UNIVERSITY OF MODENA AND REGGIO-EMILIA

Ph.D. Program in Labour, Development and Innovation

XXXIII Cycle

The cornerstone of individuals' progression: Rethinking the education after the COVID-19 pandemic

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“Utopia is on the horizon.

I move two steps closer; it moves two steps further away.

I walk another ten steps and the horizon runs ten steps further away.

As much as I may walk, I'll never reach it.

So what's the point of utopia?

The point is this: to keep walking.”

Eduardo Galeano

To Serena, who makes this world a better place.

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Abstract

In contemporary societies, schooling is a fundamental resource in enabling persons to achieve the fullest opportunity to develop their abilities. In light of this, equity and quality of the education system are among the fundamental pillars of developed countries.

The present research points out the need to build a more inclusive education system. In particular, it focuses on the analysis of the direct and indirect effects of the Covid-19 pandemic on social inequalities, by addressing some education policy proposals to overcome these disparities.

The first chapter analyses the potential social consequences of a persistent diffusion of working from home procedures after the Covid-19 outbreaks. By applying an influence function regression method to the INAPP-PLUS survey, it analyses how an increase in the number of employees who have the opportunity to work from home may impact on the distribution of labour income. Results show that the potential benefits deriving from this shift would be unequally distributed among workers.

The second chapter examines the effects that the economic cycle could produce on decisions by people to invest in post-compulsory education. Results may be particularly important in light of the negative economic trend consequent to the outbreak. Adopting a fixed effect model on panel data from EU-SILC, findings exhibit a negative relation between the economic trend and the decision to invest in education for the poorer population, while the relationship for the wealthier people is a-cyclical. Therefore, the economic cycle has a different impact on educational choices along the income distribution.

The third chapter assess the impact of national social distancing measures (i.e., the closure of schools, the main lockdown, and the shutdown of "non-essential" activities) taken by the Italian government to contrast the first wave of the pandemic. It relies on an econometric strategy composed of two sequential parts: firstly, a machine learning procedure is implemented by using a set of time series of Covid-19 cases to identify the effectiveness of lockdown measures. Afterward, an interaction terms analysis is performed to inspect some side effects of each lockdown across the Italian territory. What emerges, is a strong heterogeneity in terms of the social, educational, health and economic features among the Italian provinces.

In the last chapter, the analysis focuses on digital inequalities at school, an issue than may be aggravated by distance learning. By using PISA 2018 dataset, it explores the consequences on the short and long run that a lack of ICT facilities may produce on students who are unable to learn remotely. Findings show that, everything else equal, these students experience significant cognitive losses and they are more likely to revise downwards their plans on future education.

To sum up, the present thesis shows that changes in the labour market in consequence of the Covid-19 pandemic exacerbate the need to implement long-term interventions aimed at increasing the enrolment rate in non-compulsory education, in particular for youths from poorer households. The worsening of the economic conditions consequent to the Covid-19 widespread may be used as a driver in this sense. At the same time, it suggests that the closure of schools as a measure to contrast the pandemic could have controversial effects if it is not associated with further social distancing measures since it seems that high school students are less likely to comply with social distancing orders. Finally, the school system should provide appropriate ICT facilities and the relative capabilities to students in order to reduce learning inequalities effects. It is an urgent matter since teaching is increasingly relying on digital tools.

Abstract (italiano)

Nelle società contemporanee la scolarizzazione è una risorsa fondamentale per consentire alle persone di raggiungere la piena opportunità di sviluppo delle proprie abilità. L'equità e la qualità del sistema educativo sono perciò tra i pilastri fondamentali dei paesi sviluppati.

La presente ricerca evidenzia la necessità di costruire un sistema educativo più inclusivo. In particolare, si focalizza sull'analisi degli effetti diretti e indiretti che la pandemia Covid-19 ha avuto sulle disuguaglianze educative, suggerendo alcune proposte di *policy* volte a superare tali disparità.

Il primo capitolo analizza le potenziali conseguenze sociali di una diffusione del lavoro agile a seguito dell'epidemia. Applicando il metodo *influence function regression* all'indagine INAPP-PLUS si analizza in che modo un aumento del numero di lavoratori che hanno l'opportunità di lavorare da casa possa influire sulla distribuzione dei redditi da lavoro. I risultati mostrano che i potenziali benefici da questo mutamento sarebbero distribuiti in modo diseguale tra i lavoratori.

Il secondo capitolo si concentra sugli effetti che il ciclo economico può produrre sulle decisioni d'investimento in istruzione. I risultati sono rilevanti soprattutto alla luce degli effetti economici della pandemia. Attraverso un modello a effetti fissi sui dati panel EU-SILC, si rileva una relazione negativa tra il ciclo economico e le scelte d'investimento in educazione per la popolazione più povera mentre la parte più ricca risulta essere a-ciclica. Si nota pertanto un impatto diverso del ciclo economico sulle scelte educative lungo la distribuzione del reddito.

Il terzo capitolo valuta l'impatto delle misure nazionali di distanziamento sociale (la chiusura delle scuole, il *lockdown* generale e la chiusura delle attività economiche "non essenziali") adottate dal Governo italiano per contrastare la prima ondata di epidemia. La strategia utilizzata è composta da due parti sequenziali: è anzitutto implementata una procedura di *machine learning* sui dati del numero di casi positivi al Covid-19 per definire l'efficacia dei *lockdown*. In seguito, gli effetti delle misure sono interagiti con alcune variabili a livello provinciale. Ciò permette di notare alcune eterogeneità tra i territori in termini di caratteristiche sociali, educative, sanitarie ed economiche.

L'ultimo capitolo si focalizza sulle disuguaglianze digitali scolastiche, un problema che può essere aggravato dalla didattica a distanza. Attraverso i dati PISA 2018 si indagano le conseguenze a breve e lungo termine che la mancanza degli strumenti ICT può produrre sugli studenti non in grado di apprendere da remoto. I risultati mostrano che, a parità di altre condizioni, essi subiscono perdite cognitive significative ed è più probabile che intendano terminare la carriera scolastica prima dei propri coetanei.

In conclusione, questa tesi illustra come i cambiamenti nel mercato del lavoro a seguito della pandemia di Covid-19 aumentano la necessità di interventi di lungo periodo volti a promuovere il tasso di partecipazione nell'educazione, in particolare per i giovani meno abbienti. Il peggioramento delle condizioni economiche conseguente all'epidemia può aiutare in tal senso. Essa inoltre suggerisce che la chiusura delle scuole come misura di contrasto alla diffusione del virus potrebbe avere effetti controversi quando non è accompagnata da ulteriori restrizioni e, in generale, sembra che gli studenti delle scuole secondarie superiori siano meno propensi ad attenersi alle misure di distanziamento sociale. Infine, si dovrebbero fornire agli studenti gli strumenti ICT e le relative competenze al fine di ridurre le disuguaglianze educative. Questo è un problema urgente dato che l'insegnamento si basa sempre più sugli strumenti digitali.

Chapter 1 – Working from home and income inequality: risks of a 'new normal' with COVID-19[1]

"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, b; Qiu et al., 2020).

In this context, the opportunity to work from home (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 USA show that remote workers have quadrupled to 50% of US 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 emphasised 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, p. 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 information technology (IT), 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 et 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

[1] This work is published in the *Journal of Population Economics* with the title "*Working from home and income inequality: risks of a 'new normal' with COVID-19*" (joint with Giovanni Gallo and Sergio Scicchitano). DOI: 10.1007/s00148-020-00800-7. It has been presented at LXI Annual Conference of the Italian Economic Association (Virtual online conference, 2020), Journal of Population Economics Webinar (Virtual online conference, 2020) and Social Situation Monitor – European Commission Research Seminar (Virtual online conference, 2021).
[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-workcoronavirus.html).

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 employees as the counterfactual scenario, the Firpo et al.'s (2009) 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 11 March). 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 5 March (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 Occupational Information Network (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 abler 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 polarisation, 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 24 February–5 May 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 Sect. 4 reports the econometric methodology. Sections 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 et al., 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 ambiguous 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 also be 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 USA earn a higher wage than the other workers, but results vary by occupation, gender, parental status, and teleworking intensity. Recent studies conducted in the USA 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%.

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. (2015), Arntz et al. (2019), and 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 (2014), 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 Labour Organisation (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 USA 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 interruption 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 in Wuhan, a city in Eastern China, where in 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 the World Health Organisation named SARS-CoV-2. The disease, designated as COVID-19, caused more than 85 thousand confirmed cases in China showing a great rate of spread.

To prevent the outbreak in Italy, on 30 January 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 globalisation 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 23 February, 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 4 March, the Prime Minister signed a law forcing the closure of schools and universities and the stoppage of all sporting and social events from 5 March, with the initial aim (and hope) of reopening in 10 days. On 8 March, 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 3 days after (i.e. 11 March, the day-after World Health Organisation 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 with the previous ones. A first version of the regulation was announced on 21 March and published on 22 March, but it was modified on 25 March after the meeting between the Government, unions, and representation of the entrepreneurs. The final law tightened the measures

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

in several ways, including the following: 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 4 May, '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 (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

[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/.

Lavoro agile) in the Italian regulation, defines the smart work as an activity that, although carried out in a subordinate regime, is characterised 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). Using the Italian Labour Force Survey (LFS) for the period 2008–2013, 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% 'of the activities that can be carried out in this way' by the end of this year, 60% thereafter. On 17 June, the Minister of Public Administration declared that 90% 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,

[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).

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 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 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 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. generalised work activities and working context); and (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 characterising 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 (1220 observations). We also decided to drop self-employed from our sample (3741 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.

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

[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 Sect. 6, overall confirm the robustness of our main results presented in Sect. 5.

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 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); and (vii) time spent standing (reversely). For each item, replies of workers are overall standardised 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 Sect. 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% 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 Sect. 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 Appendix Table A.1, while Appendix Table A2 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 5000–20,000 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 attitude index and share of employees with high attitude level by group of employees

Variable	Sample composition		Annual labour income		WFH attitude	
	Mean	**Std. Dev.**	**Mean**	**Gini index**	**Mean**	**% of employees with high attitude**
Low WFH attitude	0.518	0.500	24,731	0.261	40.5	0.0
High WFH attitude	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
Aged 25-35	0.204	0.403	21,962	0.257	51.7	46.9
Aged 36-50	0.467	0.499	26,146	0.279	52.5	47.9
Aged 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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

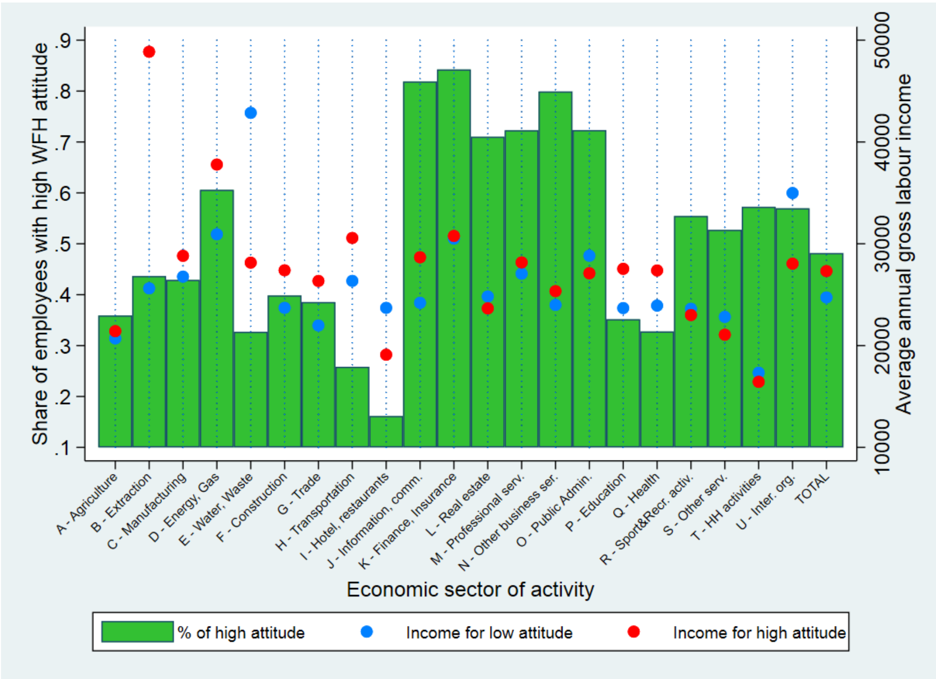
Focusing on labour income differences at 5% level only, Table 1 shows that employees with high WFH feasibility report on average a higher labour income than those doing an occupation with low feasibility levels. Also, employees appear to meanly receive a higher income if male, older (i.e. aged 51–64), 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 characterised 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 – Incidence of high WFH attitude and average labour income by activity sector



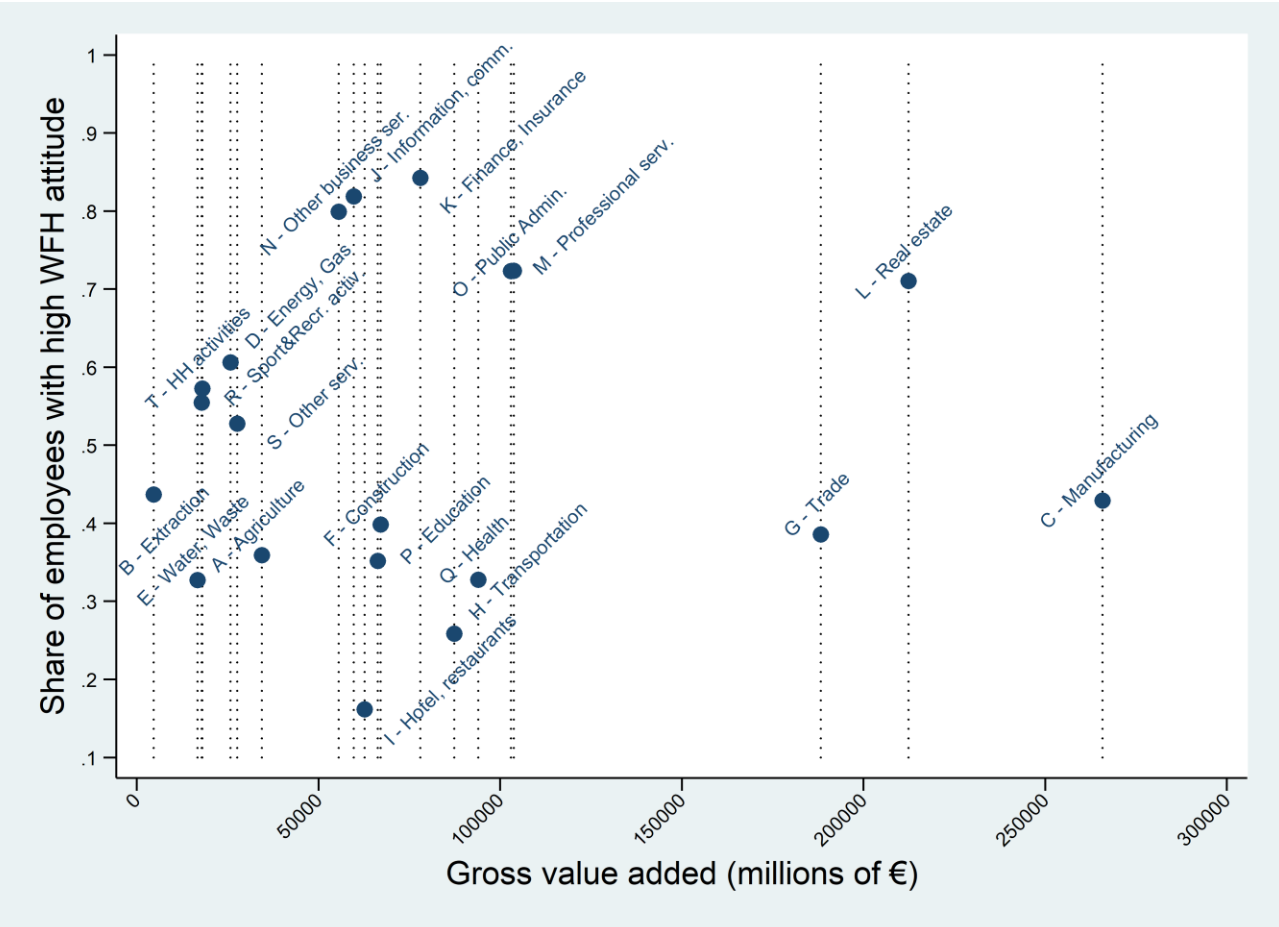
Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

[9] Preliminary evidence confirms that differently from the USA, 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).

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).

Distinguishing by activity sectors, Figure 2 points out that the categories with a higher value added are manufacturing, real estate and trade. Two of them have a WFH feasibility level lower than the median. More in general, the graph shows quite clearly that a positive relationship between the share of employees with high WFH attitude and the measure of the value added does not exist. This is an important preliminary result in order to confute the possibility that the following econometric analysis is led by the differences in the value added among the economic sectors.

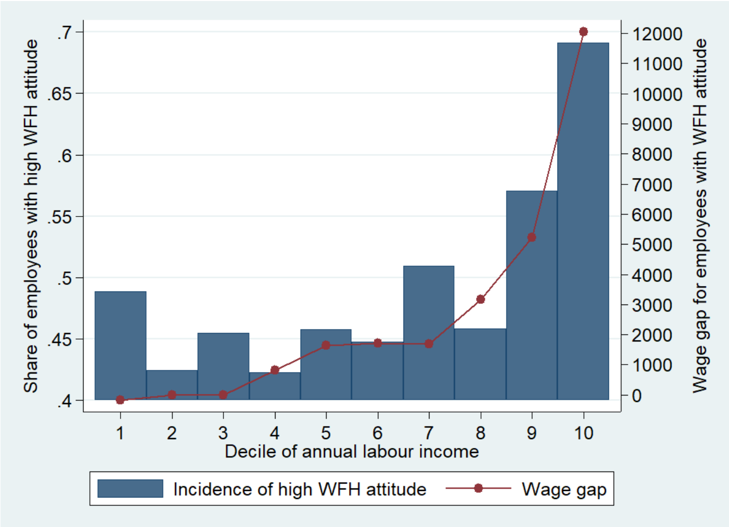
Figure 2 – Incidence of high WFH attitude and value added by activity sector



Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). Data on the value added are extracted by ISTAT 2018 and are computed by subtracting the value of intermediate consumption from the value of output.

As for potential differences across the labour income distribution, Fig. 3 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 3 – Incidence of high WFH attitude and wage gap in favor of employees with high attitude levels by decile of annual income



Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

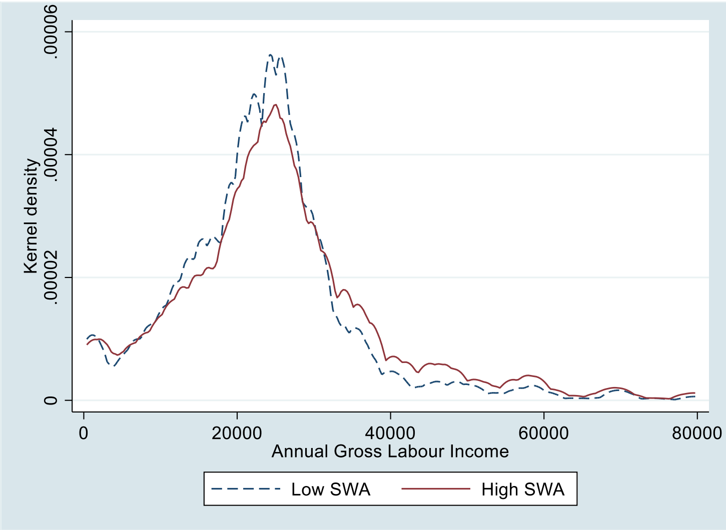
3.3 Kolmogorov-Smirnov test

In Fig. 4, 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.

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]

[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 (KS2) permits one to determine whether both distributions are identical, while the one-sided test (KS1) 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.

Figure 4 – Labour income distribution by level of WFH attitude



Notes: Descriptive statistics are computed with individual sample weights. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

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% 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 attitude

	Combined	Low WFH attitude	High WFH attitude
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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

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 organisation, 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 Sect. 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 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 recentred influence function (RIF) which is defined as

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

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 Appendix Table A1. 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 Sect. 3.2, while values of the nine deciles are presented in Appendix Fig A1. Differently from the common choice to drop female employees to minimise 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 Sect. 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 (2014) 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 (Fig. 1).

[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).

