact with risk stratification? Hereby, we intend to shed light on these questions using a detailed integrated dataset at individual and occupational level which provides information on different nature of risks (income, employment and safety). We focus on Italy, a country presenting a combination of formal and informal labour markets and being the first European economy immediately adopting measures of social distancing since the mid of March 2020. To address the first question, after having distinguished among the two populations of working and not-working from home, we dissect which are the attributes of teleworkability. By aggregating at 1-digit according to the ISCO classification and distinguishing for gender, a highly polarized occupational structure emerges with a strong concentration of opportunities to work from home for the upper four occupational groups. Working remotely is feasible for the majority of those who are at the top of the organizational hierarchy (managers, entrepreneurs and legislators), for scientific-intellectual professions, for technical professionals. It increases in administrative tasks. For the lower part of the ISCO classification the scenario radically changes. Service-based occupations, such as entertainment operators, sales workers, artisans, plant and machine operators, as well as elementary professions, see the chance for working remotely drastically shrinking or mostly nil. Then, we ask what happens to those segments not able to work remotely. In this respect, we study the probabilities of transition to unemployment (occupational risk), of getting low-income (income risk) and of job-related injuries and

diseases (health risk). We therefore identify those occupations which face stratifying risks, namely characterized by the co-occurrence of these three events. We finally estimate a probit model at individual and occupation level, accounting for a large set of covariates, and focusing on the role played by teleworkability, contractual, and gender determinants. Our results entail that, first, class attributes strongly influence the chance of working from home, second, those individuals who are not able to perform their work remotely are more exposed to transition to unemployment, to earn low wages, and to safety and health risks, third, being woman and employed with a temporary contract significantly amplify risk stratification.

Keywords: Occupational structure, Teleworking, COVID-19, Social Divides.

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#### Introduction

With the outburst of the pandemic, societies are facing a major transformation of the established organization of productive activities, in particular the way in which work is physically performed at workplaces. Related, another deep challenge concerns the exploding socio-economic divides which are associated with the pandemic. Indeed, not all segments of the population have been equally hit by the economic damages arising from the impossibility of performing their own job. For some segments, direct and indirect pandemic risks have been stratifying and conflating. This is the case of Black and Latino communities in the US which have been facing rising health and poverty risks (Selden and Berdahl, 2020; Gonzalez et al., 2020; Montenovo et al., 2020). These workers however were suffering profound injustices in terms of access to medical assistance, income insecurity and occupational segregation well before the pandemic (Millett et al., 2020). Similarly, indigenous and suburb communities in Latin America did have far less chance to stay at home during lockdowns forced to choose between income security and health protection (Dueñas et al., 2020).

From the other side of the Atlantic, the Eurozone established for the first time a common plan to finance unemployment subsidies, the SURE, because of the enormous job losses. However, European responses to tackle the labour-market impacts of the COVID-19 crisis have been heterogeneous, ranging from extensions of sick-leaves, furlough schemes, redundancy pay systems, extraordinary income transfers, suspensions of layoffs. The only common denominator across all countries has been the switch to telework. Clearly, the higher the presence of social protection schemes and of labour market institutions operating in each country, the lower the possibility that job losses will result into individual socio-economic risks. On the contrary, the higher the level of informality and the weakness of labour market institutions, the higher the associated individual risks.

In this paper we focus on a country presenting a combination of formal and informal labour markets, Italy, the first European economy hit by the pandemic and immediately adopting measures of social distancing since the mid of March 2020. Because of lockdown measures, productive activities have been overwhelmed by the imposition of teleworking. Firms and public bodies have faced the pressure to reshape their organizational set-up introducing for the first time forms of remote-working. In Italy, however, working-fromhome appears to be more a privilege for a few occupations rather than a generalized possibility. In fact, we recently documented that only thirty percent of Italian workers may work remotely (Cetrulo et al., 2020b). Those workers tend to belong to the upper echelon of the occupational distribution, are better remunerated and employed with permanent contracts. This figure is also in line with the US experience wherein, according to a web-survey carried out between April and June 2020 by Brynjolfsson et al. (2020), only one-third of the US workforce shifted to telework, confirming the previous estimate by Dingel and Neiman (2020). Other studies on advanced economies confirm this ratio, generally ranging from 30% to 50% of the workforce.

Why are there so many non-teleworkable occupations? Is teleworking only a matter of ICT usage or does it also reflect the division of labour and the underlying hierarchical layers inside organizations? What does it happen to those workers not able to telework in terms of socio-economic risks, and how does the gender dimension interact with risk stratification? Hereby, we intend to shed light on these questions using a detailed integrated dataset at individual and occupational level (Indagine Campionaria delle Professioni, Indagine delle Forze di Lavoro and Inail archive) which provides information on different nature of risks (income, employment and safety). Our results entail that, first, class attributes strongly influence the chance of working from home, second, those individuals who are not able to perform their work remotely are more exposed to transition to unemployment, to earn low wages, and to

safety and health risks, third, being woman and employed with a temporary contract significantly amplify risk stratification.

More in detail, to address the first question, after having distinguished among the two populations of working and not-working from home, we dissect which are the attributes of teleworkability. We resort to the anatomy of the Italian occupations developed in Cetrulo et al. (2020a) assigning scores to attributes of power, knowledge and learning, ICT skills, creativity, and team-working, per each 4-digit occupation. Then, we ask what happens to those segments not able to work remotely. In this respect, we study the probabilities of transition to unemployment (occupational risk), of getting low-income (income risk) and of job-related injuries and diseases (health risk). We therefore identify those occupations which face stratifying risks, namely characterized by the co-occurrence of these three events. We finally estimate a probit model at individual and occupation level, accounting for a large set of covariates, and focusing on the role played by teleworkability, job contract, and gender determinants.

The first result of our study is that class attributes strongly affect the chance of working from home. Although the use of ICT devices and related knowledge are dramatically important to remotely-work, the degree of power and autonomy exercised in decision-making processes, and therefore the positioning along internal hierarchies, significantly differs between teleworkable and non teleworkable occupations. Women look to be endowed by a lower degree of power and autonomy compared to men in teleworkable occupations, and in general to be largely concentrated in the bottom part of the ISCO classification in non-teleworkable occupations, with gender and class divides intersecting. Moving to stratification of socio-economic risks, according to our second result, those individuals who are not able to perform their work remotely are more exposed to the risk of becoming unemployed, earning a lower wage and facing significant safety and health risks. The occupations facing the highest risks include food preparation, cooking and distribution personnel, waiters

and similar professions, unqualified staff in charge of cleaning services in offices and shops, these latter being all professions with a predominant female share. Indeed, the third result entails that being woman and being employed with a temporary contract significantly amplify risk stratification.

Our empirical investigation looks at the structural determinants of occupations and it is not intended to produce now-casting (Adams-Prassl et al., 2020b), but rather to understand who are those segments experiencing risk stratification, with the aim of informing targeted policy interventions. It is by no coincidence that what before was an unequal system of organizing societies it is now getting a socially unjust one (Dosi et al., 2020) marked by exploding enduring divides.

The paper is organised as follows: in Section 2 we discuss the streams of literature relevant to inform the empirical analysis, while in Section 3 we detail data, methodology and descriptive evidence. Results are shown in Section 4 and further discussed in Section 5 which concludes the paper.

# 2. Background literature

In this section we discuss first the evidence on the diffusion and impacts of teleworking as organizational choice in usual times, while we next devote attention to teleworkability as a must in pandemic times.

# 2.1 Teleworking as a choice in usual times

The notion of "telecommuting" has been coined by Nilles (1975) with reference to the remotely execution of work tasks (including communications) at home or in other places different from the office. Early studies focusing on the diffusion of telework and related impacts on firms' and workers' performance have been stimulated by the fast diffusion of computers (Nilles, 1975) as well as by the effect of the 1970s' energy crisis on mass transport (Harkness, 1977). However, contrary to the expectation of a progressive disappearance of offices and the spreading of nomad workers operating from their "electronic cottages" (Toffler and Alvin, 1980; Makimoto and

Manners, 1997), telework has been only slowly diffusing, with the highest rates recorded in the Northern European countries, Japan and the US (Messenger, 2017). Indeed, since 1980 the proportion of employees who primarily work from home has more than tripled and the range of 'teleworkable activities' has also increased including a wide spectrum of service jobs, ranging from sales assistants and realtors to managers and software engineers (Bloom et al., 2015). Sectoral, occupational and firm characteristics are crucial to understand the extent to which a given task is "teleworkable". Indeed, "teleworkability" depends on the executed functions, availability of computers and digital infrastructures allowing to perform tasks remotely, firm managerial and organizational capabilities, worker ICT skills (Bailey and Kurland, 2002). In terms of hierarchical layers inside organizations (Huws, 1991; Huws et al., 1999; Bailey and Kurland, 2002; Corso et al., 2006; Neirotti et al., 2011), clerks, managers and professionals are seen as the most apt recipients of telework because of the more frequent use of computer, lower physical requirements and higher level of discretion and autonomy in defining the workpace characterizing those segments (Olson,1983). More recent evidence confirms the importance of adopting an occupational-based perspective to understand the patterns of telework diffusion, as the largest share of those working remotely are concentrated in specific occupational categories such as managers, professionals and, to a lower extent, clerical workers (Messenger, 2019). From micro-level occupational differences to country-level ones, telework diffusion ranges from 30% adoption rates in Sweden and Finland, to much lower rates recorded in Italy, namely 3.6% in 2018. Those differences are mainly due to heterogeneity in ICT infrastructures and in active policies aimed at promoting the diffusion of ICT skills and internal workplace flexibility (Huws et al., 1999; Messenger, 2019). Clearly, the industrial composition matters as well, with countries having larger shares of manufacturing, like Germany, less apt to teleworkability. Additionally, firm size matters being dimensionality a carrier of both

technological and organizational capabilities. At the European level, Vazquez and Winkler (2017) report that the share of teleworking labourers has increased more than 15% in ICT intensive industries during the last decade, while according to the 2015 European Working Condition Survey (EWCS), around 13.5% of European workers had experience of telework, with only 5.2% of them usually working from home (Eurofound, 2020).

Teleworking is supposed to reduce spared time (log-in), eventual unproductive working phases (breaks) and sick leaves. This seems to be confirmed by Bloom et al. (2015) which find that being assigned to telework raises individual productivity. Dutcher (2012), via a quasi-experimental setting, shows that working from home can have positive implications on productivity in the case of creative tasks, while a negative relationship is detected in the case of repetitive and low-skilled tasks.

In terms of workers satisfaction, Arntz et al. (2019), relying on the German Socio-economic panel (GSP) between 1997 and 2014, highlight the importance of workers' socio-demographic characteristics: while childless employees even working an unpaid extra-hour per week report higher satisfaction due to telework, the latter penalizes women compared to men in terms of monthly wages, therefore increasing the gender-pay gap, with women accepting wage reduction against available free time to reconcile home caring schedules (Mas and Pallais, 2017). Increasing overtime is also reported in Lott and Chung (2016).

Overall, if teleworking remains an attribute characterizing only few countries and occupations, having been generically configured as a complementary rather than a unique organizational choice, it is crucial to understand and detect which are the underlying characteristics making teleworking possible, and to estimate the socio-economic risks for those who cannot telework. This is of paramount importance nowadays since teleworking has shifted from being an organizational option (based on workers' voluntary choice) for those few innovative firms and countries of adoption, to a must

necessary to keep operating productive activities under pandemic times.

# 2.2 Teleworking as a must in pandemic times

Teleworkability significantly depends on technical attributes of occupations and on the internal division of labour and knowledge inside organizations. Jobs requiring in-person interactions, or alternatively, transforming external objects/environment and/or deploying complex and voluminous machines can hardly be performed from home. The opposite holds for jobs characterized by the use of ICT devices and software which do not require social exchanges. Therefore, the actual performed tasks, rather than the sheer sector of activity, represent the appropriate level of information to detect teleworkability.

Indeed, the explosion of the pandemic has seen the emergence of a growing literature based on occupation-level data to produce some quantitative assessment of the share of teleworkable jobs. The first study has been Dingel and Neiman (2020) which, relying on the US O\*NET dataset, gave a figure of 37% of the US workforce having the technical feasibility to work from home. According to this study, occupations able to work from home include those in STEM, education, training, and library services, legal and financial activities and managerial ones. At the opposite are those manual workers in building and grounds cleaning and maintenance, food preparation and serving, construction and extraction, and installation, maintenance, and repairing. Corroborating evidence is in Hensvik et al. (2020) which rely on the American Time Use Survey. Among the top-5 most teleworkable occupations at 4-digit, the authors report medical transcriptionists, computer scientists, economists, farmers and artists. Relying on the BIBB/BAuA Employment Survey for German jobs, Alipour et al. (2020) document that 56% of the workforce can potentially shift to telework. The estimate for Italy stands at 30% according to Cetrulo et al. (2020b). All studies report strong heterogeneity across sectors and occupations.

But the question is what happens to the rest of non-teleworkable occupations. Confirming the evidence in Cetrulo et al. (2020b), Brussevich et al. (2020), covering 35 OECD countries, find that workers less likely to work remotely are largely concentrated in sectors more hit by the pandemic, such as accommodation and food services, transportation, and retail and wholesale sectors. According to their estimates, about 15% of the workforce employed is at high risk of layoffs mostly involving vulnerable occupations, sectors and informal labour markets. Montenovo et al. (2020) report heterogeneous economic impacts of the pandemic across US subgroups. They identify as pivotal the role played by occupational characteristics (degree of teleworkability and social interaction) and industry in explaining job losses.

More comprehensive risk analyses are however scant. The exposure to health and employment risks of occupations distinguished by degree of teleworkability is analysed in Beland et al. (2020). Relying on the Current Population Survey to study the impact of stay-at-home orders on employment and wages in the US, they find higher job security for remote occupations. Consistently, Adams-Prassl et al. (2020a) report that the higher the fraction of tasks executable from home, the lower the risk for workers of being furloughed under the UK Job Retention Scheme. For Italy Barbieri et al. (2020) and Boeri et al. (2020) have looked at those sectors of activity more exposed to contagion via physical proximity, with the highest exposure registered in the health sector.

In the following, we aim at contributing to the extant literature by focusing on the underlying characteristics of teleworkability, clarifying, first, which attributes of the working activities allow to telework and, second, quantifying, from a multi-level perspective, the socio-economic risks that those who cannot telework are facing.

# 3. Data, methodology and descriptive evidence

In this section we first present the integrated dataset used to conduct the empirical investigation (Subsection 3.1), and we then move to describe our classification to distinguish those occupations which can and cannot perform their activity from home (Subsection 3.2). Health risks deriving from working activity are presented in Subsection 3.3, while gender divides in terms of teleworkable occupations are discussed in Subsection 3.4.

# 3.1 Integrated datasets description

Our empirical analysis draws on the matching of three different databases, namely the RLFC-ISTAT (Rilevazioni Forza Lavoro) which allows to recover information on the Italian labour force at individual level, the Bancadati delle Professioni-INAIL which provides occupation-based information on labour conditions, namely accidents at work and job diseases, and finally the ICP-INAPP (Indagine Campionaria delle Professioni) providing information on tasks and activities performed at workplaces. From the matching, we exploit a huge informative set, part of the so called Italian Informative System of Occupations (see Table 1 for more details).<sup>1</sup>

The RLFC collects detailed information on workers employment status, income, socio-demographic characteristics (i.e., education, age, gender, region), type of employment contract, 4-digit occupation, and sector of activity. The survey, an annually repeated cross-section, is conducted by the ISTAT three times per year with a quarterly frequency, interviewing around 250 thousand families resident in Italy, corresponding to a total of about 600 thousand individuals, across 1.400 Italian municipalities. Each family is interviewed four times in two subsequent quarters, at year t, and in the corresponding quarters at year t + 1. Our time span of analysis employs the most recent wave, 2016-2017, while the remaining available annual waves up to 2011 are used as robustness checks.

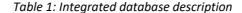
As already illustrated in Cetrulo et al. (2020a), the ICP represents the only European source comparable with the American O\*NET database, the latter being the most comprehensive database reporting qualitative and quantitative information on tasks, skills,

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<sup>&</sup>lt;sup>1</sup> For other studies employing the RLFC-ICP matched dataset see Cirillo et al. (2020); Cassandra et al. (2020).

work contexts and organisational characteristics at the 5-digit level of observation. The construction of the dataset entails a complex, multilayer strategy of data collection and information processing allowing for both detailed occupational descriptions and inter-occupational comparability. Currently, two waves of the ICP database are available (2007 and 2012) with a spectrum covering 797 occupational codes, excluding armed forces. We rely on the 2012 wave. The interviews were administered to 16,000 Italian workers to ensure statistical representativeness with respect to sectoral, occupational, dimensional and geographical heterogeneity. Both O\*NET and ICP questions are organised in six main sections, expressions of a content model that simultaneously provides information from both a joboriented and a worker-oriented perspective. The descriptors are worker characteristics (enduring abilities), worker requirements (skills and education), occupational requirements (organisational and work context), experience requirements (training, cross functional skills), workforce characteristics (labour market information) and occupation-specific information (generalised activities and work context). Therefore, descriptors are formulated by making it possible to distinguish, for instance, inner individual abilities from competences acquired on the job. For each question, two rating scales are generally provided: level and importance.