Table 3 – Unconditional effects of a positive shift in the WFH attitude 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

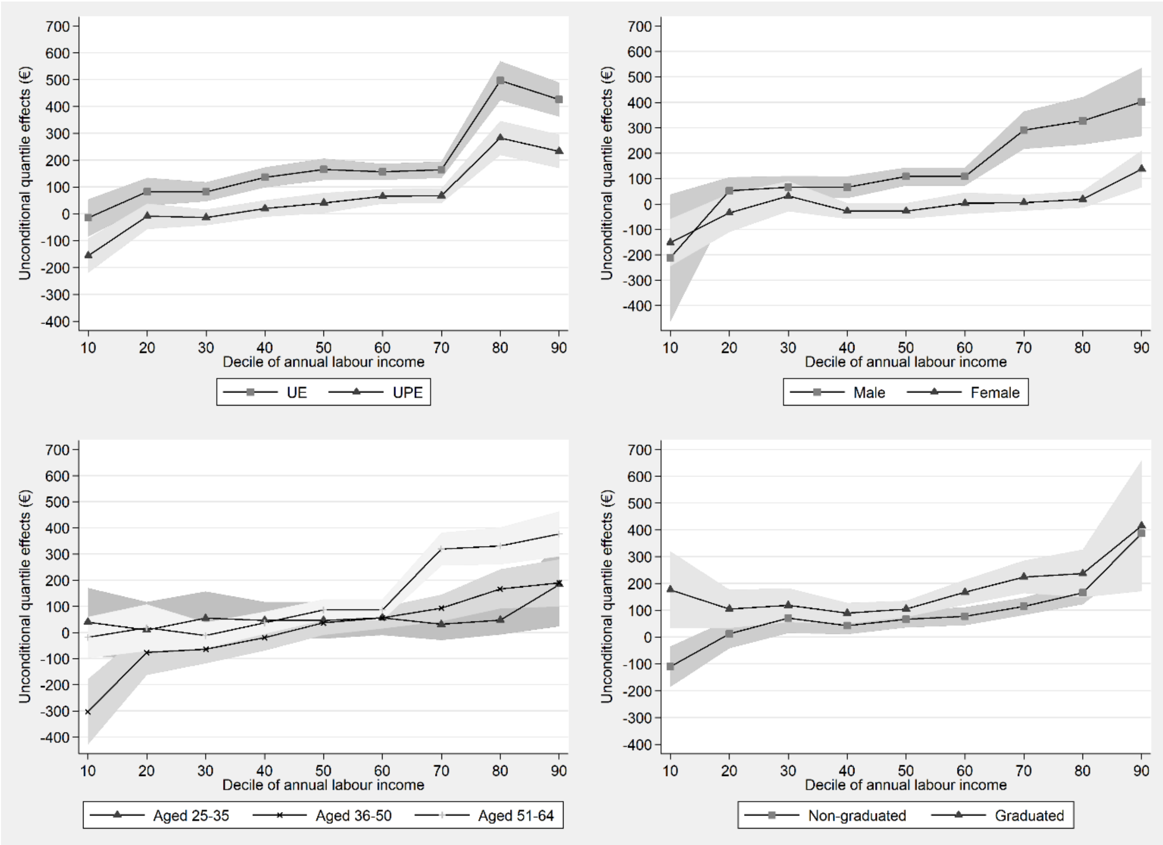
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH attitude) only. Complete estimates for the pooled sample are provided in Table A3. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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).*

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. Looking at the WFH feasibility influences along the labour income distribution (top-left panel of Fig. 5), 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 (Appendix Fig. A8).

Top-right panel of Fig. 5 points out that the wage premium deriving from a growth of WFH feasibility levels would be mainly in favour 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 Fig. 5). 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 Fig. 5 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, 2002, 2003; Acemoglu, 2002). 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 with unskilled work, thus causing an increase in wage inequality levels. Our results show that the technological change would occur to determine the hypothesised 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 polarisation, 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.

Figure 5 – Unconditional effects of a positive shift in the WFH attitude 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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. Complete estimates for the pooled sample are provided in Tables A4-A5.

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 characterising local labour markets. Specifically, under the assumption that the structure of professions and their WFH feasibility remained unchanged from 2018 to 2020 (before the pandemic spread), 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 24 February to 5 May 2020 (Civil Protection Department, 2020). 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‰). Appendix Fig 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 is 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.

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.

Table 4 – Unconditional effects of a positive shift in the WFH attitude 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*

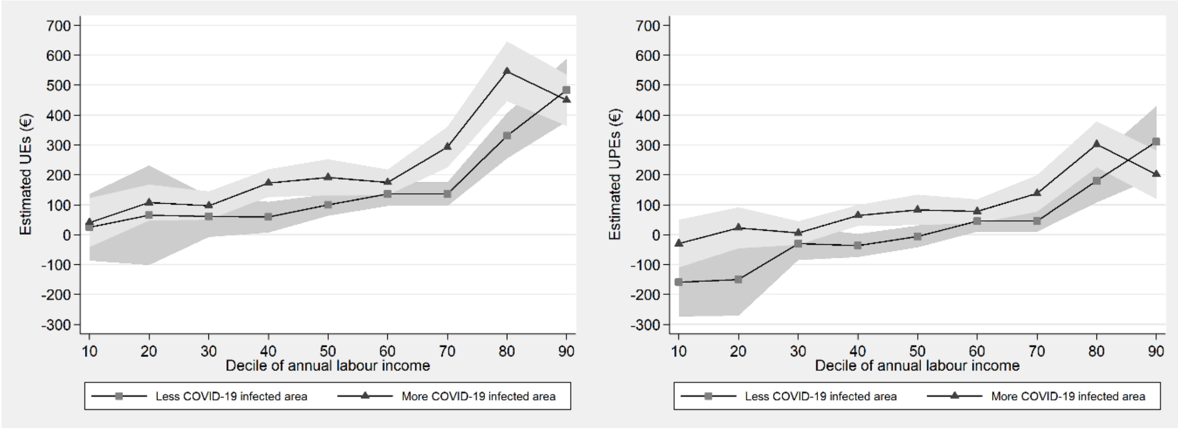
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High WFH attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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).*

Results illustrated in Fig. 6 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).

There are a number of several plausible explanations of this result. We hypothesize three different possibilities. Firstly, it could be due to the different sectoral composition between more and less COVID-19-infected area. Secondly, the salary gap between graduates and non-graduates may be higher in those areas which were more affected by the pandemic. Third, the increase in wages related to the working experience might be higher in those areas mostly affected by COVID-19.

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 favour of high-paid employees.

Figure 6 – Unconditional effects of a positive shift in the WFH attitude 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). UE estimates (on the left panel) are based on a model specification which only includes the variable of interest, while for UPE estimates (on the right panel) additional covariates are included in the model (see Section 4).

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 Sect. 3.1, a standardised 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.[12]

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,[13] 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.

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 5% 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,

[12] 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 2594 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 (Appendix 1.6) overall confirm the 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.

[13] 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.

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.

Table 5 – Unconditional effects on mean value and Gini index by item of the WFH attitude 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 attitude (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.*

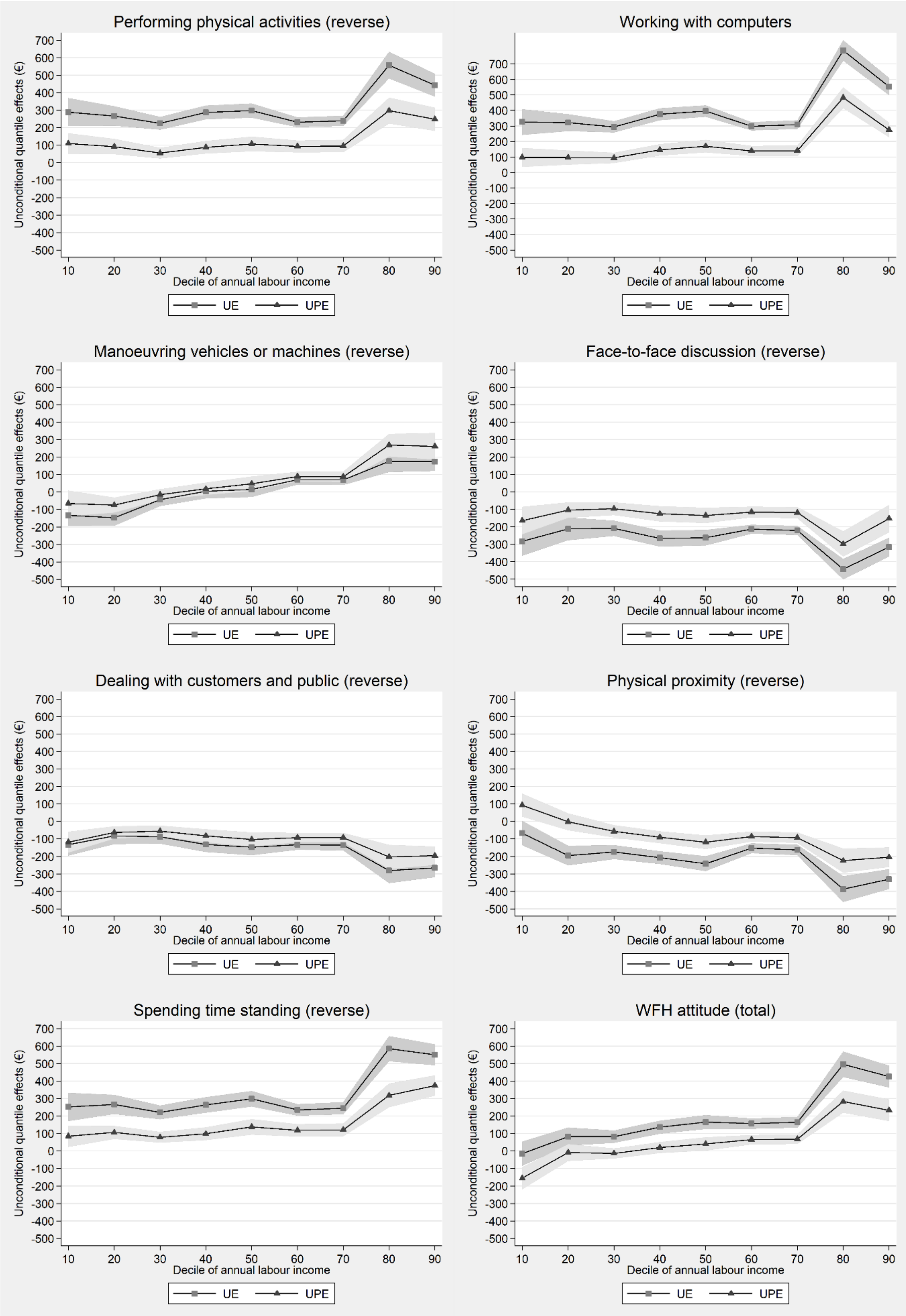
Figure 7 helps to better explain the role of a change in single items composing the adopted WFH feasibility index on the labour income inequality illustrating unconditional effects by income decile. Most of times present indeed insignificant effects on the Gini index, and thus on the income inequality, 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 7 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 summarise 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.

Figure 7 – Unconditional effects along income distribution by item of the WFH attitude 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 attitude) only. Employees with high attitude 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 which only includes the variable of interest, while for UPE estimates additional covariates are included in the model (see Section 4).

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 (9812 observations) are presented in Appendix Table B1 and the left panel of Appendix Fig B1 and strongly corroborate our main conclusions. Similarly, to be sure the adopted sample restriction strategy (detailed described in Sect. 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 Appendix Table B2 and the right panel of Appendix Fig. B1 seem to overall confirm the robustness of our main results.

Second, as anticipated in Sect. 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% 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 share 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.

Appendix Table B3 and Appendix Fig. B2 report estimation results for the continuous specification of our variable of interest, while Appendix Fig. B3 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 (Appendix Table B3). However, Appendix Fig. B2 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 Appendix Fig. B3 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. Appendix Table B4 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 Appendix Table B5 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 Fig. 6).

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 Appendix Table B6 for the effects on mean value and inequality indexes of labour income and in both Appendix Table B7 and Appendix Fig B4 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 two different sets of (probably endogenous) variables to solve this issue. Specifically, in the first set 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); and '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 Appendix Table B.6 and Appendix Table B.8. Second, we include other two determinants of the wage level: the total years of working experience (and its square) (Mincer, 1974) and the actual number of weekly working hours. Through the first variable we control for the working experience heterogeneity among employees, while the weekly working hours is a proxy of the work intensity. The estimates based on this model specification, labelled as UPE4, are showed in Appendix Table B6 and Appendix Table B9.

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. Appendix Table B10 and Appendix Figure B5 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 a 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 Sect. 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.

Looking at estimates by group of employees, results illustrated in Table 6 seem to be overall in line with conclusions stated in Sect. 5.1. In fact, high levels of WFH feasibility would go in mainly favour 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.

Table 6 – Estimated effect of performing a profession with high WFH attitude 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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).*

7. Conclusions

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' (https://www.upwork.com/resources/how-to-adjust-to-the-new-normal-of-remote-work) 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 ICP.

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 favour 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 USA, 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 USA, 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 (2020). 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 gives a boost to WFH forcing companies to invest and reorganise 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 reorganisation 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 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-organisation of the WFH and the labour market in general.

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Appendix A. Descriptive statistics and additional estimates

Table A1 – Variable description

Variable	Description
Annual gross labour income	Continuous variable representing the annual gross labour income in the main job declared by the interviewed person. All recentered influence functions on distributional statistics are based on this variable.
High working from home (WFH) attitude	Binary variable reporting the level of WFH attitude. The WFH attitude 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 attitude 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 A2 – Sample composition, mean and Gini index of annual labour income, mean value of the WFH attitude index and share of employees with high attitude level by economic sector of activity

Economic sector of activity	**Sample composition**		**Annual labour income**		**WFH attitude**	
	Mean	**Std. Dev.**	**Mean**	**Gini index**	**Mean**	**% of employees with high attitude**
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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

Table A3 – Unconditional effects on the mean and Gini index in the total sample

Variable	Mean value		Gini index	
	UE	**UPE**	**UE**	**UPE**
High WFH attitude	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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).*

Table A4 – Unconditional effects of WFH attitude along the wage distribution (UE estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH attitude	-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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).*

Table A5 – Unconditional effects of WFH attitude along the wage distribution (UPE estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH attitude	-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

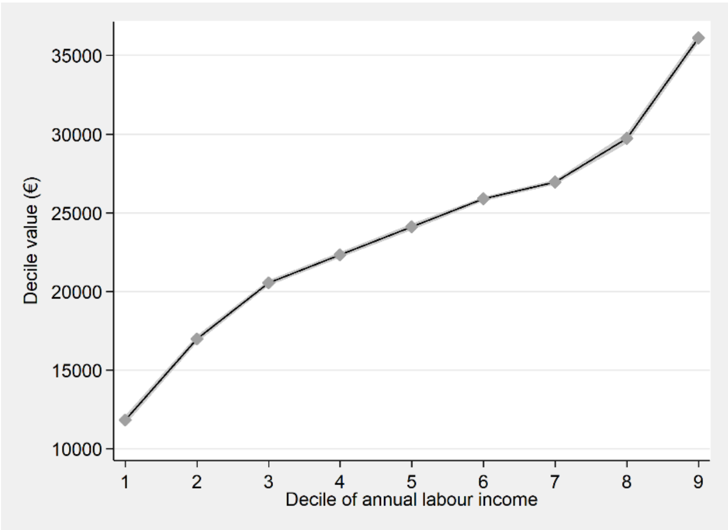
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).*

Table A6 – Unconditional effects on mean value and Gini index by item of the WFH attitude 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 attitude (total)	52.2	258.86***	97.98	0.004**	0.004**

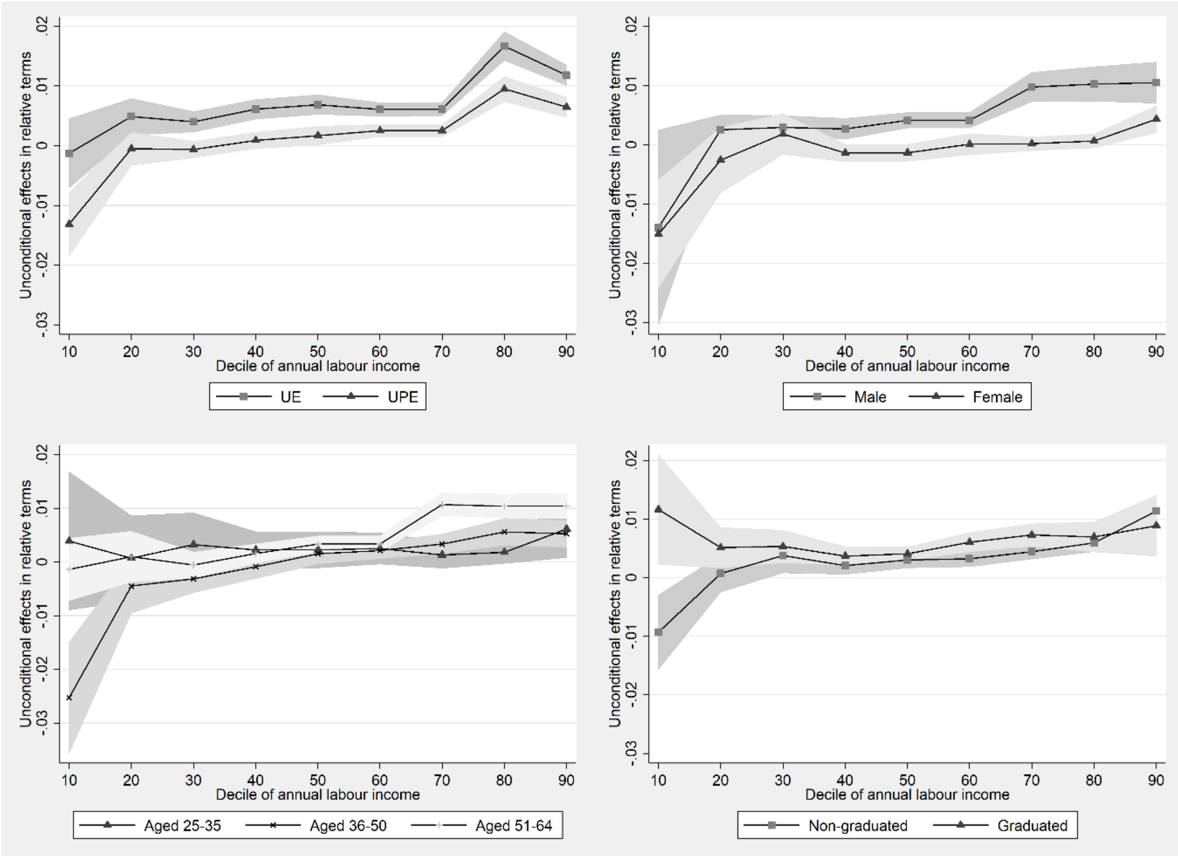
*Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Unconditional effects refer to the variable of interest (i.e. High index value) only. Employees with high index value are defined, for each item, as those 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 A1 – Income values by decile of annual labour income



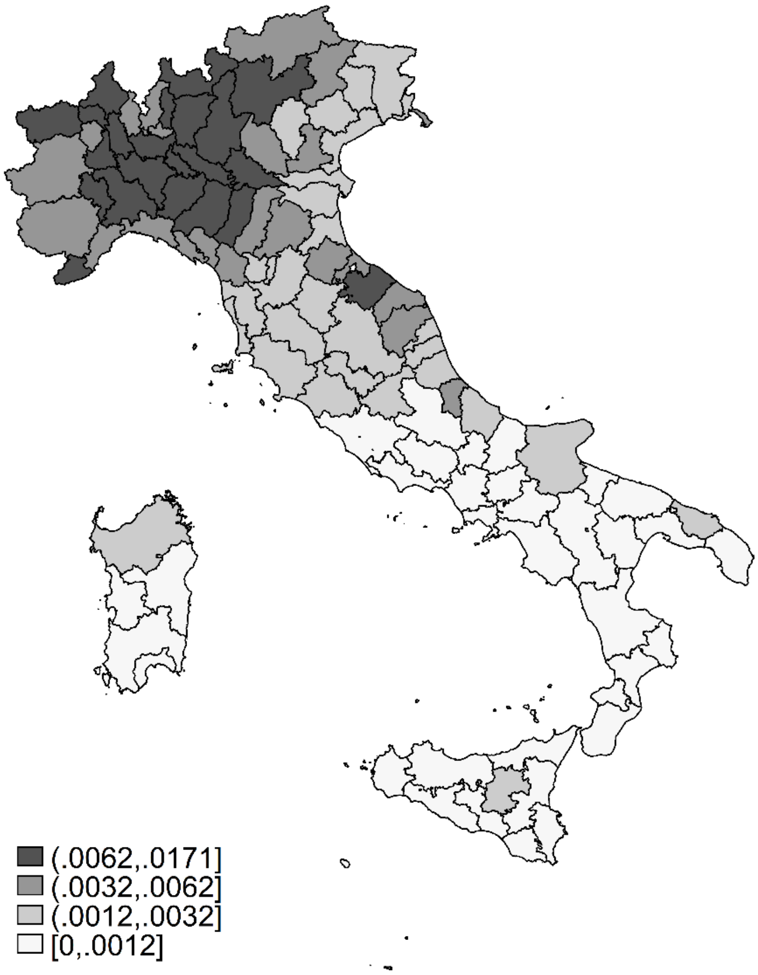
Notes: All descriptive statistics are computed with individual sample weights.