The Banca dati delle Professioni released by the INAIL (National Institute for Occupational Accident Insurance) contains information on work accidents and occupational diseases' incidence at 5-digit occupational level from 2017 to 2018. The public release of this dataset is part of an integrated project aimed at progressively matching different sources of information on occupations. To our knowledge, this is the first time the INAIL dataset is used in combination with other two sources of information on occupations. To get time-consistent estimation, we use the cross-sectional 2017 wave.



Database	Source	Year	Unit of Analysis	Observations	Variables
RILEVAZIONI FORZA LAVORO	ISTAT	2011-2017	Individuals	More than 85.000	Mad I amount
					<ul> <li>Monthly wage;</li> </ul>
					<ul> <li>Employment status (employed, not employed, inactive);</li> </ul>
					<ul> <li>Socio-demographic variables (age, gender, education, oc- cupation, geographical area, sector).</li> </ul>
INDAGINE CAMPIONARIA	INAPP-ISTAT	2012-2016 wave	4-digit occupation	506	
DELLE PROFESSIONI					<ul> <li>Selection from section G</li> </ul>
					Selection from section H.
BANCA DATI DELLE PROFES-	INAIL	2017	4-digit occupation	506	
SIONI					<ul> <li>Number of accidents at work;</li> </ul>
					<ul> <li>Number of diseases at work (e.g. osteo-muscular, oncological, ner- vous, mental diseases).</li> </ul>

# 3.2 Working from home and teleworkability

Our first step entails the identification of those occupations which can and cannot be performed from home (FH and NFH respectively thereafter). With this purpose, we start with the analysis of the ICP dataset. To identify those jobs, thirty questions belonging to the "generalised activities" (G) and "work context" (H) sections of the ICP have been selected.<sup>2</sup>

Our analysis adapts and expands the methodology proposed by Dingel and Neiman (2020). The selected questions provide insights on the relative importance of:

- performing activities involving (i) use, control and repairing of machines, equipment, vehicles, (ii) social contact, taking care of/or assisting others, (iii) email use;
- performing activities which (i) are carried out outdoors, (ii)
  require exposure to diseases and infections, (iii) imply the
  execution of risky movements or the wearing of protective
  equipment.

The correlation matrix in Figure 1 shows a relatively low degree of overlapping information among our selected variables, and this supports our choice of retaining all thirty entries.

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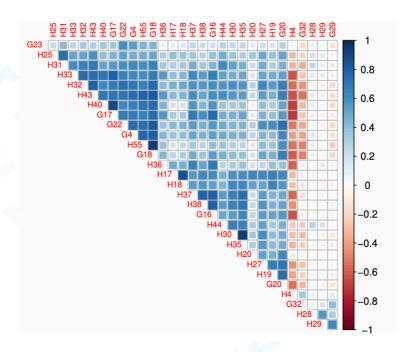
 $<sup>^{\</sup>rm 2}$  This section largely draws upon Cetrulo et al. (2020b).

For each 5-digit occupation, these variables are ranked according to an importance or frequency scale ranging from 0 to 100. For an occupation to be classified as "Not from home", most of the respondents should spend a large fraction of their working time in external environments or use equipment, machinery, tools. Alternatively, they should have continuous contact with the public.

More in detail, our indicator "Not from home" is a binary variable taking value 1 if at least one out of 29 questions (except the use of email) shows a score equal or higher than 60 (corresponding respectively to "once or several times per week" in the time scale of section H, and to "very important" in the importance scale of section G), or if the question on the use of e-mail takes a value lower than 40; viceversa the indicator is equal to zero if for all 29 questions, intensities are lower than 60, or alternatively if the question on the use of mail is higher or equal to 40.

Therefore, if for a given occupation most respondents report that it is very important to control machinery and use equipment, the latter cannot be carried out from home. Similarly, if most respondents report that they perform outdoor tasks for the majority of working time, this occupation cannot be carried out from home. Conversely, if sending e-mails represents a very infrequent activity, the occupation cannot be performed remotely. The classification is useful to identify jobs that can and cannot be executed from home based on the actual performed tasks and work contexts and starts by excluding all those occupations that require working in a well-defined physical space (e.g., because of the use of working instruments or because of intensive social contact). Of course, in case of compulsory social distancing, an occupation as primary school teacher which could not be carried out from home according to our classification, will eventually done remotely. In fact, there are tasks, largely related to activities as "taking care of others" or "working with the public" that could potentially be digitized, however at the cost of entirely reconfiguring the very nature of the profession.

Figure 1 Correlation matrix among ICP questions to construct the binary indicator



An interesting example to appreciate and validate our classification is the case of teachers which, according to the education-level, belong to different categories. In fact, while school teachers cannot work from home, almost all university professors and researchers can actually perform their job remotely. This result depends precisely on the different degree of importance attributed by workers to social contact variables, being the latter more relevant in primary education. Overall, the index performs quite well in consistently assigning the entire set of 4-digit occupations to the two groups *From Home* and *Not From Home*, in such a way that only eight occupations are manually moved from one group to another after an ex-post evaluation of the classification.

After identifying occupational categories at 4-digit, these are aggregated at 1-digit according to the ISCO classification, and then are linked to the Labor Force Survey providing information on the number of employees, wages, contractual types and socio-demographic characteristics of workers (age, gender and level of education). Table 2 presents top-ten occupations at 3-digit for each category. Occupations are ranked in terms of the number of variable

co-occurrences, out of thirty selected variables. The higher the number of co-occurrences, the higher the ranking. Occupations like woodcutters, miners, construction workers, fishermen rank among the top-professions which cannot be performed remotely. On the contrary, occupations involving specialised field knowledge, as legal or linguistic experts, managerial and executive professions are among the top ones which can be performed remotely. In terms of organizational hierarchies, occupations that cannot be performed remotely tend to be located at the low-end of the employment structure. On the contrary, those who self-organize their working activity, give orders or are responsible for high-level administrative tasks can operate remotely.

Overall, only 30% of the workforce has a job that can be done remotely, corresponding to broadly 6.7 million workers (2016 data). For the remaining part, including more than 15 million workers, activities carried out, and work context to which they are exposed do not make working from home feasible (Cetrulo et al., 2020b). This figure is in line with Dingel and Neiman (2020) reporting 37% as the share of occupations which can be done from home for the United States.

By aggregating at 1-digit according to the ISCO classification and distinguishing for gender, in Figure 2 a highly polarized occupational structure emerges with a strong concentration of opportunities to work from home for the upper four occupational groups. Working remotely is feasible for the majority of those who are at the top of the organizational hierarchy (managers, entrepreneurs and legislators), for scientific-intellectual professions, for technical professionals. It increases in administrative tasks. For the lower part of the ISCO classification the scenario radically changes. Service-based occupations, such as entertainment operators, sales workers, artisans, plant and machine operators, as well as elementary professions, see the chance for working remotely drastically shrinking or mostly nil.

Table 2: Top-ten occupations which can and cannot be performed from home (3-digit, ISCO classification). Source: ICP-RCFL (2016)

TOP-TEN OCCUPATIONS WHICH CANNOT BE PERFORMED FROM HOME

644 Specialised forestry workers

- 711 Plant and machinery operators for the extraction and initial treatment of minerals
- 724 Machinery workers in plants for the mass production of wooden items
- 743 Agricultural machinery drivers
- 841 Unqualified mining and quarrying personnel
- 842 Unqualified construction personnel and similar professions
- 716 Plant operators for the production of thermal energy and steam, for waste recovery and for the treatment and distribution of water
- 645 Fishermen and hunters
- 712 Metal processing and hot working plant operators
- 612 Craftsmen and skilled workers in the construction and maintenance of building structures
- TOP-TEN OCCUPATIONS WHICH CAN BE PERFORMED FROM HOME
- 252 Specialists in legal science
- 431 Employees in charge of the administrative management of logistics
- 254 Specialists in linguistic, literary and documentary disciplines
- 411 Secretarial and general affairs employees
- 121 Entrepreneurs and directors of large companies
- 122 Directors and general managers of companies
- 211 Specialists in mathematical, computer, chemical, physical and natural sciences
- 331 Technicians of the organization and administration of production activities
- 432 Economic, accounting and financial management employees
- 251 Management, commercial and banking science specialists

The first take home message from this battery of analyses is that working from home is more a privilege for a tiny fraction of the workforce rather than a generalized and widespread possibility. Why teleworkability is so rare? We now turn to analyse which are the underlying determinants of working from home by employing for the two categories the factor analysis developed in Cetrulo et al. (2020a), the latter developed to identify the dominant traits of the Italian occupational structure.

In this respect, the factor analysis conducted on the ICP dataset revealed that *power* attributes are the most important element to define inter-occupational variability, while *knowledge* attributes are quite widespread across occupations. Finally, *ICT skills* are very much concentrated among few occupations, mainly scientific workers.

To which extent teleworkability is affected by these determinants? Figure 3 shows the kernel density distributions at 4-digit level of the five latent factors emerging from the ICP analysis. The factors read as (i) power, entailed by activities requiring decision-making authority, influence and control over other people, (ii) cognitive and manual dexterity, entailed by activities requiring both physical and cognitive selection of appropriate tools, inspection, control over the process, (iii) ICT knowledge, (iv) team, entailed by those activities requiring

coordination with others, (v) creative, involving those activities which require creative thinking.

For the first three factors, the distinctive kernel density distributions highlight structural differences among the two categories. First of all, performing activities which entail the exercise of power attributes within organisations prevalently characterises FH occupations, confirming empirical studies underlying the importance of holding a relevant degree of autonomy, authority in doing the job, and setting deadlines in order to be able of working remotely. On the other hand, those workers performing activities which require manual dexterity and cognitive ability in dealing with production processes, or in keeping the sequence of machine tools, are largely employed in non teleworkable occupations. ICT skills, which are notably underdiffused in Italy, mainly characterise FH jobs. A similar pattern is shown by team-working which in general prevails in FH occupations. Being creative is instead an attribute not such distinctive. If teleworkability is not only a matter of executing (or non-executing) activities which require manual ability (Sostero et al., 2020), but it also regards the internal position inside organizations, say the hierarchical layer to which one belongs, it becomes even clearer why working from home is more a privilege for restricted social groups rather than a widespread opportunity.

We now turn to present some descriptive statistics on the employment evolution (2011-2016) of occupations according to the two categories (FH and NFH respectively). Indeed, if teleworking from

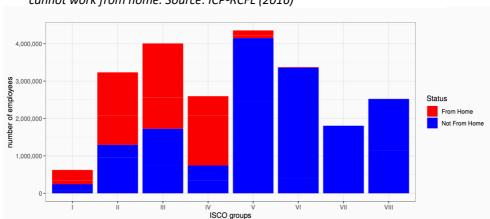


Figure 2 Distribution at 1-digit (ISCO groups) for employees which can and cannot work from home. Source: ICP-RCFL (2016)

being an organizational option becomes the only alternative, we need also to understand the degree of readiness of the Italian occupational structure in absorbing those teleworkable occupations.

During the period under analysis no relevant discontinuity in the growth rate of two groups can be observed (Figure 4), with a stable figure of less than 7 million workers employed in teleworkable jobs with respect to about 15 millions in not teleworkable jobs. Together with a stable trend in NFH occupations, regional disparities clearly emerge, being those relatively few teleworkable occupations concentrated in the North.

Figure 3: Factor scores - Kernel density distributions for FH and NFH occupations

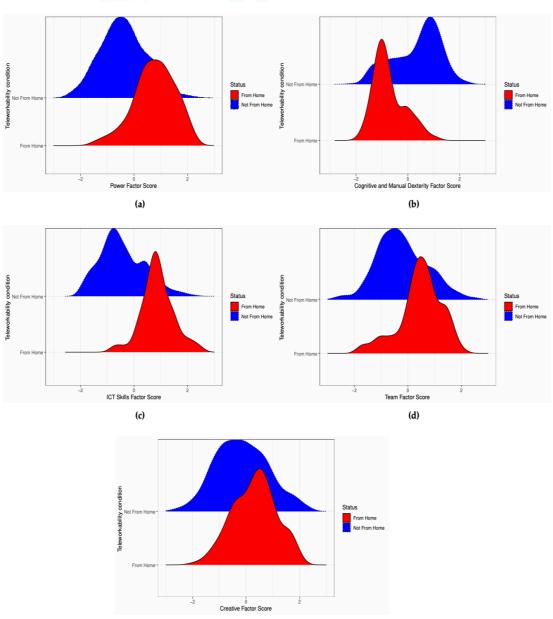
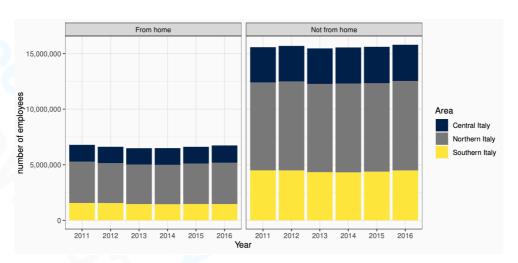


Figure 4: Time-evolution in the number of employees by regional area and teleworkability (2011-2016)



3.3 Health risk at work: physical proximity, accident rates and occupational illness

If working from home represents a privilege in terms of employment stability and income security, with the outburst of the pandemic FH occupations appear also to be the most resilient to risk of contagion. Indeed, face-to-face interactions represent one of the thirty variables included to characterize the two populations: who can telework also enjoys the chance to reduce interpersonal contacts.

Physical proximity and face-to-face interactions have been used to identify sectors of activity and related occupations more exposed to contagion risk (Barbieri et al., 2020). However, the authors retrieve this information from the ICP variable defined as "physical proximity". Although it might be sensible, we deem too restrictive the use of this ICP variable to estimate risk of contagion for two reasons: first, physical proximity might be the result of the very nature of working activity (primarily in the health sector), but also of the physical organization of workplaces (take the case of assembly workers using common spaces as canteens or wardrobes, or of open-space offices in administrative services). The use of this variable tends to confine contagion risk to a sector-specific event, leading to potential underestimation of the risk level in non-health and non-service sectors. For example, in manufacturing or in elementary occupations, workers tend to under-report face-to-face interactions and physical

proximity. However, many activities are performed in quite crowded workplaces, and sharing of workstations with other operators often occurs. Our doubt is confirmed by the distribution of physical proximity across 1-digit occupational groups: it is a prevalent variable, above 60%, only for service and sales workers while it disregards most other occupations (Figure 5.a).

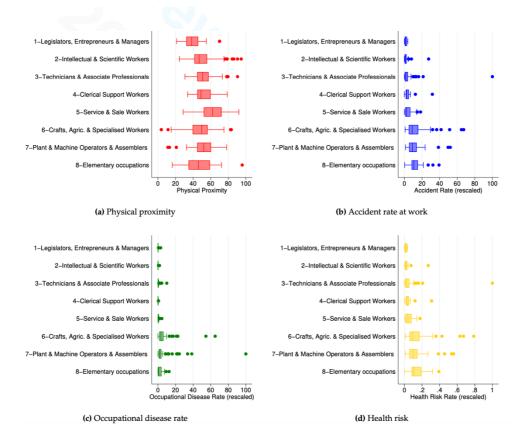
Indeed, relying on disease exposure, physical proximity and gathering, the first release of the INAIL classification on sectoral contagion risks ranked doctors, nurses, pharmacists, police agents, funeral parlours and hairdressers as the most exposed workers, while low contagion risk was assigned to manufacturing and logistics workers (INAIL, 2020a). However, recent updates on contagion at workplaces show an increasing number of cases in logistics and meat processing plants (INAIL, 2020b), wherein working and employment conditions are far from being safe even in normal times (EFFAT, 2020). Indeed, although at the beginning the highest recorded cases were in hospitals, mainly because of the lack of protective devices and adequate sanitizing procedures, recent data show a significant increase in contagion rate within sectors of activity initially classified at low risk.

To overcome these limitations, we deem appropriate to consider a more comprehensive indicator of the actual conditions of safety and health, looking at cases of accidents and occupational illnesses at work, collected by the INAIL database. In fact, even if not directly informing about exposure to contagion, structural, pre-existing information on health and safety conditions at work might proxy the status of employee protection schemes at workplaces at each 4-digit level. Note that these events are *rare* because only certified by legal procedures (Figure 5.b and Figure 5.c), however more concentrated in the bottom part of the ISCO classification.

Looking *both* at occupational illness and accident rates (health risk in Figure 5.d) will prevent the analysis from focusing only on most dangerous NFH occupations, but rather it will offer a comprehensive understanding on safety conditions at work, considering a variety of

physical and psychological risk factors. Not surprisingly, the explosion of the pandemic has also spurred inequalities in terms of health at work. As stressed by the ETUI (2020), these disparities do not only depend on the type of job performed, but they are strictly related to both socio-demographic and organisational factors. Adopting or not rigid health and safety protocols within firms becomes crucial to prevent contagion.

Figure 5: Distribution of physical proximity (ICP), accident rate at work (INAIL), occupational disease rate (INAIL), health risk (authors' elaboration combining accident and disease rates) at 1-digit (ISCO classification)



#### 3.4 Gender divides

Up to the COVID-19 crisis, male and female occupations have never been such differently affected during downturns: indeed, recent empirical evidence documents the phenomenon of *she-recession* to underline how women have been dramatically hit by the pandemic-induced crisis, either for occupational segregation in sectors more exposed to closures (manly social consumption services), or for the

highly unbalanced distribution of domestic burden, inducing many women to leave their job to taking care of children.