Figure A2 – Unconditional effects of a positive shift in the WFH attitude 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 attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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 A3 – 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 B1 – 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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 B2 – 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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 B3 – 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 attitude index) only. The WFH attitude 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 B4 – Unconditional effects on mean value and Gini index by item of the WFH attitude 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 attitude (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 B5 – 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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 B6 – 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	UPE4	UPE2	UPE3	UPE4	UPE2	UPE3	UPE4	UPE2	UPE3	UPE4
High WFH attitude	129.05**	24.31	113.017*	0.004***	0.005***	0.004***	0.004**	0.007**	0.005**	0.004**	0.006***	0.004**
Female	-887.05***	-583.24***	-588.723***	-0.002	-0.004**	-0.003	-0.003	-0.004*	-0.004	-0.002	-0.003*	-0.003
Aged 36-50	414.99***	346.10***	174.809*	0.001	0.004**	0.002	0.001	0.004*	0.002	0.001	0.003*	0.002
Aged 51-64	598.46***	493.09***	288.129	-0.000	0.004*	-0.001	-0.001	0.005	-0.002	-0.000	0.004	-0.001
Upper secondary education	384.32***	280.57***	426.417***	-0.003	-0.000	-0.003	-0.005*	-0.001	-0.005	-0.004*	-0.001	-0.004
Tertiary education	993.80***	673.39***	1,108.869***	-0.001	0.003	-0.001	-0.004	0.001	-0.003	-0.003	0.001	-0.003
Migrant within macro-region	133.09	194.85	113.642	0.009	0.007	0.009	0.011*	0.010	0.012*	0.010*	0.008	0.010*
Migrant within country	1.83	-31.34	2.842	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Foreign migrant	-76.14	-28.99	-87.741	0.006**	0.004	0.007**	0.004	0.002	0.005	0.003	0.002	0.004
Married	348.63***	279.49***	293.743***	0.003	0.005*	0.004	0.003	0.004	0.003	0.003	0.004	0.003
Household size = 2	-165.16	-94.73	-136.801	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000
Household size = 3	-303.45***	-195.10*	-234.884**	-0.002	-0.003	-0.002	-0.003	-0.004	-0.003	-0.002	-0.003	-0.002
Household size = 4	-184.45*	-68.73	-111.558	0.001	-0.000	0.001	0.001	-0.001	0.001	0.001	-0.001	0.001
Household size = 5 or more	-108.91	37.53	-32.685	0.005	0.003	0.005	0.006	0.004	0.006	0.005	0.004	0.001
Presence of minors	-41.76	-64.03	-54.713	-0.004	-0.004	-0.004	-0.005	-0.005	-0.004	-0.004	-0.004	-0.004
Small municipality	81.19	90.30	66.762	0.001	0.002	0.001	0.001	0.002	0.001	0.001	0.001	0.001
Medium municipality	-37.13	-47.20	-24.662	-0.000	-0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000
Big municipality	5.55	32.96	28.784	0.002	0.002	0.000	0.004	0.004	0.004	0.003	0.003	0.003
Metropolitan city	-59.61	-29.51	-49.469	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Center	-217.19***	-176.72***	-187.601***	0.000	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000
South	-243.20***	-153.30*	-161.217*	0.005**	0.005**	0.005**	0.006**	0.006**	0.006**	0.005**	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	
Working experience			41.434***			-0.001			-0.001			-0.001
Working experience^2			-0.584**			0.000			0.000			0.000
Weekly working hours			38.390***			0.000			0.000			0.000
Constant	2,243.14***	2,083.66***	272.700	0.025***	0.017***	0.031***	0.017***	0.007	0.026***	0.015***	0.007*	0.023***
Activity sector dummies	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Observations	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307	14,307
R-squared	0.043	0.066	0.064	0.004	0.018	0.005	0.004	0.013	0.004	0.004	0.013	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. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).*

Table B7 – Unconditional effects of WFH attitude along the wage distribution (UPE2 estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH attitude	-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 attitude level are defined as those reporting a value of the WFH attitude index over the sample media n (i.e. 52.2).*

Table B8 – Unconditional effects of WFH attitude along the wage distribution (UPE3 estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH attitude	-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 attitude level are defined as those reporting a value of the WFH attitude index over the sample media n (i.e. 52.2).*

Table B9 – Unconditional effects of WFH attitude along the wage distribution (UPE4 estimates)

Variable	p10	p20	p30	p40	p50	p60	p70	p80	p90
High WFH attitude	-156.043***	-44.281	-37.310**	-1.436	27.866	55.251***	58.554***	299.815***	268.610***
Female	-238.334***	-425,832***	-417.951***	-477.137***	-510.011***	-312.417***	-327.129***	-742.189***	-449.586***
Aged 36-50	-23.492	83.293	129.109***	113.629**	148.565***	95.303***	91.545***	221.410***	176.643***
Aged 51-64	125.131	312.874***	280.612***	292.473***	352.216***	207.312***	207.352***	405.419***	352.339***
Upper secondary education	438.631***	367.530***	340.051***	377.822***	369.810***	307.273***	319.519***	558.064***	382.692***
Tertiary education	826.805***	852.261***	776.780***	905.297***	905.721***	665.514***	693.046***	1,381.071***	1,025.123***
Migrant within macro-region	-431.699***	-179.829**	-14.067	56.576	25.4384	-2.8423	-22.120	37.742	121.256
Migrant within country	-51.754	-45.065	30.869	24.620	22.981	31.178	33.256	86.288	-79.077
Foreign migrant	-388.152**	-531.309***	-227.521***	-161.645**	-149.739*	-40.165	-35.309	42.480	62.032
Married	160.759***	85.589**	86.481***	109.522***	129.899***	104.604***	115.404***	296.173***	215.774***
Household size = 2	-190.328**	-70.173	-59.027	-60.047	-91.059*	-64.924**	-76.740**	-57.467	-31.323
Household size = 3	-172.570**	-121.895**	-108.828***	-107.565**	-146.153***	-110.677***	-125.661***	-157.783**	-45.415
Household size = 4	-195.053**	-133.158**	-99.156**	-100.021*	-105.545*	-71.320*	-80.589**	-15.701	41.279
Household size = 5 or more	-265.399**	-206.267***	-108.159*	-94.984	-98.178	-17.134	-26.772	94.995	128.017
Presence of minors	41.425	88.286***	54.280**	83.954***	67.871***	44.818**	56.599**	53.846	34.767
Small municipality	33.645	-0.209	42.971	-2.282	-11.071	-12.358	-5.146	-57.329	-42.473
Medium municipality	-6.888	3.871	34.309	12.045	5.940	-9.571	-11.374	-78.012	-50.338
Big municipality	-71.394	-48.325	11.397	-26.523	-6.4645	-23.996	-16.748	-63.040	6.950
Metropolitan city	-77.868*	-91.076*	0.405	9.160	24.629	-8.450	-1.912	58.038	79.684*
Center	-133.022***	-186.514***	-124.100***	-116.228***	-119.512***	-82.806***	-82.203***	-221.087***	-127.132***
South	-421.315***	47.568***	-150.630***	-147.802***	-148.845***	-84.624***	-84.985***	-169.062***	-121.909***
Working experience	52.290***	-0.784***	33.614***	38.587***	38.174***	24.948***	26.283***	37.007***	18.127**
Working experience^2	-860.1***	38.515***	-0.562***	-0.639***	-0.646***	-0.364***	-0.382***	-0.4675***	-0.2.65*
Weekly working hours	41.435***	-473.976***	20.884***	19.163***	18.117***	11.744***	12.346***	27.720***	25.692***
Constant	-967.391***	-473.976***	544.005***	674.572***	889.642***	1,420.849***	1,637.532***	729.086***	1,669.006***
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	0.139	0.233	0.225	0.215	0.201	0.188	0.188	0.166	0.104

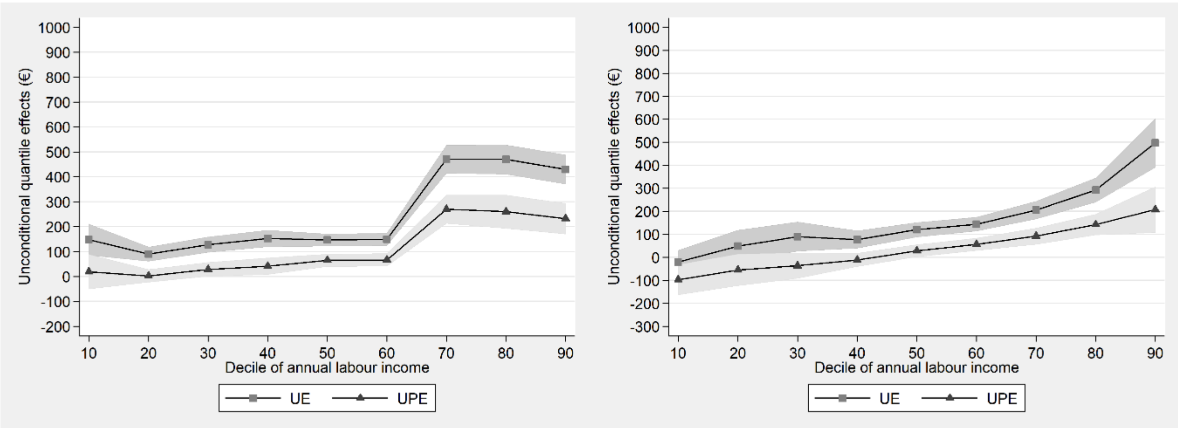
Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights; *** p<0.01, ** p<0.05, * p<0.1. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2).

Table B10 – 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**

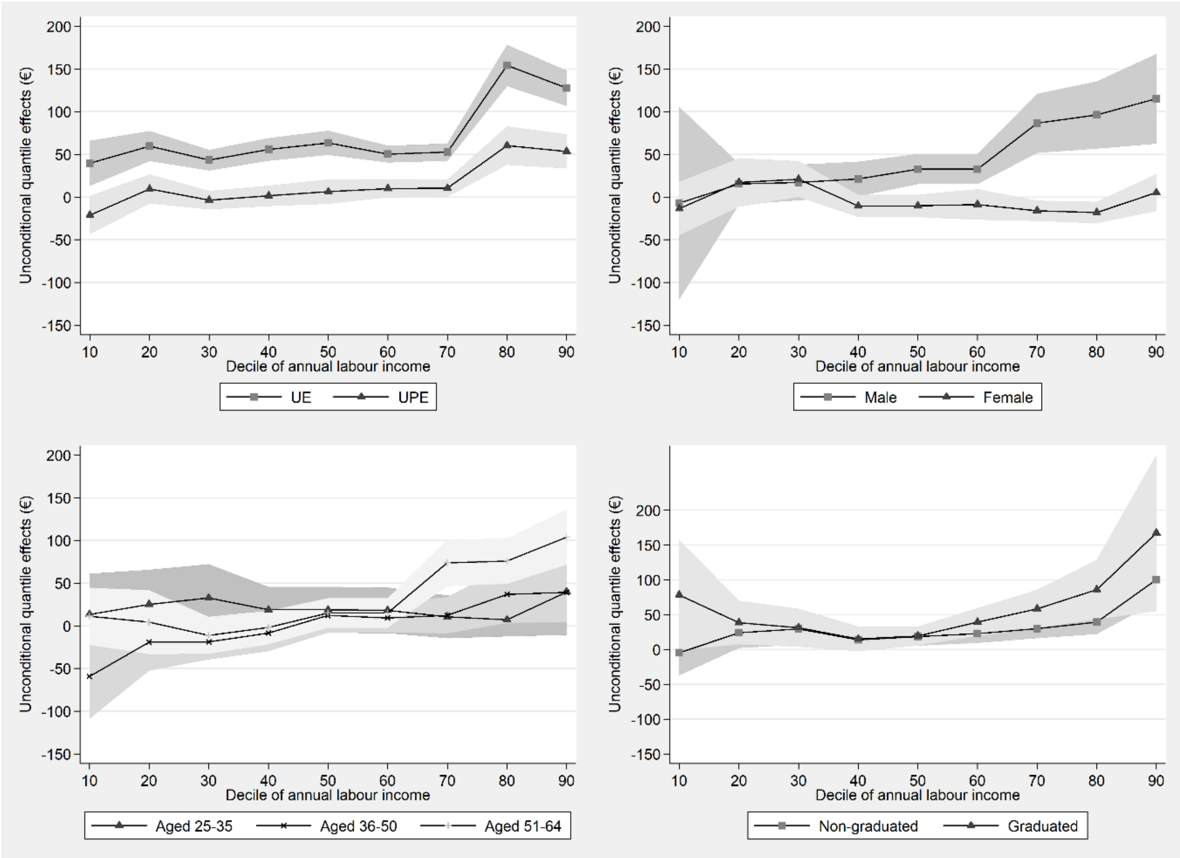
*Notes: Standard errors are clustered by NUTS-3 region; *** p<0.01, ** p<0.05, * p<0.1. The table presents coefficients of the variable of interest (i.e. High WFH attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the (non-weighted) 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 B1 – 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude 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).

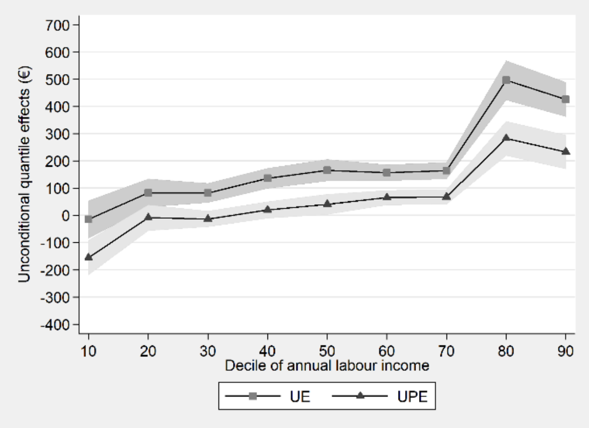
Figure B2 – Unconditional effects along the labour income distribution (variable of interest with continuous specification)



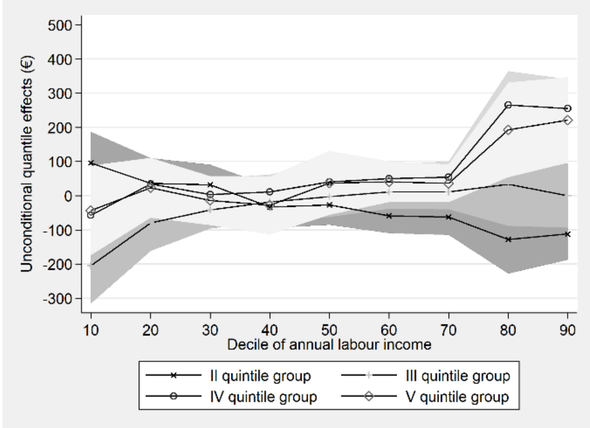
Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest (i.e. WFH attitude index) only. The WFH attitude index is a multidimensional 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 B3 – Unconditional effects along the labour income distribution (variable of interest with other specifications)

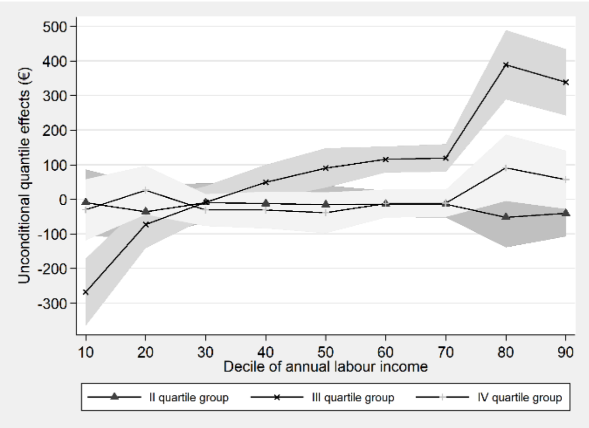
Panel A. Median of the WFH attitude index (base)



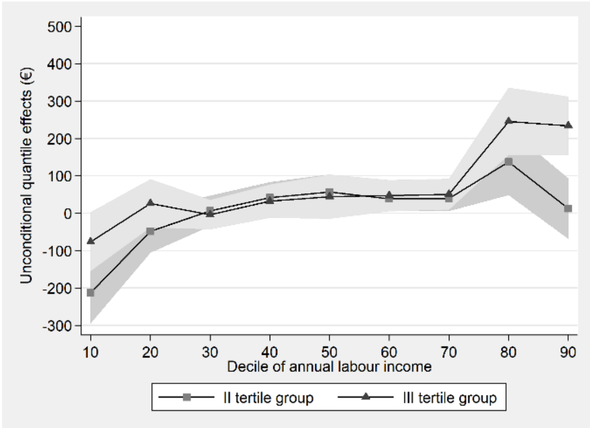
Panel B. Quintile groups of the WFH attitude index



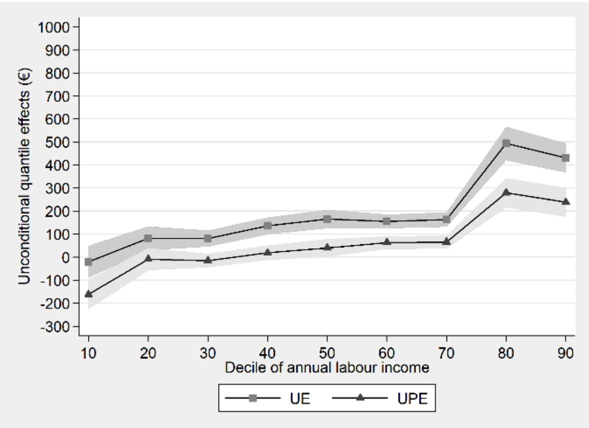
Panel C. Quartile groups of the WFH attitude index



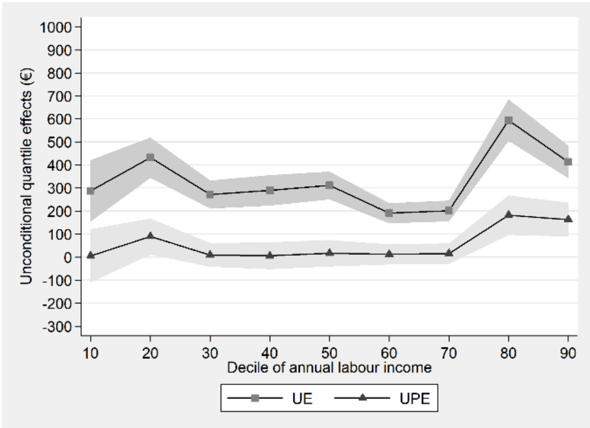
Panel D. Tertile groups of the WFH attitude index