Risks, vulnerabilities, and socio-economic hardships affecting women intersect in the pandemic phase. With reference to Italy, on the one hand, many female workers kept working because employed in so-called *essential* sectors but, on the other hand, those who carried out domestic and care jobs, such as housekeepers and carers, were largely unable to access income and welfare supports due to the still predominantly irregular and informal nature of employment relationships in this sector.

Therefore, to analyse and map vulnerabilities characterizing different professions, introducing a gender dimension enlarges our comprehension on those segments upon which the pandemic is hitting harder. Figure 6 presents the breakdown of FH and NFH occupations by distinguishing for male and female workers. Women working from home are mostly concentrated among clerical support workers doing administrative activities and to a less extent among scientific and technical professions. They hardly materialize among the top professions of the first ISCO group. Among these women, many had the chance to telework, therefore maintaining income and job, however enormously suffering the burden of conciliation between working and caring activities, primarily children education. Moving to those one who cannot telework, which indeed represent the largest fraction, they are mainly concentrated among service and sales, and elementary occupations. Those women not having the chance to telework, together with the care-work burden, had also to cope with income, employment, and safety risks.

Indeed, power and ICT skills predominantly characterize teleworkable jobs and therefore appreciable heterogeneities regard FH occupations, in accordance with Figure 3.

3,000,000

Female

2,000,000

1,000,000

INDICATION TO MAIN

Not From Home

Not From Home

Figure 6: Gender distribution at 1-digit (ISCO classification) for employees which can and cannot work from home. Source: ICP-ILFS (2016)

# 4 Estimates of risk stratification

After having identified (i) occupations which can and cannot be performed from home, (ii) the underlying attributes of teleworkability, (iii) the importance of considering a more comprehensive nature of safety conditions at work, we now move toward the empirical estimation of three forms of risks, namely employment, income, and health safety. The goal is to verify whether a different risk profile emerges with respect to the probability of losing the job, earning a low income and facing more frequently accidents at work and occupational illnesses, which will be our outcome variables, once we classify workers according to their teleworkability, also in line with the extant literature (Mongey and Weinberg, 2020).

Figure 7 shows the histograms of our three outcome variables distinguishing between FH and NFH occupations. Already at a first glance it emerges a distinctive pattern characterizing the two populations: indeed, all three events are extremely concentrated among not working from home occupations, while the frequency of occurrence strongly decays for the other group.

This evidence supports our following empirical investigation meant at quantifying the different probabilities of risk occurrence for the two groups, and the role played by other relevant socio-demographic, contractual and sectoral characteristics impacting on the latter

probabilities. Additionally, as a further extension, we assess whether male and female workers are differently hit.

4.1 Empirical strategy and variables description

The empirical analysis applies the binary response methodology on two different databases:

- a micro data-set built merging ISTAT RLFC-ICP, on which we estimate for each individual i those factors affecting the probability of (i) transition to unemployment and (ii) earning a low income;
- an aggregated data-set merging ICP-INAIL-ISTAT, where for each occupation j at 4-digit we look at those characteristics having an impact on the probability of (iii) low income and (iv) high accident risk and illness at work.

We assume that the response probability takes the following form:

$$P(y=1 \mid \mathbf{x}) = P(y=1 \mid x_1, x_2, .... x_k) = G(Z) \ G(z) = \Phi(Z) = \varphi(v) dv$$
 with  $\varphi(z)$  being a standard normal density function: 
$$\varphi(z) = (2\pi)^{-1/2} \exp(-z^2/2)$$

We perform four univariate probit models, with dependent variables expressed as binary dummies:

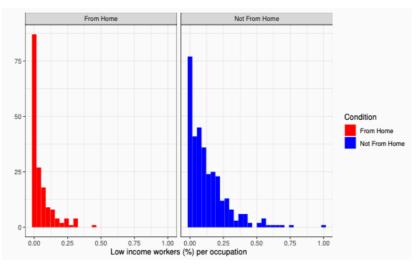
- Transition to unemployment (i): Y\_1i = 0, 1, where Y\_1i = 1 if individual i is employed at time t but he becomes unemployed or inactive at time t + 1; Y\_1i = 0 if otherwise.
- 2. Low income (i):  $Y_2i = 0$ , 1, where  $Y_2i = 1$  if the income of individual i belongs to the lowest income quartile of the entire workforce wage distribution;  $Y_2i = 0$  if otherwise.
- 3. Low median income (j):  $Y_-3j = 0$ , 1, where  $Y_-3j = 1$  if the median income of occupation j belongs to the lowest income tercile of occupations' median wages distribution;  $Y_-3j = 0$  if otherwise.

4. High health risk (j):  $Y_24j = 0$ , 1, where  $Y_24j = 1$  if the rate of accidents at work and occupational illnesses j belong to the highest tercile of the distribution;  $Y_24j = 0$  if otherwise.

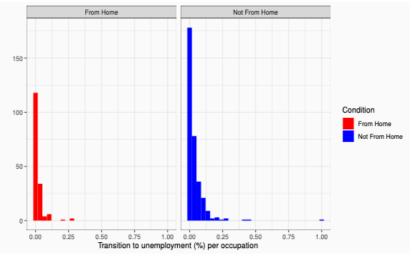
where i = individual with i = 1, ..., 85.763 and j=occupation at 4-digit with j = 1, ...487.

We estimate four univariate probit models, at individual and occupation-level, against the indicator "Working from home" built on the ICP dataset (2012) and a set of covariates expressed in terms of dummies or categorical variables, as described in Table 3. The choice of a parametric model implies the loss of information on potential heterogeneous effects for each population of interest. For example, it might be that employment risk increases for some 4-digit occupations, because of processes of restructuring of the sector of activity. However, being our covariates dummy or categorical variables, it is not possible to proceed with non-parametric probit estimations allowing for local effects of the regression coefficients, changing with the intensity of explanatory variables. Fitness of the four models has been assessed through sensitivity (detection of true positives rate) and specificity (detection of true negatives rate) analysis. ROC curves (available upon request) show a strong positive concave relationship, with areas always above 70% which indicate a more than satisfying diagnostic ability of the model with respect to power and type I errors.

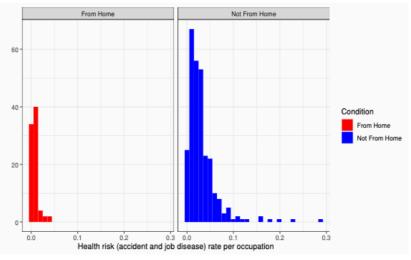
Figure 7: Histograms of the events: a) earning a low income; b) transition to unemployment; c) having an accident at work and/or occupational illness.



(a) Low income distribution



(b) Transition to unemployment distribution



(c) Occupational disease and/or accident at work rates distribution

### 4.2 Employment and income risks

Our first variable of interest is the risk of losing the job for an individual employed in a FH occupation, as a baseline, compared with an individual in a NFH occupation. To define the employment risk, we look at individual transition events from employment to unemployment or inactivity, from time t (2016) to t + 1 (2017). Given the lack of longitudinal panel data at individual level, we can capture only yearly based transitions to unemployment, therefore discarding information from longer transition spells. Likely, the baseline transition year, 2016, is not characterised by strong cyclical macroeconomic factors which could have alternatively impacted upon estimation results. Indeed, it was a period of anemic recovery since the 2008 crisis. Additionally, we are not able to capture persistent unemployment and duration effects. Those caveats should clarify about the potential underestimated figures we provide.

Table 4 (column 1) presents the probit regression coefficients. Confirming the information from Figure 7, but now controlling for a comprehensive set of covariates, the variable "Not working from home", shows a positive and significant effect on the probability of transiting to unemployment status for a worker being employed in a NFH occupation as compared to a FH occupation. This positive sign confirms the presence of an inherent higher risk of losing the job, independently from external shocks such as the pandemic, which characterizes those occupations classified as NFH, after controlling for factors such as age, gender, education level and contractual framework. We also observe that being employed in sectors such as Construction, Art and other Services significantly increases the risk of losing the job (with respect to the manufacturing sector), whereas the opposite holds for those working in Public Administration, Education, Health and Agriculture. Positive and statistically significant coefficients of the two geographical controls confirm the presence of regional disparities in terms of employment security, with workers