Panel E. Mean of the WFH attitude index

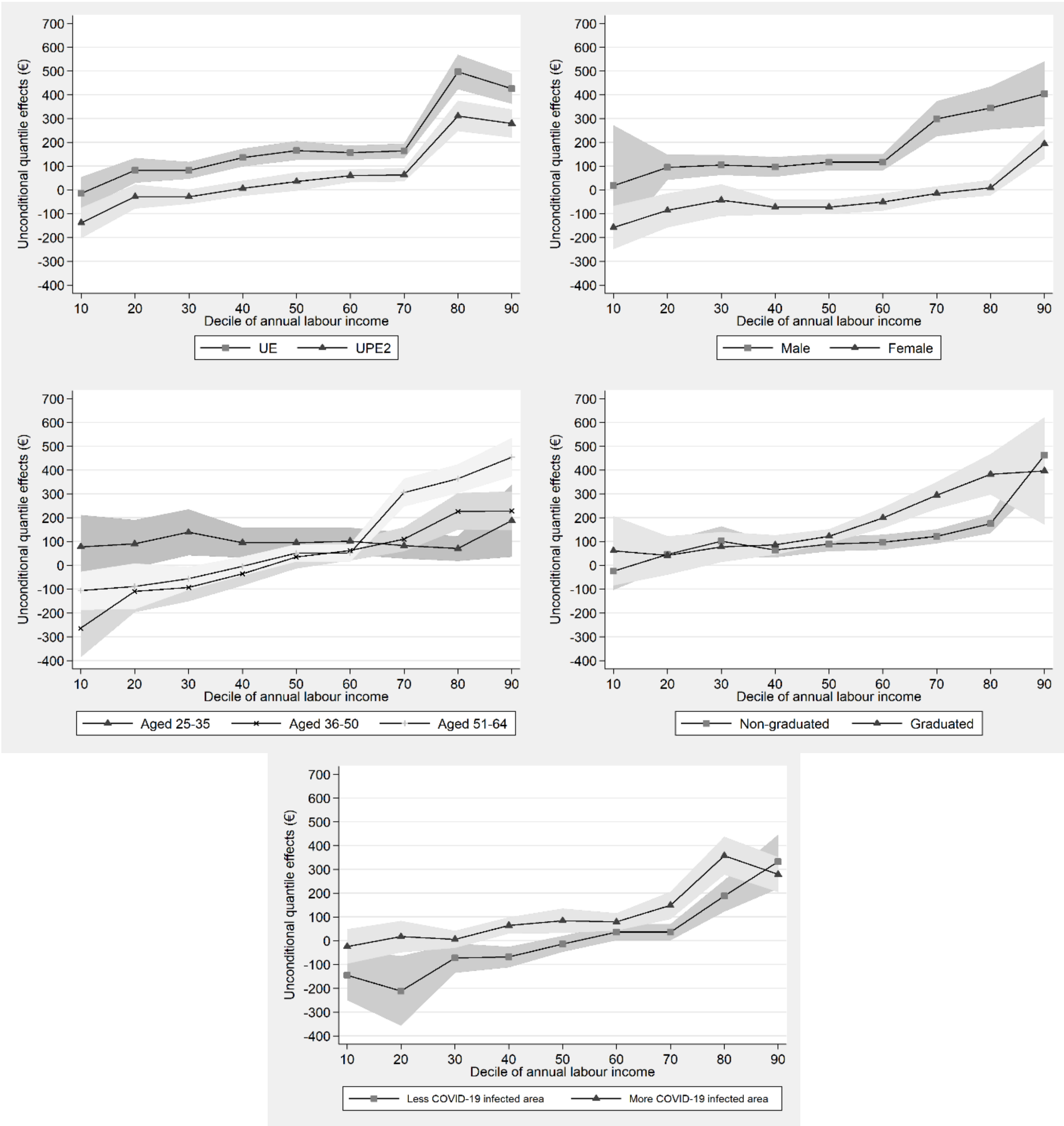


Panel F. 60% of mean of the WFH attitude index



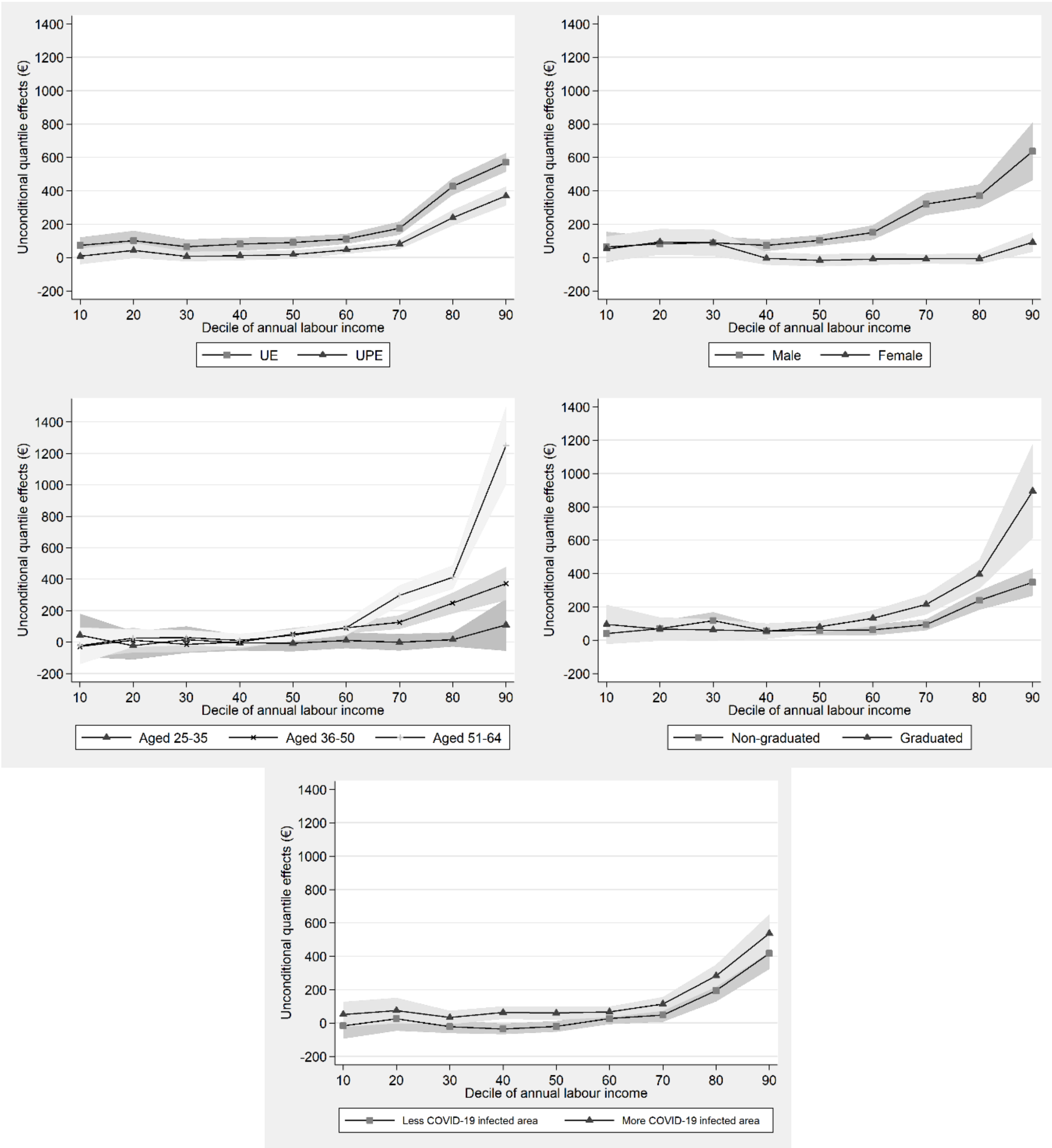
Notes: Standard errors are clustered by NUTS-3 region and estimates are computed with individual sample weights. Shadowed area report confidence intervals at 90% level. The figures present coefficients of the variable of interest only, which is defined through different specifications (expressed in Panel labels) of the same WFH attitude 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 B4 – Unconditional effects of WFH attitude 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude index over the sample median (i.e. 52.2). 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 B7.

Figure B5 – Unconditional effects of WFH attitude 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 attitude) only. Employees with high WFH attitude level are defined as those reporting a value of the WFH attitude 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.

Chapter 2 – Unequal effects of the economic cycle on human capital investment. Evidence from Italian panel data[1]

"The time to repair a roof is when the sun is shining."

John F. Kennedy

1. Introduction

In all developed countries, the school career is typically composed of two periods. The duration of the first is compulsory and is regulated by the state, while post-mandatory education is freely chosen by individuals and their families. Since education is among the main factors influencing the individual's quality of life, one of the core principles of a fair society is to remove the obstacles preventing an equal distribution of the opportunities to obtain the desired amounts and quality of schooling (OECD, 2018). Studying the determinants of education investment decisions is therefore an important task for economic researchers in order to provide useful tools to policymakers aiming to increase school enrolment rates.

Focusing on non-compulsory education, the most common approach to studying the determinants of enrolment decisions is Human Capital Theory, which considers non-compulsory education as a period when a young person spends money, time, effort, and forsakes income opportunities in anticipation of monetary and non-monetary benefits in the future (Becker, 1964).

This theory views participation in education and training as an investment that yields not only private but also social benefits (Ashton and Green, 1996). The private returns are reflected in individual earnings over time, better career opportunities, an ability to adapt to changes in the labour market, and possibly, better health outcomes (Alstadsæter, 2010; Jacob et al., 2011). Social benefits are described by the OECD as the advantages that 'include the increased productivity associated with the investment in education and a host of possible non-economic benefits, such as lower crime, better health, more social cohesion and more informed and effective citizens'.[2]

As the human capital model suggests, when a person decides whether to continue in education, he rationally compares the above-mentioned benefits to the direct (for example, tuition fees), indirect (foregone earnings), and psychic costs of doing so.

While the benefits are mainly in the long run, direct and indirect costs are conditioned by the circumstances of the present, namely, the condition of the economic cycle, which affects foregone earnings and the economic status of families in opposite directions. The crisis due to the COVID-19 pandemic, for example, has led some families to suffer a deterioration in their socioeconomic conditions, but some empirical evidence suggests that people seem to be 'staying in or returning to education rather than trying their luck in the uncertain waters of the COVID-19 labour market'.[3]

There is an extensive literature studying the effect of the economic cycle on enrolment decisions, mostly focused on tertiary education (McFarland, 1995; Dellas and Sakellaris, 2003; Long, 2014). As we will see in the next paragraph,

[1] A working paper version can be found in the GLO Discussion Paper (n. 733/2020). This work has been presented at III Annual Conference of the Italian Society of Economic Sociology (Naples, 2019) and at Doctoral research school "Marco Biagi Foundation" (Modena, 2019).

[2] https://stats.oecd.org/glossary/detail.asp?ID=5426

[3] See Financial Times (2020) "Young people in UK staying in education rather than seeking work", November, 19, https://www.ft.com/content/1654622a-8d7c-46b4-95b4-ff82066fd9fc. For an assessment of students' condition during the Covid-19 pandemic, see Murat and Bonacini (2020).

the majority of these studies agree on a counter-cyclical relationship. However, the existing literature considers the aggregate trend of the economic cycle, which has effects that can be heterogeneous across households facing different economic conditions (Gripaios et al., 1999; De Janvry and Sadoulet, 2005; Dynan et al., 2012, Berardi and Marzo, 2015).

Relying on panel data from 2004 to 2014 from the Italian component of the European Union Statistics on Income and Living Conditions (EU-SILC) survey, I aim to understand whether the economic cycle effects on individuals' schooling are homogenous across different economic conditions. Two competing consequences are suggested. During a worsening of the overall economic conditions, low-income individuals may suffer greater-than-average liquidity constraints, which can prevent them from investing in education. If this effect prevails, the inequalities in terms of access to education may increase during an economic downturn. On the other hand, their opportunity costs may be lower because their labour services are likely to be more easily substitutable and their jobs more uncertain. They would therefore be more affected by macroeconomic changes, and a worsening of economic conditions may improve their investment options more than those of the rest of the population. Therefore, the economic ups and downs of the economic cycle may lead to inequalities in access to higher education because it changes the opportunity costs of individuals in different economic conditions.

I focus my study on Italy because in this country, inequalities in the access to non-compulsory education and school attendance rates are urgent matters. Even though the university system is essentially centralized and funds are provided mainly by the central government (Aina, 2012; Abramo et al., 2018), there are significant geographical differences (Cattaneo et al., 2017). Despite the amount of funding being among the lowest in Europe (Janger et al., 2019), tuition fees are low, and in particular in public universities (Checchi, 2000), with limited variation across institutions and fields of study; moreover, students in the lowest 10% of the household income distribution are not required to pay fees.[4] Education is mandatory until 16 years of age, and the high school diploma is usually obtained at 19. The country is characterized by a general low level of educational achievement (Brunello et al., 2000) and higher dropout rates in tertiary education compared to other OECD countries (Cingano and Cipollone, 2007). Moreover, the school and university dropout rates are greater for children with less-educated and blue-collar parents (Triventi and Trivellato, 2008; Ballarino et al., 2011).[5]

My econometric strategy relies on a fixed effects model to remove the unobservable effects of the time-invariant factors, such as the unmeasured characteristics of individuals. Specifically, I perform the analysis on the entire sample to understand the overall role of the economic cycle on human capital investment decisions. After that, I investigate the heterogeneity among families facing different economic conditions, dividing the population into income quartiles and performing the same analysis on each of these. Although the first findings confirm that the economic cycle has a counter-cyclical relationship with non-compulsory schooling decisions, my results show that this is true only for the poorest people, while the relationship for the wealthier portion of the population is a-cyclical.

This study represents an important starting point to improve policy proposals tailored to deal with inequalities in access to non-compulsory education produced by the economic cycle, and even more so in light of the economic shock caused by the COVID-19 pandemic that spread across the entire world in 2020. The rest of this paper is structured as follows. The next section is a review of the literature. Section 3 presents the datasets used and some descriptive results. Section 4 shows the methodology, and Section 5 presents our main results and provides an account of a series of robustness checks. Finally, Section 6 offers some concluding remarks.

[4] https://eacea.ec.europa.eu/national-policies/eurydice/sites/eurydice/files/fee_support_2018_19_report_en.pdf

[5] Regarding the economic trend, the so-called 'Great Recession' was particularly rough for the Italian population, and especially for the lower-income population. Before this recession, income inequality had already been increasing dramatically throughout the 1990s, and at the beginning of the economic crisis it was already high (Jappelli and Pistaferri, 2009). But during the Great Recession itself, almost all poverty and inequality indicators increased. For example, the percentages of relatively poor households and of absolutely poor households rose, respectively, from 11.1% to 12.7% and from 5.2% to 6.8%, and the ratio between income owned by the top 20% of earners and the lowest 20% rose from 5.1% in 2008 to 5.6% in 2010 (Freguja, 2013).

2. Literature review

The majority of the literature studying the role of the economic cycle in human capital investments is based on data from the United States and finds a counter-cyclical relationship between economic conditions and investment decisions in education.

2.1. On the cyclicality of human capital investment

Dellas and Sakellaris (2003), studying high school graduates between the ages of 18 and 22 years old in the U.S., show that enrolment rates seem to display a counter-cyclical pattern with respect to the unemployment rate. Dellas and Koubi (2003), in their investigation of U.S. persons aged 16 to 35, explain that people are more likely to attend school during bad aggregate times. Long (2014) examines the effects of the Great Recession in the United States, and the results suggest that the net effect of the recession has been positive in terms of college enrolment levels. Betts and McFarland (1995), studying American colleges, find that the link between enrolment and the unemployment rate is significant and positive both for full-time and part-time students. Mendez and Sepuvelda (2012) provide evidence regarding the cyclicality of skill acquisition activities via both formal schooling and on-the-job training in the United States. Their results indicate that both the incidence of schooling and the time devoted to schooling are strongly counter-cyclical. Heylen and Pozzi (2007) consider 86 developed and developing countries in the period of 1970–2000. Their analysis confirms the positive effects of economic crises on human capital investment. Sakellaris and Spilmbergo (2000) analyse foreign students' behaviour in the United States. They conclude that there are two different effects of economic fluctuations on enrolment behaviour: for OECD countries, enrolment decisions are counter-cyclical, whereas for non-OECD countries they are pro-cyclical. Mattila (1982) regresses school enrolment ratios on rate-of-return variables for people in the United States. The most interesting result is the large and positive enrolment response to an increase in the rate of return to college. He also finds that school enrolments increased during recessions for young men but not for older men.

Few studies disagree with the conclusion of a counter-cyclical relationship. Polzin (1984) examines data on students at Montana University. His analysis indicates that the enrolment of first-time freshmen was influenced by hometown unemployment rates. But the effects of changes in unemployment rates were not the same for all units, and the relationship between unemployment rate and the economic cycle is uncertain. Edwards (1976) examines how school enrolment and retention rates in the U.S. respond to changes in overall business conditions. The results of the paper indicate that only one of the four teenage groups studied, non-white males, responds to cyclical upswings in employment opportunities by dropping out of school.

Outside of the United States, and regarding the cyclicality of dropouts, Schady (2004) examines the effect of the macroeconomic crisis in 1988–1992 in Peru. Results seem to suggest that households are reluctant to reduce human capital investments. Therefore, an economic recession would not cause an increase in dropout rates. Adamopoulou and Tanzi (2017) use data on three cohorts of university students in Italy to study how the Great Recession affected their dropout probability. They find that while an increase in the adult unemployment rate reduces the dropout probability of university students, a rise in the youth unemployment rate increases their probability of dropping out.

2.2. Does the economic cycle shape schooling inequalities?

Very few studies focus on the inequalities in human capital accumulation produced by the economic cycle, and their results tend to differ. Rucci (2003) investigates the impact of the Argentine crisis that began in 1998 on children's schooling decisions. The results suggest that the economic recession has negatively affected schooling decisions, and its effect is worse for youths belonging to households with parents with low levels of education. Christian (2007), using data on 18- and 19-year-old U.S. students, studies whether the unemployment rate influences enrolment in college. His results show that college enrolment is a-cyclical or very mildly counter-cyclical. He did not find any evidence that the cyclicality of college enrolment by children from non-home-owning households is different from that of children from home-owning households. Also studying U.S. data, Alessandrini et al. (2015) estimate the probability of being enrolled in college, finding that macroeconomic conditions have a negative marginal effect on education decisions. The sample was also divided into two groups in order to distinguish between high and low parental education. They find that the impact of an increase in GDP is greater for the low parental education category than for people with more highly educated parents. In Europe, Ghignoni (2016) studies the phenomenon of dropouts in Italy. Her paper shows that during the 2008 crisis, the probability of dropping out of university increased significantly for students from families belonging to the lower social classes and for less proficient/less academically oriented students compared to the pre-crisis period. In a working paper, Ayllon and Nollenberger (2016) consider young people aged 16 to 29 in 28 European countries. They find a counter-cyclical relationship between rising unemployment rates and both school enrolment and the return to education. They also conduct an analysis by population subgroups, finding that when there is an increase in unemployment, youths belonging to the most disadvantaged backgrounds are less likely to enrol in tertiary studies.

3. Data and descriptive evidence

In this work, I use data from 2004 to 2014 from the Italian component of the European Union Statistics on Income and Living Conditions (EU-SILC) survey in its longitudinal form. Panel data are very valuable for my goal because they allow reducing the volatility and random fluctuations over time with respect to cross-sectional data. The panel component of EU-SILC is therefore more precise than cross-sectional data to estimate changes over time, despite a smaller sample. For my purposes, there are three main limitations to the use of this database: its reduced number of waves (four) during which individuals are traced, the wide territorial level (NUTS-1 level),[6] and the lack of a variable specifying the exact grade of study that the person is enrolled in. The dataset contains information on 73,184 individuals each traced for four consecutive waves. Since I am interested in analysing the enrolment rate, I reduce the sample to consider only people in the typical age of non-mandatory education attendance. Italy is characterized by an average time to effective degree attainment much longer than the institutional one[7] (Contini et al., 2017). I therefore consider individuals up to the age of 29 years included. I exclude all the people declaring to be already graduated because for this category I am not able to discern between a bachelor's degree and a master's degree. Finally, I drop individuals who did not obtain a high school diploma during the four waves considered. The final sample includes 4,878 persons (19,512 observations), of which 3,180 remained in the same student status in each tracked year. The main variable used as a proxy of the economic cycle is GDP at the NUTS-1 level (expressed as a logarithm). I extracted the data on GDP from the Eurostat database and merged these with EU-SILC data.

I consider as enrolled in post-secondary education all students who already have a high school diploma and say they are currently studying (ENROL).[8] To analyse the role of the economic cycle in this decision, I consider as the main variable the natural logarithm of the GDP (LN_GDP). Additional time-varying variables at the individual level are also included: the age that the person turns in the year of the interview (AGE), the logarithm of the household equivalent income (LN_YEQ), and the percentage of government expenditure in education on the GDP (GOV_EXP). Descriptive statistics are presented in Table 1.

The EU-SILC dataset makes available detailed information on individual/household socioeconomic and demographic characteristics. The longitudinal component allows for analysing changes at the individual level over time and covers a long period starting with a positive economic cycle that was interrupted by the Great Recession, which affected Italy in 2008 through the global financial crisis and in 2011 with the consequent economic crisis, and concludes with a positive economic trend.

[6] Nevertheless, several studies, especially those conducted in the United States, rely their analysis on the economic cycle measured at the state level (i.e. Dellas and Sakellaris, 2003 and Long, 2014). Thus, Nuts-1 level represents a significantly more homogenous setting for my purpose.
[7] XVII indagine Profilo dei Laureati 2014. Bologna: Consorzio AlmaLaurea http://www. almalaurea.it/universita/profilo.
[8] Individuals enrolled in post-secondary non-tertiary education are considered free to decide whether to continue their studies upon graduation.

Table 1 – Descriptive statistics

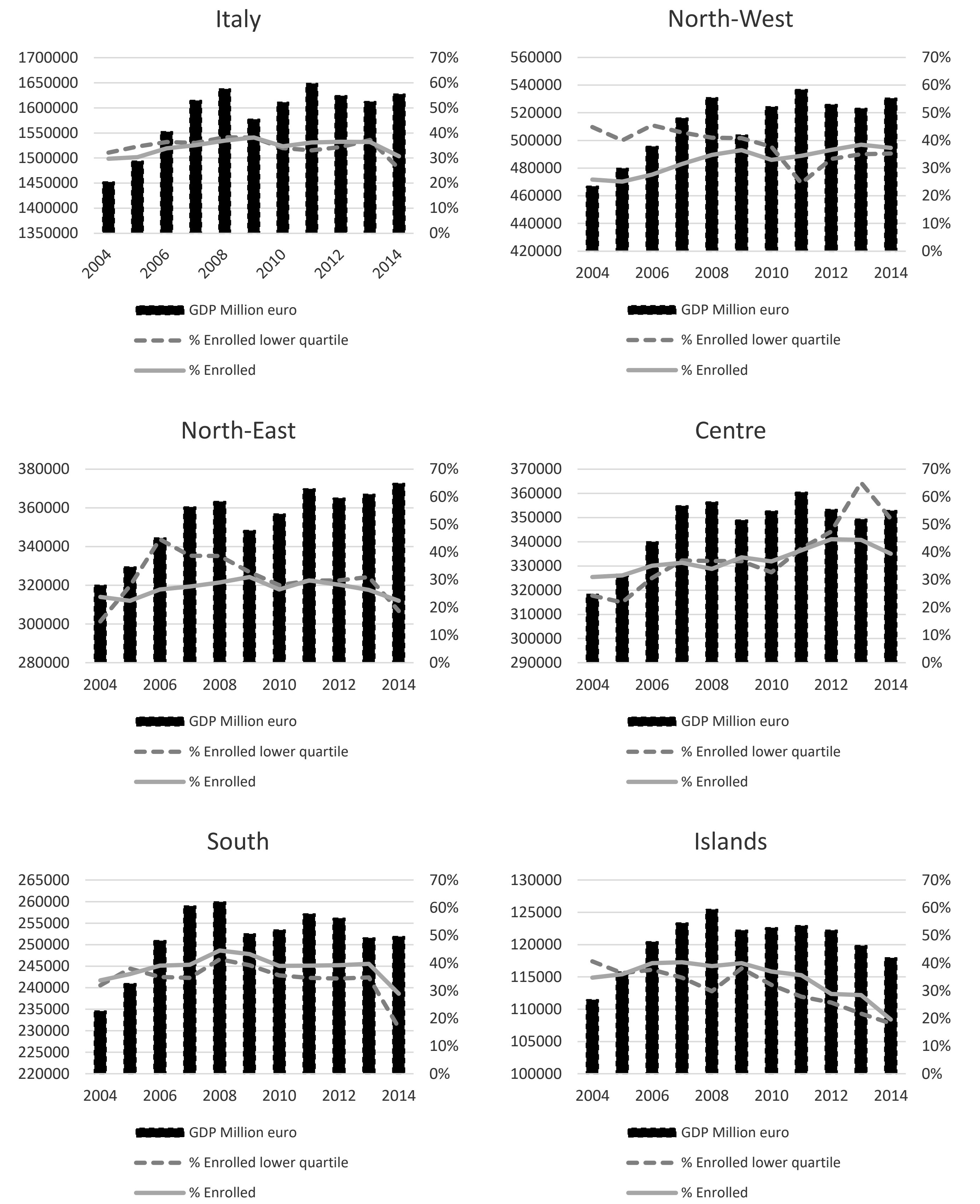
	Variable		Mean	Std. Dev.	Obs.	
Dependent variable	ENROL	overall	0.35	0.48	N =	19,512
		between		0.39	n =	4,878
		within		0.27		
Economic condition (variable of interest)	LN_GDP	overall	26.44	0.39	N =	19,512
		between		0.39	n =	4,878
		within		0.03		
Other socioeconomic covariates	AGE	overall	22.44	3.07	N =	19,512
		between		2.86	n =	4,878
		within		1.12		
	LN_YEQ	overall	9.54	0.93	N =	19,512
		between		0.74	n =	4,878
		within		0.55		
	GOV_EXP	overall	4.30	0.14	N =	19,512
		between		0.11	n =	4,878
		within		0.09		

Notes: All descriptive statistics are computed with individual sample weights. The overall and within summaries are calculated over 19,512 person-years of data. The between statistics are calculated over 4, 878 persons.

As Figure 1 shows, while the financial crisis seems to be homogeneous among the macro-areas, the economic crisis seems to produce heterogeneous effects, as in the South and Islands area the GDP decreases less than in the central and northern areas. Enrolment in post-secondary education increases in each area until 2008. After this year, the overall trend is stable in the North and in the Centre, while it seems to decrease in the other areas.

Until 2008, there is near-homogeneity between the trends of GDP and enrolment rate in each area. After this year, the differences between the two trends are significant in each macro-region. Figure 1 also highlights that the enrolment rate for the lower quartile of the population seems to be similar to the trend of the entire population in the sample. Nevertheless, the disaggregation by area shows that only in the southern areas (South and Islands) the trends are quite similar along the entire period studied. In the northern areas there are strong differences, in particular at the beginning of the period considered; in the central area the difference is seen only in the last three years.

Figure 1 – Trends in the economic cycle and enrolment rate



Notes: Elaborations of % enrolled lower quartile and % enrolled are based on EU-SILC panel data. Data on GDP are extracted from Eurostat.

4. Empirical strategy

To investigate the hypothesis that the economic cycle affects human capital investment decisions, I rely on a Probability model with individual fixed effects. This econometric strategy has the advantage to remove the effects of time-invariant unobserved characteristics and individual heterogeneity, although it is unable to control for time-varying unmeasured confounding. For this reason, I perform numerous robustness checks to reassure on the reliability of the results. This method is a sort of a difference-in-differences approach with continuous treatment that allows to measure the relationship between the macro-economic conditions and the probability to be enrolled.

Using fixed effects, we assume that something within the individual may impact or bias the predictor or outcome variables and control for this. The formal specification of the baseline model is as follows:

1) $$Y_{ijt}=\beta_1\ LN\_GDP_{jt}+\beta_2\ X_{ijt}+\beta_3 GOV\_EXP_{\ t}+\beta_4\ T_t+\varepsilon_{ij}$$

where subscript i denotes the individual, j is the macro-region of residence, and t is time. Y is the dependent dummy variable analysed (ENROL); LN_GDP is the variable of interest proxying the macroeconomic conditions. X is the vector of covariates at the individual level (which in the main analysis are LN_YEQ, LN_YEQ squared, and AGE fixed effects), GOV_EXP is the percentage of government expenditure in education on the GDP, and T controls for the time fixed effects.

The literature presented in Chapter 2 usually underestimates the possible asymmetry between positive and negative economic cycles. Nevertheless, the effect of an improvement in macroeconomic conditions may produce non-opposite effects with respect to a worsening. For this reason, in Model 2 I conduct the following analysis:

2) $$Y_{ijt}=\beta_1\ LN\_GDP_{jt}+\beta_2\ IMPROVING_{jt}+\beta_3 X_{ijt}+\beta_4 GOV\_EXP_{\ t}+\beta_5\ T_t+\varepsilon_{ij}$$

Model 2 considers all the variables of Model 1 but also includes a dummy variable (IMPROVING) that is equal to 1 if the GDP in area j is greater than the previous year and 0 otherwise. If this variable is significant, this would indicate asymmetry of the economic cycle.

As said above, several further analyses and robustness check are implemented. First, the possibility that the variable of interest could have lasting effects is among the major issues of this type of model since this would influence the causal relationship (Woolridge, 2010). To deal with this risk, I substitute the variable LN_GDP with the natural logarithm of the GDP lagged by one year (LN_GDP_LAG). The specification of this analysis is the same as Model 1 except for the variable of interest:

3) $$Y_{ijt}=\beta_1\ LN\_GDP\_LAG_{jt}+\beta_2\ X_{ijt}+\beta_3 GOV\_EXP_{\ t}+\beta_4\ T_t+\varepsilon_{ij}$$

Second, I focus on the relevance of the length of the period, or in other words, whether schooling decisions are influenced only by the current macroeconomic situation or also by that in the period just elapsed. To explore this option, I rely on the following model:

$$4)\qquad Y_{ijt}=\beta_1\ LN\_GDP_{jt}+\beta_2\ LN\_GDP\_LAG_{jt}+\beta_3\ X_{ijt}+\beta_4 GOV\_EXP_{\ t}+\beta_5\ T_t+\varepsilon_{ij}$$

In the regression in (4), I simultaneously consider both the logarithm of GDP and the logarithm of GDP lagged by one year. If the coefficients β_1 and β_2 are both significant, it means that not only the current macroeconomic condition but also its duration is relevant for human capital investment. Third, I conduct a sort of placebo test in which I repeat the analysis using a model specification where no relationship between the dependent and independent variables occurred based on a priori knowledge (Athey and Imbens, 2017). Assuming that individuals are not more influenced by the macroeconomic condition of the next year than the current one, I substitute the variable of interest in Model 1 with the same variable but referring to the following year (LN_GDP_$n+1$). The model is presented here:

$$5)\qquad Y_{ijt}=\beta_1\ LN\_GDP\_n{+}1_{jt}+\beta_2\ X_{ijt}+\beta_3 GOV\_EXP_{\ t}+\beta_4\ T_t+\varepsilon_{ij}$$

In other words, in the placebo test the outcome is replaced by a pseudo-outcome that is known to not be affected by the treatment. A positive result of the placebo test means that the coefficient $\beta_1$is not significant because a relationship between the two variables does not exist.

Other analyses conducted regarding the inclusion of different or additional variables in Model 1 include the substitution of the variable of interest with the natural logarithm of GDP pro capita (LN_GDP_CAP; Model 6), the inclusion of further covariates in the model specification (i.e. a categorical variable, HOUSEHOLD_DIMEN, distinguishing when the household size remains constant, increases or decreases, a dummy variable, SWITCH, identifying when the individual moves into a different household, a dummy variable, FAMILY_GRADUATE, indicating when a family member graduates, a dummy variable, PARENT, indicating the parental status, Model 7),[9] the exclusion of LN_YEQ squared from the covariates (Model 8), the substitution of the variables LN_YEQ and LN_YEQ squared with the dummy 'Capacity to face unexpected financial expenses' (UN_FIN_EX), which is a proxy of household economic security (Model 9), and the inclusion of time-invariant covariates (i.e. female and macro-region fixed effects, Model 10).

In the second part of this paper, I analyse the effect of the economic cycle distinguishing by household economic condition. As mentioned above, persons who decide to continue their studies after compulsory education are not randomly assigned with respect to economic status and their parents' social conditions (Checchi et al., 2013). For this reason, I prefer not to compute the quartiles of population on the basis of the restricted subsample but consider the entire initial sample. Since I build a fixed effects model, I adopt two different methods, (A) and (B), to disaggregate the sample into population quartiles.

Through method (A), the quartiles into which the population is divided are calculated on the basis of income in each year. Adopting this method, quartiles are made up by the same number of persons each year and the distinction of a persons' economic condition is in-depth (for instance, the fourth quartile is composed of the poorest people in that year). Another characteristic of this method is that a person may switch between different quartiles during the period of

[9] I decided not to include these independent variables in the main analysis, because no one has an additional explanation on the heterogeneity of the dependent variable, as also confirmed by the results of the jointly statistical significance (Wald) test.

observation if they improve or worsen their economic condition compared to the rest of the population. Since the fixed effects model does not consider the observations that remain in a quartile for just one year, through this method I only count observations that have remained in the same quartile for 2 years or more.

Adopting method (B), I assign to each person the quartile most prevalent during the four years of observation. If a person is in two or more different quartiles for the same number of years, I consider the lowest quartile. This method is almost specular with respect to the first: a person is tracked during all four years and he/she is considered in the same quartile also if a change at the tail-end of the years observed represents a structural change. Let me take the example of a person who improves his wage at the fourth year of the tracked period, thanks to a promotion. His household income belongs to the second quartile during the first three years, and it climbs to the third quartile in the last year of observation. Through this method, this person is considered as being in the second quartile in each period.

Table 2 presents descriptive data on the logarithm of income comparing the two methods. The subsamples of the first and second quartiles are larger and the mean is higher in method (B) than in method (A) because it includes observations that are in the upper quartiles for one or two years.

Table 2 – Disaggregation of income in quartiles

(A) LN_YEQ		**Mean**	**Std. Dev.**	**(B) LN_YEQ**	**Mean**	**Std. Dev.**
Fourth quartile	Overall	8.66	1.35	Fourth quartile	9.07	1.12
N = 5,131	Between		1.03	N = 8,956		0.81
n = 2,007	Within		0.85	n = 2,239		0.77
Third quartile	Overall	9.49	0.12	Third quartile	9.71	0.36
N = 5,042	Between		0.11	N = 5,172		0.21
n = 2,522	Within		0.07	n = 1,293		0.29
Second quartile	Overall	9.82	0.11	Second quartile	9.98	0.28
N = 5,017	Between		0.10	N = 3,168		0.17
n = 2,459	Within		0.06	n = 792		0.21
First quartile	Overall	10.30	0.30	First quartile	10.39	0.34
N = 4,322	Between		0.24	N = 2,216		0.29
n = 1,794	Within		0.14	n = 554		0.17

Notes: All descriptive statistics are computed with individual sample weights. The overall and within summaries are calculated over N person-years of data. The between statistics are calculated over n persons.

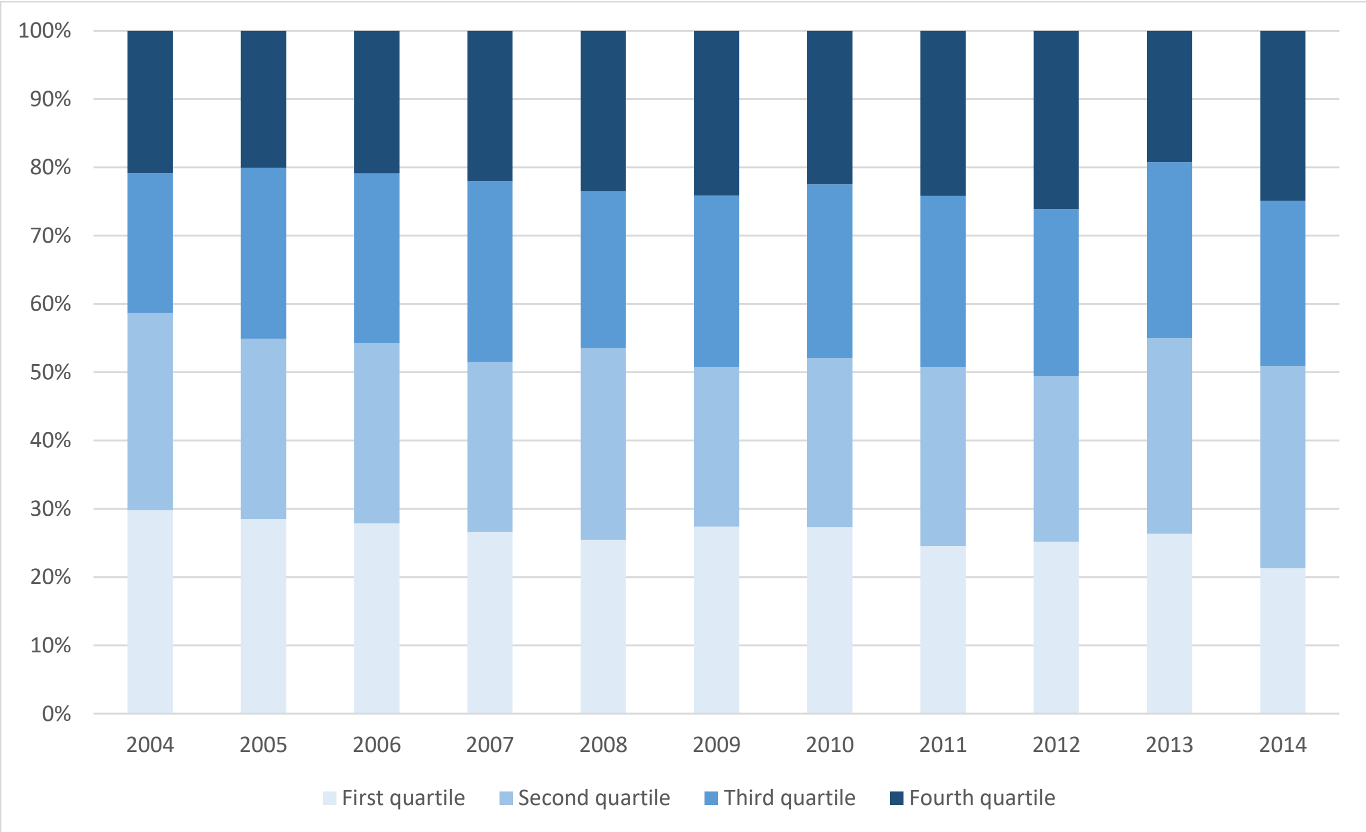
Figure 2 displays the trend in the economic composition of university enrolment disaggregating the entire population by income quartiles. It underlines that during the first five years of observation, more than half of those enrolled in post-secondary education are in the poorer part of the population. From 2009, the percentage is stable at 50%. It is also possible to notice a general decrease in the share of the lowest quartile over time (30% in 2004, 21% in 2014) and a concurrent increase, especially until 2009, of the wealthier half of the population (enrolment of students in the fourth and the third quartiles comprised, respectively, 21% and 20% of total enrolments in 2004 and 25% and 24% in 2014).

5. Results

The main assumption of the fixed effects model is that time-invariant individual characteristics should not be correlated with other characteristics. For a correct analysis, it is therefore important to test whether error terms are correlated. I conducted a Hausman test that allows examining whether the unique errors are correlated with the regressors (Green, 2008). The results are reassuring and indicate that the fixed effects model performs well, since the overall statistic has p-value equal to zero and I can reject the null hypothesis that individual effects are random.

Table 3 provides the marginal effects of the estimated variables of interest in all models. The complete results are presented in Table A1 of the Appendix. Specifically, row 'Model 1' reports the marginal effect calculated from the main analysis. The coefficient is negative and strongly significant, meaning that the relationship between the economic cycle and the enrolment decisions is counter-cyclical. A 1% increase in GDP is associated with a reduction of the probability to be enrolled of 1.2%. In analysis (2), I consider the case in which there is a difference between a positive and negative change in economic conditions on the dependent variable. Adding this variable (IMPROVING) to regression (1), I am able to explore the asymmetry of the economic cycle. As shown in the Model 2 row of Table 3, while the variable GDP remains significant and negative, the variable IMPROVING is not significant. This finding suggests that the marginal effect of GDP has the same effect in both sides of the economic cycle. These results are consistent with those of Dellas and Sakellaris (2003), who examine whether there are differences between expansions and contractions and conclude that the response of enrolment seems to be symmetric in the two stages of the business cycle.

Figure 2 – Quartile composition of enrolment in post-secondary education by year



Notes: The computation of the quartiles in each year is based on the entire population sample.

Analysis (3) is conducted considering the lagged variable of interest. The marginal effect is smaller than the previous one (–0.3%) but remains negative and significant ('Model 3' row). In analysis (4), I consider both current GDP and GDP lagged. This analysis is important in order to understand whether the duration of the economic cycle can also affect enrolment decisions. As we can see in the row 'Model 4', the GDP variable remains negative and significant while the lagged variable is positive and not significant. This finding suggests that investment in education is influenced only by the current economic condition, not by the length of the period. Following this, the placebo test is conducted to demonstrate that the effect of the economic cycle does not exist when it 'should not' exist. I regress the status of student on the GDP not of the same year but of the following year (for example, the variable ENROL in 2004 is regressed on the GDP in 2005). A positive result of the placebo test may indicate a non-significant correlation between the two variables. The results are in the 'Model 5' row and show that the marginal effect is not significant when we test for a relation that should not exist.

As explained above, several further analyses are conducted to check the robustness of the coefficient and the cause–effect relationship between the two variables: considering the natural logarithm of the GDP pro capita as the variable of interest (‘Model 6’ row), adding further independent time-varying variables (‘Model 7’ row), supposing a linear effect of household income on the probability of being enrolled and thus excluding LN_YEQ squared from covariates (‘Model 8’ row), substituting the income variable with the dummy ‘Capacity to face unexpected financial expenses’, which is a proxy of the household’s economic security (‘Model 9’ row), and adding the time-invariant covariates (i.e. female and macro-region fixed effects, ‘Model 10’ row). All results strongly confirm the counter-cyclical relationship between the economic cycle and human capital investment.

Table 3 – Overall role of the economic cycle on human capital investment decisions - Marginal effects

	VARIABLES OF INTEREST					
ANALYSIS	LN_GDP	LN_GDP_LAG	LN_GDP n+1	LN_GDP_CAP	IMPROVING	N. of Observations
(Model 1)	-0.012***					6,760
(Model 2)	-0.011***				-0.001	6,760
(Model 3)		-0.003*				6,760
(Model 4)	-0.022***	0.009				6,760
(Model 5)			0.000			6,760
(Model 6)				-0.012***		6,760
(Model 7)	-0.012***					6,760
(Model 8)	-0.012***					6,760
(Model 9)	-0.012***					6,760
(Model 10)	-0.012***					6,760

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

5.1. Is it an overall effect?

I now disaggregate the impact that the economic cycle produces on enrolment by considering different economic characteristics. The economic conditions may lead to different responses to a change in circumstances as poorer households are more affected by a worsening of the economy. I conducted the analysis for each quartile of income defined through the two different methods, (A) and (B), explained in Section 4.

Following method (A), the population is divided into quartiles calculated for each year. Through this scheme, the analysis is conducted on a smaller number of persons because the units that do not remain in the same quartile for two or more consecutive years are not included. The advantage of this method is that the analysis considers the real relative economic situation of individuals.

Results of both models are reported in Table 4 and in Table A2 in Appendix. Using method (A), the marginal effect of GDP is negative and significant for the subgroup in the first quartile and has the same coefficient as the overall analysis (–1.2%). The second and third quartiles are negative but not statistically significant different from zero. The wealthier quartile is positive and statistically non-significant. This first analysis seems to suggest that only the lower part of the income distribution is affected by the economic cycle.

A further analysis is conducted to control this result. Since the second and the third quartiles are negative, I check that the non-significance is not due to the size of the sub-samples (respectively, 1,084 and 990 observations). I therefore consider the two subgroups together in a further analysis (Table 4 and Table A2). Through this robustness check, I consider not just the 2,074 observations in the previous analysis but also the individuals switching from the second to the third quartile after one year (and vice versa). The new coefficient is negative and non-significant, confirming the previous result.

Using method (B), I divide the population in quartiles of income, assigning to each person the quartile prevalent during the four years of observation. As explained above, this method has different advantages and disadvantages with respect to method (A).

As shown in Table 4, the lower quartile of the population is affected negatively by an increase in the economic cycle and presents the same marginal effect as in the previous analysis (–1.2%). The second income quartile of population turns out to be negatively influenced, and the marginal effect is almost the same as for the first quartile (–1.4%). Finally, this method of disaggregation confirms that persons in the wealthier half of the population are not affected by the economic cycle as the coefficients are not significant and nearly zero.