Table 3: Probit's variables (individual and occupational level data)

located in Southern and C	ontral I	taly being more exposed to risks of			
located in Southern and C	Cilciaii	taly being more exposed to risks of			
unemployment with respect to their colleagues in the North.					
,					
Table 3: Probit's variables (individual and occupational level data)					
Variable	Туре	Values			
Individual level data					
$Y1_i$ : Transition wide	Dummy	1/:6			
T <sub>i</sub> : Transition wide	Dummy	1 (if employed at time $t$ and unemployed or inactive at time $t+1$ ), 0 (if otherwise)			
$Y2_i$ : Low income	Dummy	$\boldsymbol{1}$ (if income belongs to the first quartile of income distribution), $\boldsymbol{0}$ (if otherwise)			
OCCUPATIONAL LEVEL DATA					
$Y3_j$ : Low income	Dummy	1 (if the median wage belongs to the lowest tercile of income distribution), 0 (if otherwise)			
$Y4_{j}$ : High health risk at work	Dummy	1 (if the health risk belongs to the highest tercile of the health risk			
		distribution, that equals to the sum of job accidents and occupa- tional illnesses), 0 (if otherwise)			
Not From Home	Dummy	1.0			
Female	Dummy	1 (if sex=female), 0 (if sex=male)			
Age Group	Categorical	1 (if age=16-35), 2 (if age=36-50), 3 (if age=51-75)			
Education level	Categorical	1 (if level =lower secondary), 2 (if level =secondary), 3 (if level =			
Job Contract	Categorical	bachelor), 4 (if level = master)  1 (if contract = permanent), 2 (if contract = temporary), 3 (if con-			
Job Contract	Categoricai	tract = autonomous)			
Area	Categorical	1 (if area = Northern Italy), 2 (if area = Central Italy), 3(if area =			
Agriculture	Dummy	Southern Italy) 1 (if nace = 1), 0 (if otherwise)			
Mining and Quarrying	Dummy	1 (if nace = 2), 0 (if otherwise)			
Manufacturing	Dummy	1 (if nace = 3-9), 0 (if otherwise)			
Electricity Gas Water & Waste	Dummy	1 (if nace = 10), 0 (if otherwise)			
•	Dummy	1 (if nace = 11), () (if otherwise)			
Construction	Dummy	1 (if nace = 11), 0 (if otherwise) 1 (if nace = 12), 0 (if otherwise)			
Construction Wholesale Transport & Accommodation	Dummy	1 (if nace = 12), 0 (if otherwise)			
Construction Wholesale Transport & Accommodation Information & Communication	Dummy Dummy	1 (if nace = 12), 0 (if otherwise) 1 (if nace = 13), 0 (if f otherwise)			
Construction Wholesale Transport & Accommodation Information & Communication Financial & Insurance Act	Dummy Dummy Dummy	1 (if nace = 12), 0 (if otherwise) 1 (if nace = 13), 0 (if f otherwise) 1 (if nace = 14), 0 (if otherwise)			
Construction Wholesale Transport & Accommodation Information & Communication Financial & Insurance Act Real Estate Activities	Dummy Dummy	1 (if nace = 12), 0 (if otherwise) 1 (if nace = 13), 0 (if f otherwise) 1 (if nace = 14), 0 (if otherwise) 1 (if nace = 15), 0 (if otherwise)			
Construction Wholesale Transport & Accommodation Information & Communication Financial & Insurance Act	Dummy Dummy Dummy Dummy	1 (if nace = 12), 0 (if otherwise) 1 (if nace = 13), 0 (if f otherwise) 1 (if nace = 14), 0 (if otherwise)			

Table 4: Probit models (micro data 2016-2017)

	(1)	(2)
	Unemployment Risk	Low Income
Not From Home	0.187***	0.374***
T 1	(5.31)	(18.41)
Female	0.197***	0.749***
26 5014	(7.41)	(44.76)
36-50 years old	-0.222***	-0.257***
F0.7F	(-7.90)	(-13.64) -0.448***
50-75 years old	-0.358***	
I d d d 11	(-10.84) 0.230***	(-21.05)
Lower secondary education level		0.717***
Cocon damy adversation layed	(4.67)	(24.74)
Secondary education level	0.0815	0.498***
P 1 1 2 2 1 1	(1.80)	(18.94)
Bachelor education level	0.185*	0.141**
Towns and Combined	(2.52)	(3.19)
Temporary Contract	0.780***	0.271***
	(25.80)	(12.11)
Autonomous Contract	0.0628*	-1.458***
Comton Italy	(1.97) 0.119***	(-44.12) 0.145***
Center Italy		
Cth It-l	(3.71)	(7.61)
Southern Italy	0.369***	0.348***
A	(13.97)	(20.08)
Agriculture	-0.236***	0.671***
W: 40	(-3.72)	(16.84)
Mining & Quarrying	-0.223	0.341*
TI	(-0.89)	(1.97)
Electricity Gas Water & Waste	-0.153	-0.0982
	(-1.13)	(-1.47)
Construction	0.280***	0.182***
IA/h alacala Transment & A 1-4	(5.95)	(4.50)
Wholesale Transport & Accommodation	0.0602	(19.07)
Information & Communication	(1.60)	(19.07) 0.177**
miormation & Communication	0.0124	
Financial & Insurance Activities	(0.12) -0.301*	(2.72) -0.206**
rmancial & insurance Activities	-0.301 (-2.16)	(-3.22)
Real Estate Activities	0.298*	0.573***
Real Estate ACTIVITIES		
Professional Scientific Support Activities	(2.16) 0.130**	(5.25) 0.790***
Professional Scientific Support Activities		
	(2.66)	(26.86)
Public Administration, Education & Human Health	-0.396***	0.0517
	(-7.56)	(1.85)
Art & Other Services	0.292***	1.067***
	(6.33)	(35.60)
_cons	-2.339***	-2.251***
	(-38.09)	(-60.73)
N	82,177	85,763
$PseudoR^2$	0.124	0.256

Figure 8, left panel, presents the average marginal effects for NFH occupations. This effect, as expected, turns out to be relatively small (1.1%) because of the "rare" event we are measuring (one year-based transition to unemployment), and to a lesser extent, because of the high number of observations. Other relevant worker attributes which increase the probability of transition to unemployment, or inactive status, are being woman and young, holding a low education title. Indeed, temporary workers experience an employment risk 8% higher

t statistics in parentheses p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

with respect to workers with a permanent contract. In the current post lock-down phase, reports on the labour market released by the ISTAT record a huge rise in job losses for temporary workers (ISTAT, 2020).

Our second measure of risk concerns the probability of earning a low income. Income risks are particularly important to be analysed because of the reduced access to work for those individuals who cannot operate from home. Therefore, it is pivotal to understand the pre-existing probabilities of getting a low income whenever a worker employed in a NFH job stops doing its own activity for social distance measures and related policy regulation. To study the probability of earning a low income, we distinguish among four wage quantiles, namely low, medium-low, medium-high and high. We intentionally focus on the low wage quantile since we want to assess whether NFH occupations, receiving less income, have also less access to precautionary savings in case of income shocks.

Table 4, column 2, shows the probit regression coefficients for income risk. The coefficient of the NFH variable is positive and statistically different from zero, implying that belonging to an occupation which cannot be performed remotely inherently increases the probability of earning a low wage. Figure 8, right panel, presents the average marginal effects. The effect of NFH is now sizeable and much bigger than the corresponding one on employment risk (around 6%). This occurs also because of the higher persistence characterizing the wage distribution, which from year to year tends to show a relatively stable support. With respect to the role played by other covariates, being woman now increases the probability of earning a low income of 15%. Indeed, holding a temporary contract increases the probability of earning a low income of 8%. Also in this case regional disparities are at stage, with Southern and Central workers recording higher risks of earning a low income. With respect to sectoral heterogeneity, only workers in Finance and Insurance Activities exhibit a lower income risk (compared to the base

manufacturing group), as shown by its negative and statistically significant coefficient.

Figure 9 presents differentiated marginal effects by gender and contractual categories highlighting gender divides and role of precariousness.

#### 4.3 Safety risks

After having identified employment and income risks, we now move toward the estimation of safety risks. To accomplish the latter task, we employ the occupational level dataset ICP-INAIL-ISTAT whose unit of observation is not the individual (as in previous analyses) but the occupation at 4-digit level. More precisely, we investigate whether occupations that cannot be performed from home are more likely to be characterized by a higher health risk (built as the sum of accidents at work and occupational illnesses) and, as robustness check, also by a lower level of income. To control for several factors and to be consistent with the previous estimations, we exploit information from the labour force survey to build gender, regional, sectoral, education and contractual dummies. The routine adopted is as such that if the 60% of workers of a given occupation are e.g., female, that occupation is defined as "female dominated" and so on.

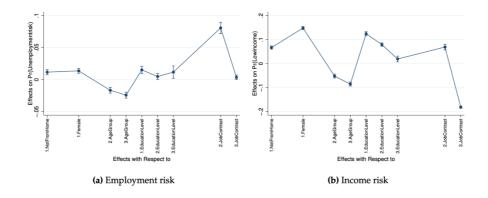
According to Table 5, the coefficient of NFH is positive and statistically different from zero in both probit models. This outcome confirms the result obtained in the previous analysis concerning the risk of low wage, but it also adds an important information related to the dimension of health and safety at work. Indeed, as shown in Figure 10, moving from teleworkable to not teleworkable jobs increases the probability of facing a higher safety risk at work by more than 30%. Clearly, the computed probabilities are much higher than the one presented in the previous section because in this case the analysis is based on occupational rather than individual level data, increasing by construction the average marginal effects. Regarding the role played by other covariates, while belonging to a female/temporary contracts dominated profession strongly increases the probability of getting a

low income, safety risks are higher in male dominated professions with permanent contracts.