Table 4 – Marginal effects of the logarithm of GDP in each income quartile

Method	QUARTILE N°	LN_GDP	N. of Observations
(A)	1	-0.012***	1,523
	2	-0.026	1,084
	3	-0.000	990
	4	0.003	1,021
(A2)	1	-0.012***	1,523
	2–3	-0.014	2,720
	4	0.003	1,021
(B)	1	-0.012***	3,384
	2	-0.014***	1,660
	3	-0.000	1,000
	4	-0.000	716

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

Both approaches to disaggregation present potential endogeneity between household economic condition and enrolment decisions, i.e. when an individual starts working, there is an increase in the income of the household, which can therefore move to a higher quartile. On the other hand, a young person deciding to enrol in non-mandatory education can increase family costs, moving it to a lower quartile. My disaggregation methods may therefore present bias. Unfortunately, the survey used does not allow for controlling this issue through ad-hoc questions. Thus, I control for this potential reverse causality by computing the quartiles of population on the basis of the householders' available income only.

The coefficients, reported in Table A3 in the Appendix, strongly corroborate my main results since they are all non-significant, except for the lower quartile (–1.2%) and the higher quartile, whose coefficient is equal to zero.

These findings have positive and negative implications: on a positive note, a worsening of economic conditions allows low-income individuals to acquire more education and reduce their gap with respect to the rest of the population. On the other hand, during a positive economic cycle low-income young people are less inclined to invest in non-compulsory education, while their peers remain indifferent.

6. Discussion and policy implications

In line with the literature, the present analysis finds a counter-cyclical relationship between the economic cycle and human capital accumulation. The improvement of macroeconomic conditions, therefore, reduces the probability of an individual being enrolled in non-compulsory education. However, previous contributions overlook the heterogeneity of this phenomena among families facing different economic conditions. My results show that this is an important factor to consider: while a 1% increase GDP reduces the probability of the poorest individuals being enrolled in non-compulsory education by 1.2%, the population in the wealthier part of the income distribution is not influenced. This finding is in line with Alessandrini et al. (2015), who show that an increase in GDP has a greater effect on enrolment for students with low levels of parental education than those whose parents have a high level of education.

This result also confirms that the low-income population is more affected by variations in the economic cycle than the rest of the population. In other words, when a worsening of economic conditions occurs, the reduction of opportunity costs cuts deeper for poorer populations than for the wealthy. This is due to the fact that they are more often employed in unskilled jobs and are more easily replaceable. Moreover, we could expect that the burden of direct costs for education to be greater the lower the individual's income. In Italy, this effect may be mitigated by the system of student fees, which, as explained in the introduction, are among the lowest in Europe and are not paid by one student in ten (Checchi, 2000). As Contini et al. (2018) explain, direct costs in Italy are not a reason why low-income students decide to not study. It will be important to develop further analyses focusing on the role of fees and grants in preventing the rise of inequalities in the access to higher education during economic cycles.

The most important political implication suggested by this analysis involves the strengthening of measures promoting enrolment in non-compulsory education, in an economic and especially in a cultural way, when economic conditions improve. In particular, this should be applied to youths from poorer households. As Checchi (2006) points out, higher average educational attainment is correlated with smaller differences in educational achievement among the population, leading to reduced income inequality as a results of better employment opportunities and greater social mobility. In this respect, the present paper may represent a starting point to study another serious problem in Italy: the dropout phenomenon from secondary education and post-secondary education. It is not possible to analyse how changing macroeconomic conditions my lead to upper-secondary dropout using EU-SILC data. This will be the focus of the next analysis conducted with a different dataset. Furthermore, limitations of the data do not allow the study of the determinants of university dropout. In particular, it may be of interest for economists to explore the effects of changes in household economic conditions on educational achievement.

The OECD (2018) describes education as the cornerstone of individual's progression through life, and it must be based on the principle of equity: every person should have the same opportunities to gain skills and to be fulfilled, regardless of their economic and social condition. For this reason, it is crucially important that research into the economics of education provides policymakers with the necessary tools to build a fairer society.

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Appendix

Table A1 – Overall role of the economic cycle in human capital investment decisions—Marginal effects

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)	(Model 8)	(Model 9)	(Model 10)
LN_GDP	-0.012***	-0.011***		-0.022*			-0.012***	-0.012***	-0.012***	-0.012***
IMPROVING		-0.001								
LN_GDP_LAG			-0.003*	0.009						
LN_GDP_n+1					0.000					
LN_GDP_CAP						-0.012***				
GOV_EXP	-0.003***	-0.007*	-0.001**	-0.005*	-0.007	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***
LN_YEQ	0.000	0.001	0.000	0.001	0.004	0.000	0.000	0.000		0.000
LN_YEQ squared	0.000	0.000	0.000*	0.000	0.000	0.000	0.000			0.000
UN_FIN_EX									0.000	
HOUSEHOLD_DIMEN increases							0.000			
HOUSEHOLD_DIMEN decreases							0.000			
SWITCH							-0.001			
FAMILY_GRADUATE							0.000			
PARENT							0.000			
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-invariant covariates	No	No	No	No	No	No	No	No	No	Yes
Observations	6,760	6,760	6,760	6,760	6,760	6,760	6,760	6,760	6,760	6,760

*Notes. *** p<0.01, ** p<0.05, * p<0.1. The base level for coefficients on HOUSEHOLD_DIMEN is "remain constant".*

Table A2 – Marginal effects of covariates in each income quartile

Model:			(A)	
Quartile:	1	2	3	4
LN_GDP	-0.012***	-0.026	0.000	0.003
GOV_EXP	-0.001	-0.006	0.000	-0.002
LN_YEQ	0.000	0.061	0.000	-0.027
LN_YEQ squared	0.000	-0.003	0.000	0.001
Time fixed effects	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Observations	1,523	1,084	990	1,021

Model:		(A2)	
Quartile:	1	2–3	4
LN_GDP	-0.012***	-0.014	0.003
GOV_EXP	-0.001	-0.004	-0.002
LN_YEQ	0.000	0.063	-0.027
LN_YEQ squared	0.000	-0.003	0.001
Time Fixed Effects	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes
Observations	1,523	2,720	1,021

Model:			(B)	
Quartile:	1	2	3	4
LN_GDP	-0.012***	-0.014***	0.000	0.000
GOV_EXP	-0.002***	-0.005	0.000	0.000
LN_YEQ	0.000	0.008	0.000	0.000
LN_YEQ squared	0.000	0.000	0.000	0.000
Time fixed effects	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Observations	3,384	1,660	1,000	716

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

Table A3 – Quartiles of population on the basis of the householders' available income—Marginal effects

Quartile:	1	2	3	4
LN_GDP	-0.012***	-0.014	-0.013	0.000**
GOV_EXP	0.000	-0.004	-0.014	0.000
LN_YEQ	0.000	-0.008	-0.008	0.000
LN_YEQ squared	0.000	0.000	0.000	0.000
Time fixed effects	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes
Observations	949	823	1,372	1,949

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

Chapter 3 – Identifying policy challenges of COVID-19 in hardly reliable data and judging the success of lockdown measures[1]

"To know is to know that you know nothing."

Socrates

1. Introduction

The fight against the novel coronavirus outbreak requires a mix of different social distancing measures. Decisions on implementing, stopping, or renewing restrictive measures require quick and reliable information about infection trends and the impact of already implemented measures. At the same time, however, time is needed before the effects of particular measures can be observed, and there is a delay from contagion until the moment when it appears as a confirmed case in official statistics, i.e., the detection delay. In addition, people may react to the virus and anticipate social distance restrictions (using, e.g., media reports, the internet, and their own observations). All of these factors complicate the accurate identification of changes in the pattern of contagion.

We propose a machine learning procedure to identify structural breaks in pandemic dynamics induced by lockdowns using regional data. With an iterative procedure based on the Akaike information criterion (AIC), we select the best model that gives us the relative impact of each lockdown measure and the date when the corresponding structural breaks are recorded in the data.

We move in the same direction as Casella (2020) and Dehning et al. (2020), who calibrate a detection delay in epidemic models. Our model is not epidemic but involves a theoretical, data-driven approach that allows avoiding any prior assumptions about the number and time distribution of the structural breaks. Thus, we neither assume, ex ante, that all lockdowns are effective nor do we exclude further structural breaks. The lack of restrictions also allows coping with possible announcement effects that may reduce the final detection delay.[2] Moreover, we do not need to assume that each measure has the same delay. This is important since, as shown in our analysis, delays vary consistently from one lockdown to another.

We consider the case of Italy, the first non-Asian country where COVID-19 resulted in a large number of deaths. Three national lockdowns were implemented: the closure of schools (including universities), the main lockdown, and the shutdown of non-essential economic activities. According to our results, the first lockdown started to effectively slow the daily growth of COVID-19 cases 17 days after its introduction, and the detection delay in the structural break determined by the second lockdown was even larger (19 days). In addition, we highlight that the school closure had a greater impact despite the relatively weaker prescriptions. This may confirm that, in particular in the case of an unprepared country,

[1] This work is published in the *Journal of Population Economics* with the title "*Identifying policy challenges of COVID-19 in hardly reliable data and judging the success of lockdown measures*" (joint with Giovanni Gallo and Fabrizio Patriarca). DOI: 10.1007/s00148-020-00799-x. It has been presented at Marche Polytechnic University Research Seminar (Virtual online conference, 2020) and Journal of Population Economics Webinar (Virtual online conference, 2020).

[2] The relevance of perceptions on the spread of the COVID-19 virus has been deepened in Milani (2020).

this first measure also has an announcement effect, making people adopt less risky behaviors beyond the official prescriptions. In contrast, the last lockdown was hardly effective.

After discussing these results, we use the interaction terms analysis to inspect some side effects of the specific lockdowns across the Italian territory. Finally, we show that the proposed machine learning procedure can also be used in a real-time methodology to promptly detect any changes in the outbreak pattern. In this case, the structural breaks predicted with shorter series are the same, and they can be correctly identified from the first day after they occurred, with the exception of the third and least effective lockdown. This evidence reveals that important policy implications can emerge from procedures like the one we developed, since the first lockdown's effects on the spread of COVID-19 could have been detected at the beginning of the political debate on the possible implementation of the business lockdown.

The structure of the paper is as follows. Section 2 contains a review of the recent literature related to our analysis, while Section 3 briefly describes the Italian case (features and timing of the lockdowns) and provides some descriptive evidence. Section 4 presents the econometric strategy. The following four sections present the results. Section 5 shows the results of the machine learning procedure that allows determining the detection delays. Section 6 analyses the coefficients of the best model selected, while in Section 7 we include some interactions with space-variant variables in the structural break model to assess for lockdown-specific features. Section 8 provides an ex post validation of model sensitivity. The last section offers some concluding remarks. Robustness checks are reported in the Appendix together with a description of the data.

2. Related literature

The academic effort of analysing and forecasting the pandemic dynamics of COVID-19 is huge. However, the quality of many studies does not always correspond to a comparable quality of the available data. The time series of confirmed cases are the most relevant example. This is not only because of the dependency of the data on the number of swabs and thus on the different testing policies and capacities. A further problem comes from the delay between contagion and its recording in official statistics.

Different delays combine to determine the overall one. The first and more commonly assessed delay is the incubation time, which ends when the first symptoms emerge, a timespan that the literature suggests is about 5.2 days and may last up to 14 days, as reported by Backer et al. (2020), WHO (2020), and Lauer et al. (2020), among others,[3] and that may be related to the features of the infected individual. In the analyses of spatial data, this might involve a bias related to the corresponding features of the population in different territorial units. In addition, unless a person is tested for other reasons, once symptoms appear, a medical consultation may occur only after some days, with individuals waiting for some time in the hope of seeing an improvement in their condition, and in particular when the population has little knowledge and is not accustomed to the virus. Time may also be necessary for individuals to be allowed to take the test, in particular when extensive testing policies are not set up and swabs are limited to cases with severe symptoms. Furthermore, available technologies and health system quality also impact the time needed to analyse the swabs. A final delay occurs for the confirmed case to be included in official "daily" statistics. All of these delays can be very different both in space and time.

[3] Some empirical studies actually report a wider range for the COVID-19 incubation period, even up to 24 days after exposure to the virus; however, these cases must be considered as outliers (Bai et al., 2020; Guan et al., 2020).

The literature usually determines the overall delay by considering only the average incubation time. The extent of this delay varies from 10 days, as in Pedersen and Meneghini (2020), to 2 weeks, as in Qiu et al. (2020). Some others consider a higher, though exogenously fixed, delay to take into account the other components of the detection delay. For instance, Fanelli and Piazza (2020) consider 20 days, while Remuzzi and Remuzzi (2020) use 15–20 days.

The only exceptions are Casella (2020) and Dehning et al. (2020). The first calibrates the additional components of the detection delay by using data from China and Italy's Lazio region to argue against the option of this data to assess feedback control strategies. The second, focusing on Germany, considers lockdown delays on restricted and early ranges. Indeed, more than a methodological challenge, this is a relevant issue for the assessment of proper policies since many countries are going to relax social distancing measures using daily data as signals of inherently exponential growth paths restarting. Furthermore, in the same countries such delays might vary in time because of changing test policies and swab analysis capacities. This might be particularly relevant outside East Asia, for countries having found themselves not prepared to manage the virus in its early stages and having learned how to cope with it through the mistakes made over time. Variation in this delay may also be related to the level of contagion, in the case of saturated health facilities and testing infrastructure. Moreover, testing technology has been changing throughout the pandemic, reducing the time required to perform the test and analyze the swabs (Sheridan, 2020; Edwards, 2020). Finally, lockdown measures may change the various delays both directly by changing the features of the infected population and indirectly through the different channels mentioned above.

Although the research aims differ from ours, another study analysing the COVID-19 outbreak is worthy of mentioning as it also adopts a machine learning methodology. Liu et al. (2020) indeed combine disease estimates from an agent-based mechanistic model and Internet searches on Baidu, via cluster-level machine learning procedures, to forecast COVID-19 contagion in Chinese provinces in real time. Their methodology allows for the production of stable and accurate forecasts 2 days ahead of current time in most of Chinese provinces.

3. The case of Italy

Italy was the first non-Asian country to experience the rapid and extensive spread of COVID-19. Based on data provided by the Italian Civil Protection Department (2020),[4] Fig. 1 shows the dynamics of positive cases, hospitalizations, and deaths from the 24th of February onwards.

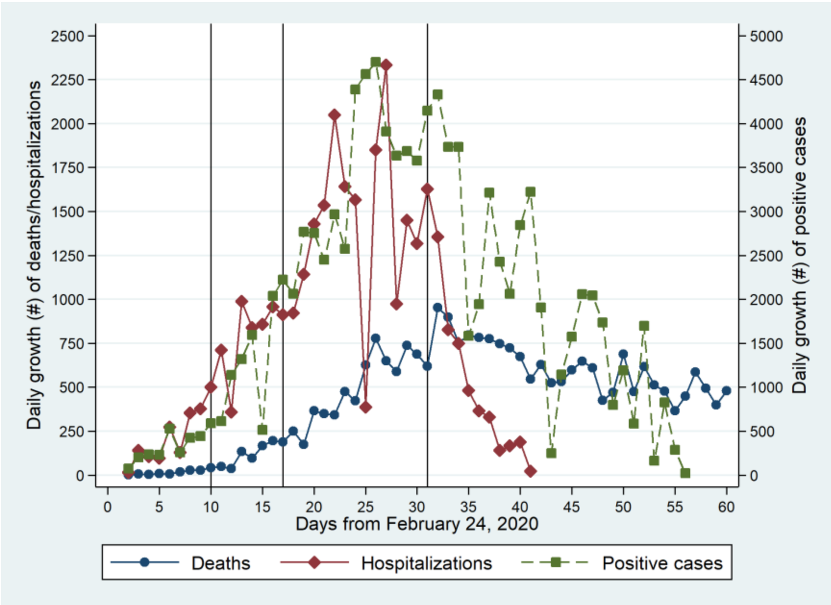
The dynamics of positive cases and hospitalized people became significant by the end of February, with an exponential trend reaching a peak in the second half of March; afterwards, the respective variations took a declining path. Deaths followed a similar path, with approximately a 10-day delay, although levels were still significant at the end of April.

A first measure taken by the national government to prevent the outbreak was implemented on the 30th of January, before the virus was officially detected in the country. This involved blocking all flights to and from China and declaring a state of emergency, thus allowing for higher discretional policies. On the 21st of February, when a cluster of cases was detected in the Lombardy region, the government decided to declare "red areas" and tried to isolate some small municipalities. Nevertheless, the virus spread throughout the northeast of the country, and on the 23rd of February, Italy became the European country with the highest number of infected people recorded.

[4] Civil Protection Department. Repository of COVID-19 outbreak data for Italy. https://github.com/pcmdpc/COVID-19. Accessed on April 24, 2020. For an assessment of such database quality and selection biases, see Depalo (2020).

From the beginning of March, the Italian government reacted to the emergency through a series of increasingly stringent rules for social distancing. Italy has been the first European country to implement significant restrictions to citizens' mobility and personal freedom. The first measure at the national level was announced and signed by the Prime Minister, Giuseppe Conte, on March 4 and became effective the day after. The main restriction concerned the suspension of school activities for all grades.[5]

Figure 1 – Daily growth of COVID-19 deaths, hospitalizations and positive cases at the national



Source: Civil Protection Department (2020). Notes: 'Positive COVID-19 cases' refers to the overall number of COVID-19 cases, excluding those who died or recovered. The three vertical lines represent the days on which the school lockdown, main lockdown and business lockdown were introduced, respectively.

On March 8, the Italian government signed another extraordinary restriction act for Lombardy and another 14 northern provinces (i.e., Modena, Parma, Piacenza, Reggio Emilia, Rimini, Pesaro–Urbino, Alessandria, Asti, Novara, Verbano–Cusio–Ossola, Vercelli, Padova, Treviso, and Venezia). This measure became effective the day after, although the national press spread the news the day before the act was signed. On March 12, the day after the World Health Organization declared a "pandemic" and with the virus already spreading to other regions and provinces, the Italian government extended the same measures to the whole country.[6] The measures involved the shutdown of all commercial and retail business activities, except for those considered basic necessities. Even food services such as bars and restaurants were closed, with the exception of take-away services. Furthermore, mobility was restricted to going to work, shopping for food, and emergencies.

The vertical lines in Fig. 1 correspond to the starting dates of the national lockdown measures. The third vertical line on the graph, on March 26,[7] corresponds to the last containment measure adopted: the closure of all "non-essential" economic activities. The enforcement of this lockdown had a fuzzy evolution: a first version of the decree was announced on March 21, published on March 22, and then

[5] http://www.governo.it/sites/new.governo.it/files/DPCM4MARZO2020.pdf.
[6] http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299
[7] https://www.gazzettaufficiale.it/eli/id/2020/03/26/20A01877/sg

modified after a meeting with workers' unions and entrepreneur representatives.[8] After this measure, only 53% of firms were allowed to remain open (Centra et al., 2020).

Many studies have tried to forecast the contagion dynamics in Italy (Remuzzi and Remuzzi, 2020; Grasselli et al., 2020; Fanelli and Piazza, 2020), or in Italy and other countries (see among others, Zhang et al., 2020). Some studies have also focused on the lockdown's effect, trying to evaluate the impact in terms of saved lives and contagion reduction (Lavezzo et al., 2020; Hsiang et al., 2020). Casella (2020) compares two types of restrictive measures: the tight lockdown adopted in China and the significant but less severe measures adopted in the Lazio region (the closure of schools and the main lockdown). He develops a control-oriented model capturing the control-relevant dynamics to homogenize territories. He concludes that suppression strategies can be effective if enacted very early, while mitigation strategies are prone to failure.

Pedersen and Meneghini (2020) implement a SIQR (Susceptible, Infectious, Quarantined, Recovered) model through which they evaluate the effect of lockdown measures in the north of Italy using data until March 19. They conclude that restriction measures slowed down the exponential growth rate but did not incisively reduce the spread of COVID-19. Giordano et al. (2020) propose a SIDARTHE (Susceptible, Infected, Diagnosed, Ailing, Recognized, Threatened, Healed, Extinct) model able to predict the epidemic's trend. Considering the period from February 20 to April 5, they analyze how the progressive restrictions have affected the spread of the epidemic. They found that lockdown measures had a moderate effect, probably due to their incremental nature. The main conclusion of the paper is that lockdown measures have to be combined with widespread testing and contact tracing to defeat the virus. The document redacted by Direzione Centrale Studi e Ricerche INPS (DCSR – INPS 2020) tries to quantify the effect of the third lockdown measure by exploiting spatial variation in the degree of closure of economic activities. This report claims that the reduction in COVID-19 cases started from the day the decree was introduced, without any delay. In any case, all of these studies, except Casella (2020), suffer from the same set of limitations in terms of the specification of the detection delay that was stressed above. Furthermore, except for the DCSR-INPS study, they are more focused on the forecasting of possible future scenarios and none performed a retrospective analysis of the features of the different kinds of restrictive measures.

Finally, what the literature has understated is that measures have both direct impacts due to the specific measures adopted and the particular dates on which they are enforced, and indirect effects for which things can be different and the distinction between lockdowns fuzzy. A prominent example is the announcement effect. Indeed, COVID-19's reproduction number also depends on individual behaviours such as avoiding skin contact between people or hand washing, which can be modified by the perception and knowledge of the virus. Both the announcement and implementation of restrictive measures can have a relevant impact on these, in particular in a country that has been one of the most affected by the novel coronavirus.