Table 5: Probit models (occupational level data 2016)

Not From Home			
Not From Home   0.860***   1.169***   (4.54)   (4.74)   Female   1.160***   -0.445   (6.13)   (-1.95)   Permanent   -0.565***   0.459**   (-3.59)   (2.61)   Degree   -1.488***   -1.378**   (-4.74)   (-2.99)   North   -0.451**   -0.0580   (-2.84)   (-0.34)   Agriculture   1.175***   0.462   (3.48)   (1.38)   Manufacturing   0.275   0.625**   (1.37)   (2.92)   Electricity Gas Water & Waste   0.0409   1.335**   (0.06)   (2.85)   Construction   -0.134   0.667*   (-0.42)   (2.12)   Wholesale Transport & Accommodation   0.341   0.602*   (1.38)   (2.30)   Real Estate Activities   1.856**   0   (3.04)   (.)   Professional Scientific Support Activities   0.894*   0.270   (2.41)   (0.67)   (-4.46)   (1.26)   (-4.46)   (1.26)   (-4.46)   (1.26)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)   (-4.46)		(1)	(2)
Female         (4.54)         (4.74)           Female         1.160***         -0.445           (6.13)         (-1.95)           (-0.565****         0.459**           (-3.59)         (2.61)           Degree         1.488***         -1.378**           (-4.74)         (-2.99)           North         -0.451**         -0.0580           (-2.84)         (-0.34)           Agriculture         (3.48)         (1.38)           Manufacturing         0.275         0.625**           (1.37)         (2.92)           Electricity Gas Water & Waste         0.0409         1.335**           Construction         -0.134         0.667*           (-0.42)         (2.12)           Wholesale Transport & Accommodation         (1.38)         (2.30)           Real Estate Activities         1.856**         0           Real Estate Activities         0.894*         0.270           Public Administration, Education & Human Health         -0.408         0.376           Art & Other Services         0.665*         0.290           (2.16)         (0.84)           -cons         -0.887***         -2.140***           -0.7887***         -2.140**			
Female         1.160***         -0.445           (6.13)         (-1.95)           Permanent         -0.565***         0.459**           (-3.59)         (2.61)           Degree         -1.488***         -1.378**           (-4.74)         (-2.99)           North         -0.451**         -0.0580           (-2.84)         (-0.34)           Agriculture         1.175***         0.462           (3.48)         (1.38)           Manufacturing         0.275         0.625**           (1.37)         (2.92)           Electricity Gas Water & Waste         0.0409         1.335**           Construction         -0.134         0.667*           (-0.42)         (2.12)           Wholesale Transport & Accommodation         0.341         0.602*           (1.38)         (2.30)           Real Estate Activities         1.856**         0           (3.04)         (.)           Professional Scientific Support Activities         0.894*         0.270           Public Administration, Education & Human Health         -0.408         0.376           (-1.46)         (1.26)         0.665*         0.290           (-2.16)         (0.84) <td>Not From Home</td> <td></td> <td>1.169***</td>	Not From Home		1.169***
Permanent			(4.74)
Permanent         -0.565***         0.459**           C3.59)         (2.61)           Degree         -1.488***         -1.378**           (4.474)         (-2.99)           North         -0.451**         -0.0580           (-2.84)         (-0.34)           Agriculture         (1.175***         0.462           (3.48)         (1.38)           Manufacturing         0.275         0.625**           (1.37)         (2.92)           Electricity Gas Water & Waste         0.0409         1.335**           Construction         -0.134         0.667*           Vholesale Transport & Accommodation         (1.38)         (2.30)           Real Estate Activities         (1.38)         (2.30)           Real Estate Activities         1.856**         0           Professional Scientific Support Activities         0.894*         0.270           Public Administration, Education & Human Health         -0.408         0.376           Art & Other Services         0.665*         0.290           (2.16)         (0.84)         -0.126           -cons         -0.887***         -2.140***           -0.897**         -2.140***         -0.406           -0.591*	Female	1.160 ***	-0.445
C3.59   C2.61     Degree			
Degree -1.488*** -1.378** (-4.74) (-2.99) North -0.451** -0.0580 (-2.84) (-0.34) Agriculture -1.175*** 0.462 (-2.84) (-0.34) Agriculture -1.175*** 0.462 (-2.84) (-0.34) Manufacturing -0.275 0.625** (-1.37) (2.92) Electricity Gas Water & Waste -0.0409 1.335** (-0.06) (-2.85) Construction -0.134 0.667* (-0.42) (2.12) Wholesale Transport & Accommodation -0.341 0.662* (-0.42) (2.12) Wholesale Transport & Accommodation -1.856** 0 Real Estate Activities -1.856** 0 Professional Scientific Support Activities -1.856** 0 Professional Scientific Support Activities -0.894* 0.270 (-2.41) (0.67) Public Administration, Education & Human Health -0.408 0.376 (-1.46) (-1.26) Art & Other Services -0.665* 0.290 (-2.16) (0.84)0.887*** -2.140*** -2.140*** -2.140***	Permanent	-0.565***	0.459**
North		(-3.59)	(2.61)
North         -0.451**         -0.0580           Agriculture         (-2.84)         (-0.34)           Agriculture         (3.48)         (1.38)           Manufacturing         0.275         0.625**           Electricity Gas Water & Waste         0.0409         1.335**           Electricity Gas Water & Waste         (0.06)         (2.85)           Construction         -0.134         0.667*           (-0.42)         (2.12)           Wholesale Transport & Accommodation         (1.38)         (2.30)           Real Estate Activities         1.856**         0           (3.04)         (.)           Professional Scientific Support Activities         0.894*         0.270           Public Administration, Education & Human Health         -0.408         0.376           (-1.46)         (1.26)         0.665*         0.290           (2.16)         (0.84)         -0.887***         -2.140****           _cons         -0.887***         -2.140****           _6.95)         -0.950         -0.950	Degree	-1.488***	-1.378**
Agriculture (-2.84) (-0.34) Agriculture (1.175*** 0.462 (3.48) (1.38) Manufacturing (0.275 0.625** (1.37) (2.92) Electricity Gas Water & Waste (0.06) (2.85) Construction (-0.134 0.667* (-0.42) (2.12) Wholesale Transport & Accommodation (0.341 0.602* (1.38) (2.30) Real Estate Activities (1.38) (2.30) Professional Scientific Support Activities (3.04) (.) Professional Scientific Support Activities (2.41) (0.67) Public Administration, Education & Human Health (-0.408 0.376) Art & Other Services (0.65* 0.290) (-2.16) (0.84) _cons (-0.887*** 2.140*** (-0.95)  N 487 485		(-4.74)	(-2.99)
Agriculture 1.175*** 0.462	North	-0.451**	-0.0580
Manufacturing		(-2.84)	(-0.34)
Manufacturing     0.275     0.625**       (1.37)     (2.92)       Electricity Gas Water & Waste     0.0409     1.335**       (0.06)     (2.85)       Construction     -0.134     0.667*       (-0.42)     (2.12)       Wholesale Transport & Accommodation     (3.341     0.602*       (1.38)     (2.30)       Real Estate Activities     1.856**     0       (3.04)     (.)       Professional Scientific Support Activities     0.894*     0.270       Public Administration, Education & Human Health     -0.408     0.376       (-1.46)     (1.26)       Art & Other Services     0.665*     0.290       (2.16)     (0.84)       _cons     -0.887***     -2.140***       _cons     (3.94)     (-6.95)       N     487     485	Agriculture	1.175***	0.462
Construction   Cons		(3.48)	(1.38)
Electricity Gas Water & Waste	Manufacturing	0.275	0.625**
Construction		(1.37)	(2.92)
Construction -0.134 0.667*  (-0.42) (2.12)  Wholesale Transport & Accommodation 0.341 0.602* (1.38) (2.30)  Real Estate Activities 1.856** 0 (3.04) (.)  Professional Scientific Support Activities 0.894* 0.270  Public Administration, Education & Human Health -0.408 0.376  (-1.46) (1.26)  Art & Other Services 0.665* 0.290 (2.16) (0.84)  _cons -0.887*** -2.140***  (-3.94) (-6.95)  N 487 485	Electricity Gas Water & Waste	0.0409	1.335**
C-0.42  (2.12)   Wholesale Transport & Accommodation		(0.06)	(2.85)
Wholesale Transport & Accommodation 0.341 0.602* (1.38) (2.30)  Real Estate Activities 1.856** 0 (3.04) (.)  Professional Scientific Support Activities 0.894* 0.270 (2.41) (0.67)  Public Administration, Education & Human Health -0.408 0.376 (-1.46) (1.26)  Art & Other Services 0.665* 0.290 (2.16) (0.84)  _cons -0.887*** -2.140*** (-3.94) (-6.95)  N 487 485	Construction	-0.134	0.667*
(1.38) (2.30)   Real Estate Activities   1.856**   0     (3.04)   (.)     Professional Scientific Support Activities   0.894*   0.270     Public Administration, Education & Human Health   -0.408   0.376     Public Administration, Education & Human Health   -0.408   0.376     Art & Other Services   0.665*   0.290     (2.16)   (0.84)     _cons   -0.887***   -2.140***     (-3.94)   (-6.95)     N   487   485		(-0.42)	(2.12)
Real Estate Activities     1.856** (3.04) (.)       Professional Scientific Support Activities     0.894* (2.270) (2.41) (0.67)       Public Administration, Education & Human Health     -0.408 (0.376) (-1.46) (1.26) (0.665* (0.290) (2.16) (0.84)       Art & Other Services     (2.16) (0.84) (-0.887*** (2.140****) (-3.94) (-6.95)       N     487 (485)	Wholesale Transport & Accommodation	0.341	0.602*
(3.04) (.)   Professional Scientific Support Activities   0.894*   0.270     (2.41) (0.67)     Public Administration, Education & Human Health   -0.408   0.376     (-1.46) (1.26)     (4.146) (1.26)     (-1.46) (1.26)     (2.16) (0.84)     (-0.887***   -2.140***     (-3.94) (-6.95)     N   487   485		(1.38)	(2.30)
Professional Scientific Support Activities 0.894* 0.270 (2.41) (0.67) Public Administration, Education & Human Health -0.408 0.376 (-1.46) (1.26) Art & Other Services 0.665* 0.290 (2.16) (0.84) -cons -0.887*** -2.140*** (-3.94) (-6.95)  N 487 485	Real Estate Activities	1.856**	0
C2.41		(3.04)	(.)
Public Administration, Education & Human Health (-0.408 0.376 (-1.46) (1.26) Art & Other Services 0.665* 0.290 (2.16) (0.84) _cons -0.887*** -2.140*** (-3.94) (-6.95)  N 487 485	Professional Scientific Support Activities	0.894*	0.270
Art & Other Services (-1.46) (1.26)  Art & Other Services 0.665* 0.290 (2.16) (0.84)  _cons -0.887*** -2.140*** (-3.94) (-6.95)  N 487 485		(2.41)	(0.67)
Art & Other Services 0.665* 0.290 (2.16) (0.84) _cons -0.887*** -2.140***	Public Administration, Education & Human Health	-0.408	0.376
(2.16) (0.84) -0.887*** -2.140*** (-3.94) (-6.95)  N 487 485		(-1.46)	(1.26)
_cons     -0.887***     -2.140****       _(-3.94)     (-6.95)       N     487     485	Art & Other Services	0.665*	0.290
(-3.94) (-6.95) N 487 485		(2.16)	(0.84)
N 487 485	_cons	-0.887***	-2.140***
		(-3.94)	(-6.95)
$PseudoR^{2}$ 0.307 0.237	N	487	485
	$PseudoR^2$	0.307	0.237