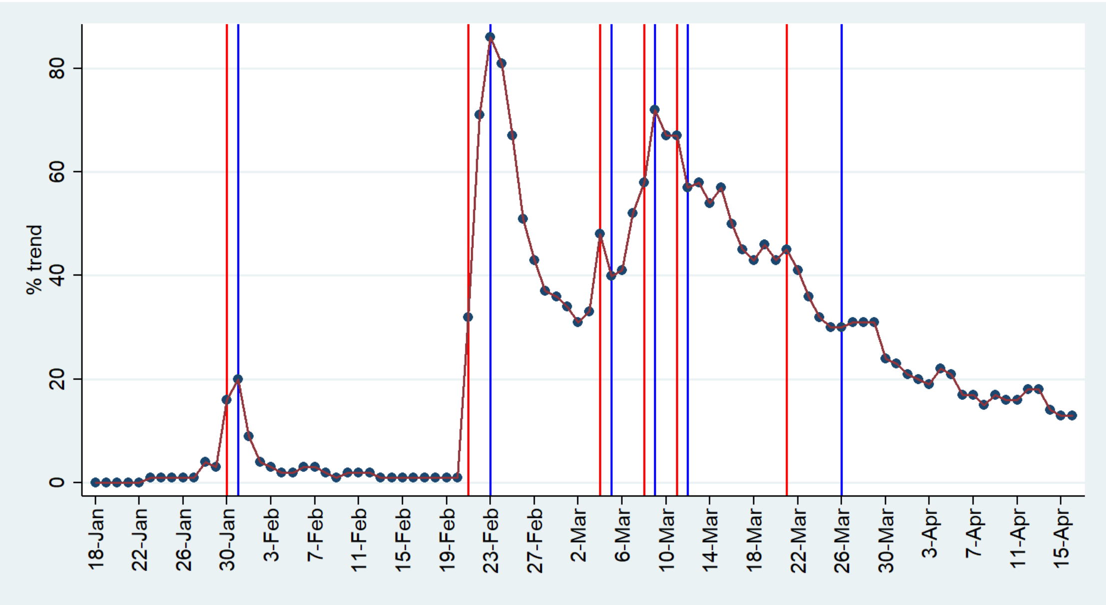
Figure 2 reports the Google Trends in Italy for "Coronavirus Italia" from mid-January to mid-April 2020.[9] The red line corresponds to the announcement date of the corresponding restrictive measures, whose actual introduction corresponds to the blue line. The first peak in Google searches corresponds to the date of air traffic closure between China and the state of emergency announcement. The second peak is recorded at the announcement and implementation of "red-zones" in some northern municipalities. The next peak occurs on the 4th of March, when the first national lockdown was

[8] http://www.governo.it/node/14363

[9] Google trends analysis has recently gained interest as it can successfully be applied to many different purposes including forecasting, nowcasting, and detecting health issues and well-being (Askitas and Zimmermann, 2015a). In economic analysis, they have recently been used to nowcast unemployment (Askitas and Zimmermann, 2009), well-being (Askitas and Zimmermann, 2015b), and also the influence of epidemic processes (Ginsberg et al., 2009).

announced. From this day onwards, the Google searches increased up to the implementation of the subsequent lockdown in the northern regions and started to decline on March 12, when the second lockdown was implemented at the national level. The upsurge of interest in the phenomenon related to the announcement of the previous restrictive measures might have affected the epidemic's path independently from the direct impact of the specific measures.

Figure 2 – Google Trends for "Coronavirus Italia" in Italy



Source: Authors' elaborations from https://trends.google.it.

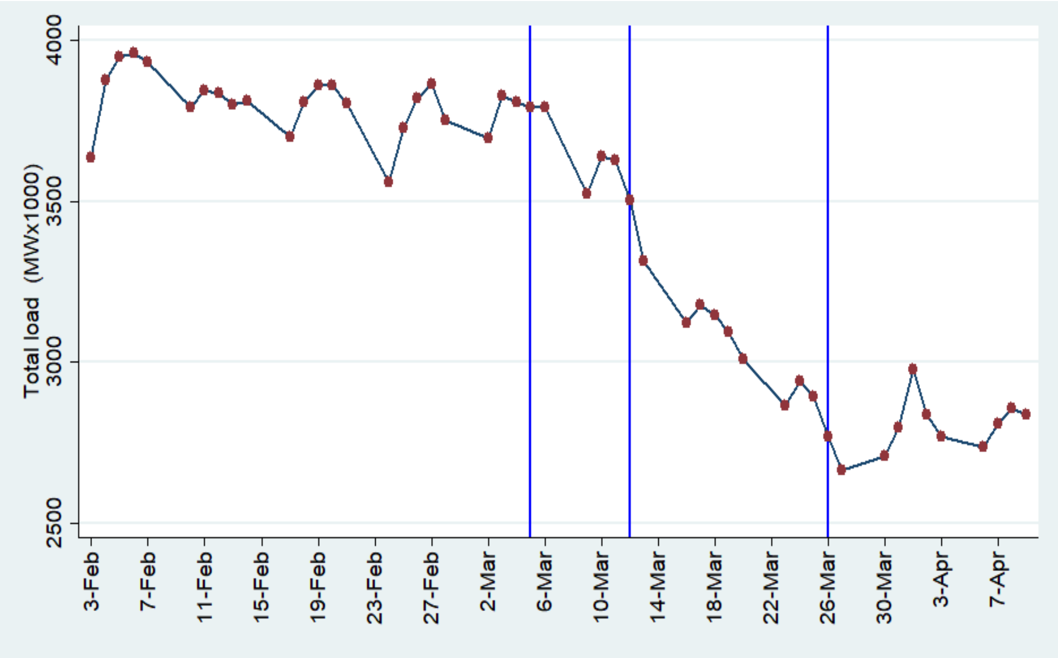
The same increased awareness might have other indirect effects through a massive shift of white-collar workers towards smart working (see Bonacini et al., 2020) and the decision of many firms to reduce their overall activities because of the incoming fall in final demand. Figure 3 displays the trends in electricity consumption in Italy from February 3 to April 9, 2020. Blue lines correspond to the dates when the three national lockdowns were implemented. The reduction in electricity consumption begins with the first lockdown, but it decreases sharply after the second (main) lockdown. Thus, standard economic activities seem to have decreased their electricity consumption already after the first lockdowns, although the shutdown was imposed only on a minority of economic activities—mainly schools, food facilities, and some retail, leisure, and cultural activities. The last lockdown, which imposed the closure of all (remaining) non-essential activities, seems to have had a lesser impact on energy consumption, which even showed a slight increase some days later.

All these descriptive indicators reinforce the need for a non-epidemic econometric strategy to deepen the detection delay issue and to assess the effects of the different lockdowns by also inspecting possible indirect and side effects. This is what we try to do in the next section.

4. Econometric strategy

Our underlying hypothesis is that the lockdown involves a structural change in the dynamics of the contagion. This structural change occurs after a time span, the detection delay. This might vary from one lockdown to another according to the specificity of the lockdown, the changing policies on testing, the progressive technological improvement in the analysis of test results, and the change in the administrative procedures for counting COVID-19 cases. Moreover, we assume no priors about the features of the dates when these structural breaks should occur, nor about their number, thus avoiding assuming ex ante that all or some of the three lockdowns are effective or that some other factors have caused additional structural breaks.

Figure 3 – Daily energy consumption in Italy, weekends excluded



Source: Authors' elaboration from https://www.terna.it.

The econometric strategy is composed of two sequential parts. In the first, we analyse the overall effect of the lockdown on the dynamics of COVID-19 cases by using a machine learning algorithm of model selection to select the best structural change dates. Since there actually turn out to be three, we can thus obtain the delay for each of the three lockdowns and obtain the best model to assess their effectiveness. However, the result is not the delay of the lockdowns but the date when they become effective, since, as we discussed in Section 3, a portion of lockdown effects could be related to their announcement in previous days. In the second stage, we exploit the spatial variability of some variables by studying their interaction with the structural break dynamics.

For the first part, we consider the following baseline panel data model specification:

$$\Delta y_{it}=\alpha+\boldsymbol{\beta X_{it}}+\gamma y_{i(t-1)}+\gamma_1 I_t^{t1} y_{i(t-1)}+\gamma_2 I_t^{t2} y_{i(t-1)}+\ldots+\gamma_k I_t^{tk} y_{i(t-1)}+\theta_t+\eta_i+\varepsilon_{it}$$

where y_{it} is the number of COVID-19 cases in province i at time t, $\boldsymbol{X_{it}}$ is a vector of two time varying province-level control variables: the number of recovered and the number of deaths at the regional level weighted by the share of province level COVID-19 cases over the regional level ones.[10] A more detailed

[10] Our imputation corresponds to the hypothesis of fixed recovery and mortality rates over the same region. It is worth noting that in Italy, the health system is public (although with a large share of private provision), with management and government totally in charge of regional authorities.

description of both the dependent variable and control variables can be found in Appendix (Table A1). The variables I_t^{tj} are time-variant dummies taking a value of 1 when $t \geq t_j$ and 0 elsewhere and k is the number of lockdowns considered. The dummy variable I_{ti}^{t2} also has the province index since for the 26 provinces that experienced the second lockdown 3 days before (i.e. on March 9th rather than March 12th), we correspondently give it a value of 1 also for $t_j - 3 \leq t < t_j$. θ_t and η_i are respectively time and province dummy variables and ε_{it} is the error term.

For a given k and $t_1 \dots t_k$, the model is a panel model with time and space fixed effects and k structural breaks for the effect of the lagged variable y on its variation at time t, where t_j corresponds to the time at which the structural break occurs. To select the best k and t_j, we use a machine learning algorithm by estimating the model for k varying from 0 to 5 for all the possible combinations of the t_k parameters, from the 5th of March to the 24th of April.

The same procedure is repeated for different specifications of the model that exclude, alternately, the control variables and the time dummies. Specifically, we define 1) Model 1 as the model specification with neither time dummies nor control variables; 2) Model 2 as the specification with time dummies but no control variables; 3) Model 3 as the specification with both time dummies and control variables; 4) Model 4 as the specification with control variables but no time dummies.

The best specification of the model is assessed by applying the Akaike information criterion on all three model estimations and all possible combinations of k $t_1 \dots t_k$. For further robustness, we perform the same test also including a quadratic specification of the $y_{i(t-1)}$ variable or substituting absolute values with values relative to province-level population. Finally, the Bayesian information criterion (BIC) of model selection is also applied alternatively to the AIC, and results are confirmed. On the final model selected, we conduct the standard Chow test for each structural break.[11]

The machine learning methodology selects k = 3 and the optimal t_1, t_2, t_3, for each model specification. Thus, we can analyze the coefficients of the best model selected to assess the relative impact of each of the three lockdowns. For this model we also perform some further robustness checks that are reported in the Appendix.

For the last part, we add to the best model selected the interaction with some variables of interests[12]

$$\Delta y_{it} = \alpha + \boldsymbol{\beta X_{it}} + \gamma y_{i(t-1)} + \delta_0 z_i y_{i(t-1)} + \gamma_1 I_t^{t1} y_{i(t-1)} + \delta_1 z_i I_{ti}^{t1} y_{i(t-1)} + \gamma_2 I_t^{t2} y_{i(t-1)} + \delta_2 z_i I_t^{t2} y_{i(t-1)}$$
$$+ \gamma_3 I_t^{t3} y_{i(t-1)} \gamma y_{i(t-1)} + \delta_3 z_i I_t^{t3} y_{i(t-1)} + \theta_t + \eta_i + \varepsilon_{it}$$

where z_i is a province-variant time-fixed variable that will be different for specifications we perform among a set of variables of interest. We consider each variable separately as it allows us to test, together with the changing impact of the variable over the four time span set up by the three lockdown thresholds t_1, t_2 and t_3, also the impact of adding the variable on the coefficients of the baseline model. The variable z_i without interaction is omitted since we already consider province fixed effects.

[11] See Wooldridge (2016, Ch. 13) for a thorough explanation of the methodology adopted.
[12] For the sake of clarity, we add the interaction terms both to the number of COVID-19 cases (y_{it}) and to the structural breaks.

5. Identification of structural breaks

The methodology presented in Section 4 allows for the identification of the dates of structural breaks in the path of COVID-19 cases. The procedure automatically selects the number and dates of structural breaks and the best model specification using the Akaike information criterion (AIC). The model with three structural breaks is always selected as the best one, indicating that the three lockdowns have all had significant impacts. We thus define the corresponding date of the structural break as the effectiveness date of each lockdown.

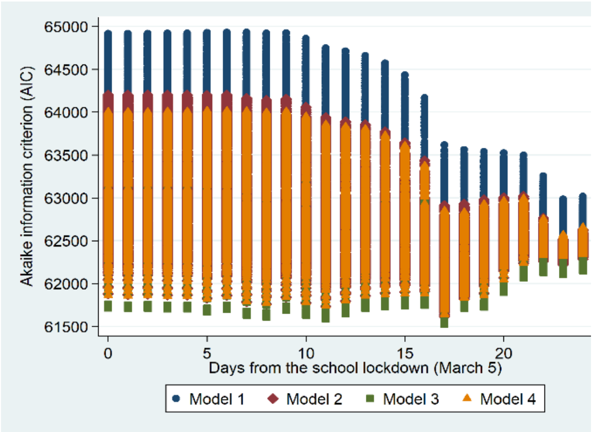
For the sake of simplicity, to comment on the results of the machine learning algorithm, we present here the best model selection through a clearer step-by-step procedure. In this case, to find the best model, we first select the effectiveness day for the first lockdown (LD1), making the dates of the two other lockdowns vary; then, we select the effectiveness day for the second lockdown (LD2), fixing LD1 according to the first step. Finally, we select the effectiveness day for the last lockdown (LD3), setting LD1 and LD2 according to steps two and three. This nested iterative procedure gives the same results as the non-nested (unrestricted) one presented in Section 4. Figure 4 a shows the AICs of all of the corresponding regressions, for each combination of parameters and model specification presented in Section 4, using the days from the introduction of the lockdown as reference. We recall that the best model, and thus the combination of days/parameters representing the detection delay of the lockdowns, corresponds to the model with the lowest AIC value.

Results in Fig. 4 highlight that models that perform better in explaining the trend of COVID-19 cases are those where the algorithm sets the LD1 effectiveness day 17 days after its introduction (i.e., March 22). Interestingly, the school lockdown therefore appears to become effective after a number of days greater than the standard incubation period of the novel coronavirus (2–14 days after exposure to the virus, as reported by Backer et al. (2020), WHO (2020), and Lauer et al. (2020), among others), confirming the relevance of the further components of the detection delay. The same effectiveness day for LD1 is further confirmed by the other model specifications we developed. From the estimations illustrated in Fig. 4, we can also argue that Model 3 (i.e., the model specification including time dummies and the number of deaths and recovered at the provincial level) is the best one to explain the trend in COVID-19 cases, as its AIC values are always smaller than those reported by the other models.

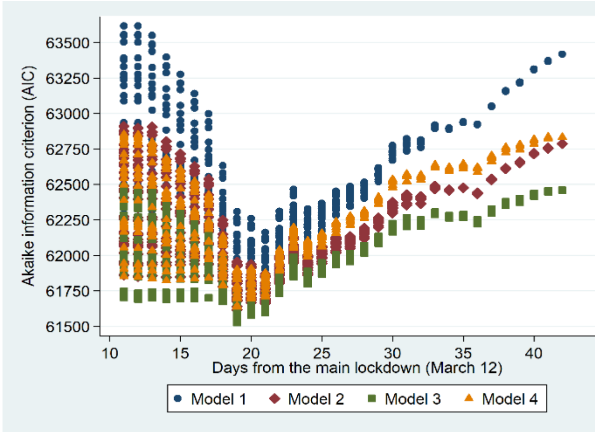
Once the effectiveness day for LD1 is identified, we select the day from which LD2 became effective by looking at models with the lowest AIC values among those presenting this constraint. As a simplification of the algorithm results, panel B of Fig. 4 therefore shows the AIC values of models where effectiveness days for LD2 and LD3 vary and the one for LD1 is fixed and is equal to 17. Estimates in Fig. 4b highlight that the combinations of parameters that better perform in explaining the trend in COVID-19 cases are those where the algorithm sets LD2's effectiveness at 19 days after its introduction. This means that the main lockdown starts to be effective on March 28 for Lombardy and the other 14 provinces listed in the Prime Ministerial Decree of the 8th of March 2020, and on March 31 for the rest of Italy. In this case as well, the detection delay of LD2 seems to be greater than the presumed incubation period for COVID-19, but the same evidence is confirmed by the other model specifications we developed. The long detection delay of LD2, which is even greater than of the LD1 one, may be explained by the fact that the highest daily growth values of people hospitalized because of the novel coronavirus at the national level were registered just a few days after the introduction of the main lockdown (see Fig. 1 for details). The massive burden of patients suffered by the local health systems in that period, as well as the critical growth of COVID-19 cases, probably slowed down the conducting and analysis of swab tests, thus further delaying the day from which the daily count of COVID-19 cases at the provincial level reports the start of LD2's effectiveness.

Figure 4 – Akaike information criterion values by model specification and values of the t_j parameters

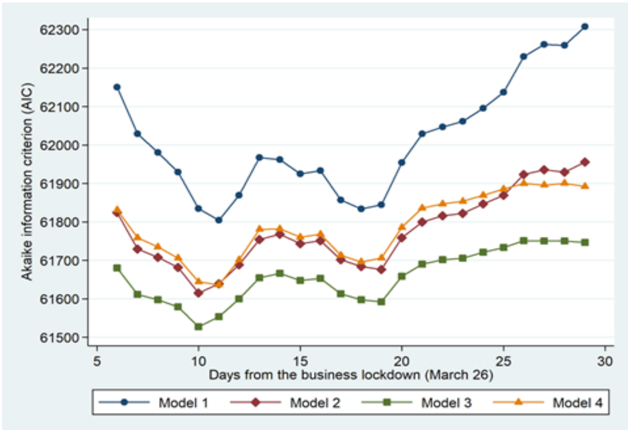
Panel A. School lockdown (LD1)



Panel B. Main lockdown (LD2)



Panel C. Business lockdown (LD3)



Notes: The LD1 effectiveness day in models illustrated in Panel B is set to 17 days after the introduction of LD1. The LD1 and LD2 effectiveness days in models illustrated in Panel C are set to, respectively, 17 and 19 days after their introductions.

Finally, keeping constant the effectiveness day for LD1 (i.e., 17 days after its introduction) and for LD2 (i.e., 19 days after its introduction), this simplification of the machine learning algorithm results displays the day from which LD3 became effective (panel C of Fig. 4). In contrast to what is seen in panels a and b of Fig. 4, the estimates presented here do not show a perfect concurrence between the model specifications analysed in terms of the LD3 effectiveness day. In particular, the business lockdown became effective 10 days after its introduction (i.e., April 5) according to Models 2 and 3, while the LD3 effectiveness day occurred 1 day later (i.e., April 6) in Models 1 and 4. This slight difference in results is likely related to the exclusion of time dummies in the last two model specifications, which does not allow controlling for possible time-variant (but space-invariant) factors. LD3 has thus been the lockdown with the shortest detection delay (i.e., 10/11 days versus 17 days for LD1 and 19 days for LD2). There are different potential reasons for this evidence. First, the greater knowledge regarding the novel coronavirus among the Italian population probably led to a reduction in symptom signalling. Second, the improvement of pandemic management abilities by local authorities, together with the mitigation of the health crisis in most affected areas, probably resulted in a decrease in the average time to swab potentially infected people and to communicate test results. Third, the technology regarding COVID-19 tests improved, leading to swabs that provide test results in a shorter period of time (Sheridan, 2020; Edwards, 2020). Finally, the marked increase in the number of swabs performed daily (see Figure A1) might have also played an effective role in reducing the detection delay.

The AIC value of the best specification is 61,527.2. The Chow test accepts the structural break hypothesis for each of the structural breaks in each model specification. The same optimal specification is chosen using the alternative Bayesian information criterion (BIC). In the Appendix (Table A2), we report some further robustness checks on the model specification we use to identify the detection delays of the three lockdowns. In particular, we test the results of our machine learning algorithm (i) including, without and with time dummies, a quadratic (instead of linear) term for the lagged COVID-19 cases and its interactions with lockdown variables (i.e., Models 5–6); (ii) replacing control variables at the provincial level with those at the regional level (i.e., Model 7); and (iii) adding as a control variable the number of swab tests conducted at the provincial level (i.e., Model 8).[13] Robustness check results in Table A2 overall confirm, for each lockdown, the same effectiveness days we detect in our best model specification (i.e., Model 3). The only specification reporting different delays (especially for LD3) is Model 5. This discrepancy, however, may be explained by the fact that, not including time dummies, Model 5 is not able to catch time-variant province-invariant factors, such as the improvements in swab test technology that occurred at the end of March. Figure A2 in the Appendix shows how the model fits actual data provided by the Civil Protection Department for the two regions most affected by the novel coronavirus (i.e., Lombardy and Emilia-Romagna) and the most populated region for each of the two other macro-regions of Italy (i.e., Lazio for the centre and Campania for the south).

6. Lockdown effects on the trend of COVID-19 cases

The optimal identification of structural breaks allows us to estimate the relative effects on the dynamics of COVID-19 cases limiting as much as possible any arbitrary assumptions.