Figure 8: Average marginal effects on employment and low income risks -Regression in Table 4



t statistics in parentheses \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Figure 9: Differentiated marginal effects by gender and contractual categories from probit estimates in Table 4

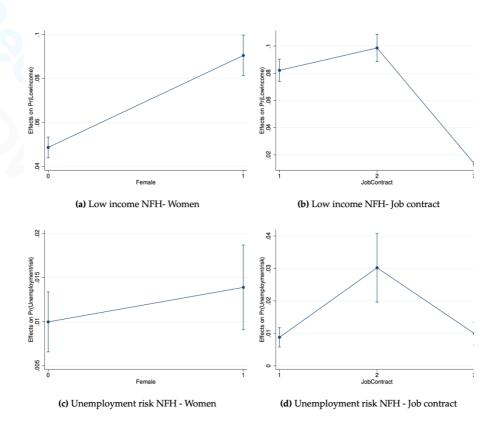
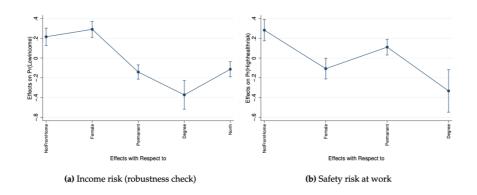


Figure 10: Average marginal effects on low income and health risks from probit estimates in Table 5



# **5 Discussion and conclusions**

With the outbreak of the COVID-19 pandemic, although heterogeneously in terms of timing and intensity, governments opted for social distancing measures directed at reducing interpersonal

contacts, the latter being identified as the main source of contagion. In this context, advising or requiring workers to work from home represented one of the key measures included in the 'anti-COVID 19' social distancing policy packages (OECD, 2020). Currently, telework keeps being the preferred organizational option to meet a twofold goal: (i) ensuring the continuity of productive activities, (ii) keeping the frequency of social interactions (and the risk of contagion) low. Employers' interest to implement this flexible (and less costly) working practice is growing, despite a clear understanding on its functioning and effects is still missing. Big private companies and public administrations have very quickly allowed their employees to work from home. The second contagion wave has again fostered teleworking in public bodies, while trade unions are calling for national collective agreements to clearly define the boundaries and the modality of telework.

Such a pandemic-induced spreading of telework is showing heterogeneous effects on labour market segments: indeed, maintaining full-time working hours and switching to telework represent a suitable option only for a fraction of the working population, belonging to the upper echelon of hierarchies, being employed in occupations not requiring manual and cognitive dexterity, endowed by ICT-knowledge. Therefore, although telework represents an important safety net in terms of health, employment, and income security, it can also turn out into an inequality-enhancing mechanism between those who can and those who cannot work from home.

All in all, switching to telework requires good economic outlook for firms, organizational and technological capabilities. Companies with negative prospects are more likely to fire employees, reduce working hours (and wages), stop temporary hiring, rather than switching to telework. The lack of technological infrastructures (i.e., high-speed Internet, adequate computers, and ICT devices) and organizational capabilities might prevent to opt for telework, increasing unemployment risks for their employees, currently largely contained

by lay-off suspensions. Therefore, telework, and thus opportunities for employment and income continuity, are likely to be unevenly distributed across sectors, firms, occupations and workers not only in the short but also in the medium term.

In this paper, we aimed at assessing the presence of enduring divides between Italian workers that can work from home and those who cannot. This distinction, grounded on the study of occupational characteristics and their telework feasibility, turns out to be revealing of stratifying vulnerabilities in terms of income remuneration, employment stability and safety at work. Our results show that NFH workers record higher probabilities of earning low wage, losing job, experiencing accidents at work and occupational illnesses with respect to FH workers. Women and temporary workers face stratifying and conflating risks. The empirical evidence, referred to 2016-2017 Italian labour force data, shows the existence of enduring differences that are likely to explode in phases of downturns and crises, as already signaled by short-term occupational data. Indeed, first available statistics confirm the higher incidence of job losses among NFH and precarious workers (see, for instance, Guven et al. (2020) for Australia; Montenovo et al. (2020) for USA; Adams-Prassl et al. (2020a) for the UK). All this couple with a stagnant labour demand in teleworkable occupations, almost concentrated in the North of Italy. Consequently, labour and social protection policies should aim at reducing rather than exacerbating those divides, starting with flexible shifts, extension of sick leaves, full-paid paternal and maternal leaves, secure income stability. At the same time, fostering social dialogue and promoting the adoption of effective health and safety protocols through the direct involvement of workers and trade unions is crucial (ILO, 2020).

Finally, when discussing about telework, we need to distinguish between telework as an organizational option and telework as the only choice. In the first case, it should be conceived as part of a policy strategy pushing for shorter and more flexible working time, preventing and limiting all the documented side effects, such as

increasing work intensification and unpaid overtime, difficulties in balancing working and private life and risk of burnout, being only some of the drawbacks reported by workers (Messenger, 2019), by means of contractual regulations. Second, given the lack of conclusive evidence on firm performances, on the processes of knowledge diffusion, on creativity, on collaborative practices among workers, a complete switch to telework is not advisable as well.

Future lines of research entail the study of heterogeneity across teleworkers, in terms of occupational categories, sectors of activity and employer characteristics. What is more, if telework will essentially turn into working from home, availability of adequate private spaces, responsibility of looking after kids and doing houseworks will strongly influence the overall consequences of telework across hierarchical positions and gender.

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