As explained in Section 4, we estimate lockdown effects on the spread of COVID-19 in Italy through a fixed-effects panel model based on four different specifications and using as dependent variable the daily growth in COVID-19 cases at the provincial level. Lockdowns are included in all model specifications as interactions between their specific time dummy and the variable reporting the overall number of COVID-19 cases at the provincial level at time t-1. Specifically, the dummy LD1 is equal to 1 from March 22 onwards (i.e., the 27th day after February 24); the dummy LD2 is equal to 1 from March 28 onwards for both Lombard provinces and the other 14 provinces listed in the Prime Ministerial decree dated March 8, 2020, while it is equal to 1 from March 31 onwards (i.e., the 36th day after February 24) for the remaining Italian provinces; the dummy LD3 is equal to 1 from April 5 onwards (i.e., the 41st day after February 24) in Models 2 and 3, while it is equal to 1 from April 6 onwards in Models 1 and 4 (see Section 5 for details).

Estimation results of Model 1 indicate that all three lockdowns resulted in a significant alleviation in the spread of COVID-19 once they became effective (Table 1). Looking at magnitudes, the school lockdown appears to be the most important one in reducing the growth of cases in Italy (the difference in interaction coefficients between LD1 and LD2 is statistically significant at the 1% level). The predominant effect produced by the school lockdown is likely to be related to its ability to reduce mobility and keep a large portion of the population (composed of children, upper secondary school and university students, teachers and professors, and parents with child-care tasks) at home.

In contrast, Table 1 highlights that the business lockdown was the one with the smallest alleviation effect on the growth of cases in Italian provinces (the difference in interaction coefficients between LD3 and

[13] The information regarding the number of swab tests suffers the same issue reported by the number of COVID-19 deaths and recovered cases: it is not available at the provincial level—only at the regional level. For this reason, also in this case, the variable is calculated for each province weighting regional COVID-19 swab tests by the share of regional COVID-19 cases reported by the same province.

LD2 is statistically significant at the 1% level). Similarly to LD1, the reason for the smaller effect of LD3 is probably linked to the lower number of people involved in the business lockdown (i.e., workers in "non-essential" economic sectors of activity). The smaller magnitude of the LD3 interaction variable may also be related to two other important aspects. First, economic activity was seriously indirectly affected already, as a result of the main lockdowns (see the discussion of Fig. 2 in Section 3). Second, the sectors of activity defined as "essential" by the Italian government were not necessarily less exposed to COVID-19. Third, many companies belonging to "non-essential" economic sectors requested and obtained exemptions from the lockdown from local authorities.[14]

Table 1 shows that estimated effects of the three lockdowns on the growth of COVID-19 cases, as well as the main conclusions of our analysis, remain overall the same when including time dummies in the model specification (Model 2) and/or the controls for the number of deaths and recovered at the provincial level (Models 3 and 4).

Table 1 - Effects of the three lockdowns on the daily growth of COVID-19 cases (fixed-effects panel model)

Variables	Model 1	Model 2	Model 3	Model 4
COVID-19 cases $_{t-1}$	0.120***	0.117***	0.125***	0.129***
	(0.012)	(0.013)	(0.012)	(0.010)
LD1 * COVID-19 cases $_{t-1}$	-0.059***	-0.060***	-0.058***	-0.057***
	(0.007)	(0.007)	(0.008)	(0.008)
LD2 * COVID-19 cases $_{t-1}$	-0.031***	-0.028***	-0.027***	-0.029***
	(0.001)	(0.002)	(0.002)	(0.002)
LD3 * COVID-19 cases $_{t-1}$	-0.015***	-0.015***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.003)	(0.003)
Number of deaths			0.011	0.021
			(0.040)	(0.039)
Number of recovered			-0.052**	-0.067***
			(0.021)	(0.017)
Constant	8.165**	0.200	0.178	6.511**
	(3.227)	(1.710)	(1.636)	(2.676)
Time dummies	No	Yes	Yes	No
Observations	6,313	6,313	6,313	6,313
R-squared	0.428	0.455	0.463	0.444
Number of provinces	107	107	107	107

*Notes: Standard errors in parentheses are clustered by Italian province. *** p<0.01, ** p<0.05, * p<0.1.*

As a sensitivity analysis, in the Appendix (Table A3), we replicate the analysis presented in Table 1 for our best model specification (Model 3) in some subsamples. First, given that daily counts of new COVID-19 cases may be affected by different (unobservable) strategies by local authorities (e.g., the

[14] An investigation reported by IlFattoQuotidiano on April 25, 2020, shows that almost 200 thousand companies requested an exemption to the lockdown from the local authorities, and the majority of them are located in Lombardy, Veneto, or Emilia-Romagna, the three Italian regions most affected by the novel coronavirus. Link: https://www.ilfattoquotidiano.it/2020/04/25/coronavirus-quasi-200mila-aziende-riapertein-deroga-durante-il-lockdown-il-558-nelle-regioni-piu-colpite-prima-la-lombardia/5782265/. Other pieces of evidence in the same direction are reported here: https://www.adnkronos.com/soldi/economia/2020/04/07/allarme-sindacati-mila-azie.nde-chiedono-deroga-stop-governo-vigili_fib07RmwjTQwb0bEvLF51L.html; https://www.quibrescia.it/economia-4/2020/04/27/ritorno-al-lavoro-piu-di-15-mila-richieste-in-deroga-inprefettura/560734/.

number of swabs conducted or analysed), we run Model 3 estimates in a subsample considering even (or odd) days only. Second, as Lombardy has been the most COVID-19-affected region and its provinces may represent outliers, we replicate Model 3 estimates in a subsample excluding 12 Lombard provinces. Third, we exclude 26 provinces listed in the Prime Ministerial Decree of the 8th of March 2020, in order to explore the potential heterogeneity in the LD2 alleviation effect since the main lockdown was introduced 3 days in advance in these provinces. Finally, we replicate our analysis referring to COVID-19 case variables defined in relative terms with respect to the provincial population. Specifically, both the dependent variable and the lagged COVID-19 case variables were divided by the number of inhabitants at the provincial level and then multiplied by 10,000. Results of these sensitivity analyses in Table A3 overall confirm the robustness of our evidence on lockdown effects on the daily growth of the cases of the novel coronavirus at the provincial level. Interestingly, when excluding provinces listed in the Prime Ministerial Decree of the 8th of March 2020, no significant differences are observed in the LD2 effect, whereas LD3 had a similar impact to LD2 in this case. However, the latter evidence is likely to depend on the fact that the 26 provinces that started the main lockdown on March 9 (rather than March 12) are all in the north of Italy (except for Pesaro–Urbino), the area of the country where both most of the "essential" economic sectors are located and where many more exemptions from the business lockdown have been requested.

7. Interactions with province-level characteristics

Because of the strong heterogeneity across Italian provinces in terms of demographic and economic characteristics (see, among others, Bratti et al. 2007; Gallo and Pagliacci 2020), in this section, we explore to what extent some of them interacted with the three COVID-19 lockdowns. To do this, as explained in Section 4, we add interaction terms with the variable of interest in Model 3 (i.e., our best model specification; see Section 5).

The flourishing literature studying differential rates of compliance to social distancing highlights that both individual social and political characteristics and contextual variables are strong determinants. Chiou and Tucker (2020) and Wright et al. (2020) study the correlation between income and the propensity to comply with social distancing orders. The first finds that both income and internet access are positively correlated with the ability to stay at home. The second suggests that the poorest communities are the least likely to comply with social distancing orders. Allcott et al. (2020), Barrios and Hochberg (2020), and Painter and Qiu (2020) document for the USA that Republicans are less likely to respect social distancing orders. Egorov et al. (2020) reach a coherent conclusion showing that the reduction in mobility is stronger in more multi-ethnic cities and those with higher levels of xenophobia. Simonov et al. (2020) point out a negative correlation between Fox News viewership in US regions and the propensity to stay at home during the pandemic. Doganoglu and Ozdenoren (2020) explain that generalized trust is associated with less social distancing. Borgonovi and Andrieu (2020) note that a larger drop in social mobility is correlated with higher social capital. Finally, Beland et al. (2020), using a difference-in-differences approach on US data, find that stay-at-home orders unequally increased unemployment rates since younger, less-educated, and immigrant workers were more affected by the lockdown experience.

We focus here on four categories of demographic and economic characteristics. First, we look at provincial territory and infrastructure (i.e., population density, proximity to a hospital, proximity to a railway station) to observe whether restrictive measures were more effective on commonly crowded places. Second, we explore heterogeneous effects at provincial level by some characteristics of the local health system and disease vulnerability (i.e., share of hospital dismissals of people aged 65 or above, past mortality rates for infectious diseases). The first variable wants to detect whether the (likely) greater presence of the elderly (i.e., vulnerable people reported highest COVID-19 mortality rates) in the hospitals played a role on the outbreak, while the second variable should shed light on some kind of "historical" local vulnerability to infectious diseases. Third, we analyze the territorial dimensions regarding students and nursing homes (i.e., share of high school and university students in the total population of persons aged 64 or less, number of nursing homes), because they were subject of an important and deep public debate for, respectively, the controversial effects of closing schools and the incorrect management of restrictive measures in the first stage of pandemic. Fourth, in line with the literature on the compliance to social distancing measures, we consider two variables describing the local labor market and income levels (i.e., unemployment rate among people aged 15–74, share of poor households in the total population based on administrative data) to indicate whether the lockdown measures were less effective in the poorer areas. More details on these variables are presented in the Appendix (Table A1).[15]

Estimates in Table 2 show that the spread of COVID-19 has been more severe in Italian provinces with higher population density or where a greater number of provincial inhabitants live in municipalities with at least one hospital or railway station (i.e., our proxies of proximity to a hospital/railway station). This evidence is largely expected because hospitals and crowded places like railway stations or metropolitan areas have probably been important sources of contagion (Lau et al. 2004; Koganti et al. 2016). Nonetheless, as reported by the structural break coefficients of population density, more densely populated provinces are those in which the three lockdowns have been more effective, thus the ones where the daily growth of COVID-19 cases decreased the most in the last part of our reference period. These results are consistent with those of Qiu et al. (2020). Instead, the proximity to a hospital or a railway station increased the LD3 alleviation effect only. Looking at the characteristics of the local health system and disease vulnerability, the last two columns of Table 2 indicate that the spread of COVID-19 was lower in provinces with more hospital dismissals of the elderly in the previous year and where the mortality rate for infectious diseases was higher in the past.[16] In the latter case, the interaction term with the number of COVID-19 cases at time t-1 is insignificant. After the introduction of lockdowns, however, the coronavirus infection is relatively greater in these areas. This evidence suggests that lockdown measures may be less effective in less healthy provinces. The same evidence is also confirmed by the third column of Table 3, i.e., the one regarding nursing homes.

The share of high school and university students in the provincial population aged 64 or less, as well as the presence of nursing homes, also had a significant role in explaining the trend of COVID-19 cases (Table 3). The daily growth of COVID-19 cases appears higher in the first stage of the pandemic in provinces with a greater share of university students, and the school lockdown alleviates this effect, as does the business lockdown, probably because of the working students.[17] Instead, our estimation results

[15] We performed the interaction terms analysis considering further relevant variables, such as the share of females, the foreigners or elderly on the total provincial population, the aged dependency ratio, the share of people living in isolated buildings, and the amount of net exports from Europe and the rest of the world. Nonetheless, we decided not to present these estimates because of an overall lack of statistical significance on either lockdown variable coefficients or the interaction terms with the same analyzed variables (or both). That leads to results difficult to interpret or to an evidence of no significant differences on lockdown effects across the country when comparing provinces by that specific variable.More details are available upon request to the authors.

[16] Similar evidence appears when looking at the provincial-level past mortality rate for malignant tumors, mental illness, heart diseases, and respiratory diseases. Results are available upon request to the authors.

[17] The variables reporting the number of university students impute them to the Italian province in which the university is located, but the national institute of statistics (ISTAT) also provides the same information referring to native/residence provinces. When we look at the incremental effect of university students on lockdown impacts using this other variable, we observe that it has no significant effect on LD1 and even worsens the LD2 alleviation effect on the daily growth of COVID-19 cases. This interesting difference may be explained by the fact that university students came back home, increasing infections of the novel coronavirus in their native provinces. Further evidence of this phenomenon is reported by different national newspapers. Links to some of these include https://www.corriere.it/cronache/20_marzo_08/coronavirus-l-esodo-nord-sudcontrolli-treni-autobus-arrivo-1100582c-612c-11ea-8f33-90c941af0f23.shtml;

suggest that the opposite occurred in provinces with larger relative numbers of high school students. The public debate on LD1 had indeed pointed to the possible controversial effects of closing schools without further social distancing measures because the alternative use of time by teenagers could expose them more to infections.

Table 2 – *Interactions of province level characteristics (infrastructures, local health system and diseases vulnerability) with lockdowns (fixed-effects panel model)*

Variables	Variable of Interest (VoI)				
	Population density	Proximity to a hospital	Proximity to a railway station	Hospital dismissals of the elderly	Mortality for infectious diseases
COVID-19 cases $_{t-1}$	0.097***	0.078***	0.071***	0.411***	0.129***
	(0.011)	(0.015)	(0.020)	(0.101)	(0.019)
LD1 * COVID-19 cases $_{t-1}$	-0.039***	-0.036***	-0.035**	-0.196***	-0.060***
	(0.004)	(0.010)	(0.014)	(0.066)	(0.012)
LD2 * COVID-19 cases $_{t-1}$	-0.023***	-0.027***	-0.030***	-0.088***	-0.038***
	(0.003)	(0.003)	(0.004)	(0.010)	(0.004)
LD3 * COVID-19 cases $_{t-1}$	-0.006***	-0.007***	-0.005**	-0.072***	-0.014***
	(0.001)	(0.002)	(0.003)	(0.014)	(0.005)
VoI * COVID-19 cases $_{t-1}$	0.014***	0.045**	0.054*	-0.305***	-0.006
	(0.001)	(0.021)	(0.032)	(0.104)	(0.019)
VoI * LD1 * COVID-19 cases $_{t-1}$	-0.008***	-0.024	-0.029	0.146**	0.002
	(0.001)	(0.015)	(0.024)	(0.065)	(0.010)
VoI * LD2 * COVID-19 cases $_{t-1}$	-0.001***	-0.001	0.003	0.065***	0.012***
	(0.000)	(0.004)	(0.006)	(0.011)	(0.004)
VoI * LD3 * COVID-19 cases $_{t-1}$	-0.002***	-0.007***	-0.010***	0.066***	0.001
	(0.000)	(0.002)	(0.003)	(0.014)	(0.005)
Number of deaths	-0.016	0.028	0.051*	0.015	0.025
	(0.036)	(0.026)	(0.027)	(0.035)	(0.035)
Number of recovered	-0.063***	-0.044**	-0.046**	-0.063***	-0.055***
	(0.020)	(0.017)	(0.018)	(0.019)	(0.020)
Constant	0.211	0.201	0.189	0.248	0.185
	(1.398)	(1.508)	(1.505)	(1.565)	(1.398)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	6,313	6,313	6,313	6,313	6,313
R-squared	0.493	0.492	0.493	0.482	0.469
Number of provinces	107	107	107	107	107

*Notes: Standard errors in parentheses are clustered by province. All variables of interest are normalized at mean 1, before being interacted with lockdown variables. *** p<0.01, ** p<0.05, * p<0.1.*

Finally, last two columns of Table 3 highlight that lockdown effects differ when accounting for the spread of unemployment and poverty at the provincial level. As for the poverty definition, we used administrative data on declarations of ISEE (namely, Indicatore della Situazione Economica

https://rep.repubblica.it/pwa/locali/2020/03/20/news/coronavirus_tra_i_contagiati_in_puglia_tanti_genitori_dei_ragazzi_rientrati_da_nord_il_15_aveva_la_febbre-251761879/.

Equivalente, i.e., an indicator combining equivalized household income and wealth and that is generally declared when applying for social benefits in Italy). For each province, we consider as poor households those declaring an ISEE value lower than 6000 euros. These two economic dimensions seem not to have influenced LD1's effect on the growth of COVID-19 cases, but they significantly reduced the effect of LD2. This evidence may be related to the fact that, in Italian provinces with high unemployment and poverty rates, a larger portion of the population was probably already at home (or, at least, it moved less frequently) before the main lockdown. Moreover, the lower effect of the main lockdown in provinces with more poor households may also be explained by the fact that the poor often live in larger households or in lower health conditions (Lanjouw and Ravallion, 2020; Sarti et al., 2017). By keeping the poor at home more, LD2 might have exposed them to a greater risk of infection.

Table 3 – Interactions of province level characteristics (incidence of students, nursing homes, local labour market and income levels) with lockdowns effects (fixed-effects panel model)

Variables	Variable of Interest (VoI)				
	High-school students	University students	Nursing homes	Unemployment rate	Poverty rate
COVID-19 cases $_{t-1}$	0.482***	0.083***	0.175***	0.110***	0.095***
	(0.144)	(0.010)	(0.023)	(0.018)	(0.026)
LD1 * COVID-19 cases $_{t-1}$	-0.254**	-0.039***	-0.090***	-0.058***	-0.045**
	(0.098)	(0.006)	(0.016)	(0.012)	(0.019)
LD2 * COVID-19 cases $_{t-1}$	-0.075***	-0.025***	-0.037***	-0.038***	-0.037***
	(0.024)	(0.003)	(0.002)	(0.003)	(0.003)
LD3 * COVID-19 cases $_{t-1}$	-0.056**	-0.007***	-0.018***	-0.003	0.001
	(0.024)	(0.002)	(0.004)	(0.003)	(0.004)
VoI * COVID-19 cases $_{t-1}$	-0.390**	0.032***	-0.067***	0.016	0.042
	(0.153)	(0.008)	(0.024)	(0.052)	(0.052)
VoI * LD1 * COVID-19 cases $_{t-1}$	0.215**	-0.018***	0.043***	0.002	-0.020
	(0.102)	(0.006)	(0.016)	(0.039)	(0.040)
VoI * LD2 * COVID-19 cases $_{t-1}$	0.053*	-0.002	0.013***	0.022***	0.016***
	(0.027)	(0.002)	(0.003)	(0.005)	(0.006)
VoI * LD3 * COVID-19 cases $_{t-1}$	0.049*	-0.005***	0.009*	-0.021***	-0.022***
	(0.026)	(0.001)	(0.005)	(0.007)	(0.007)
Number of deaths	-0.005	0.022	0.019	0.028	0.016
	(0.039)	(0.027)	(0.037)	(0.032)	(0.035)
Number of recovered	-0.062***	-0.047***	-0.061***	-0.039**	-0.042**
	(0.019)	(0.017)	(0.019)	(0.019)	(0.018)
Constant	0.193	0.225	0.239	0.191	0.188
	(1.447)	(1.478)	(1.590)	(1.588)	(1.583)
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	6,313	6,313	6,313	6,313	6,313
R-squared	0.479	0.497	0.476	0.477	0.471
Number of provinces	107	107	107	107	107

*Notes: Standard errors in parentheses are clustered by province. All variables of interest are normalized at mean 1 before being interacted with lockdown variables. *** p<0.01, ** p<0.05, * p<0.1.*

Since the spread of the novel coronavirus increases the future economic and non-economic damages, this territorial analysis raises great concerns about the effects of the main lockdown on income inequalities. At same time, the opposite signs on inequalities are related to the third and less effective lockdown. This is not an expected outcome as the target of the business lockdown was to reduce the number of people leaving home for work-related reasons, producing a greater effect in provinces with more active labor markets. This peculiar outcome raises further doubts on the selection process of "essential activities" since it seems to be biased towards more developed and richer regions,[18] the ones most affected by the virus.

8. Ex post validation of the model's early detection performance

In this section, we try to assess the strength of our methodology to detect early the incurring structural break along the infection path. We re-simulate the performance of our model along our reference period (February 24–April 24) through a real-time procedure. We start by applying our methodology to a restricted sample that consists of the first 15 days of the pandemic only (i.e., until March 10) and then progressively increasing the length of the time series up to the whole set of data considered in the main analysis.

Since we start from a very short set of data, the estimated coefficients tend to be less significant and the dates recognized as changing points may vary slightly. To strengthen the methodology adopted here, we therefore add two constraints to our model selection procedure. All in all, we only require that the best model selection for reduced samples has the same robustness properties as the full sample case. First, we require the estimated coefficients for both lagged cases (i.e., COVID-19 cases at time t-1) and structural breaks to all be statistically significant (at least) at the 10% level. Second, once the best model is selected for a k number of breaks (i.e., we identify the set of dates for breaks reporting the lowest AIC value), we impose that the best selection of dates does not change for the first k breaks when a k + 1 number of breaks is considered. Note that these conditions are always satisfied in the case of the full time series because both coefficients are indeed significant and the dates of the structural breaks are nested by the number of breaks considered.

Figure 5 shows estimated effects—referring to the best model selected—for lagged cases and the three lockdown interactions on the daily growth of cases by the length of the analysed time series. The coefficient of lagged cases is always insignificant when our best model specification (i.e., Model 3; see Section 5) for zero and one break is estimated on samples of 15 to 26 days after February 24 (i.e., to March 10 or March 21, respectively).[19] In estimates on samples at least 21 days long, a first structural break is actually identified by our model selection procedure on day 21 (i.e., March 16), 6 days before the definitive effectiveness day we highlighted in Section 5 (if, as we believe, this break coincides with LD1). However, the statistical insignificance of lagged cases leads us to not consider it as a "best model." The statistical significance criterion starts to be satisfied when the analyzed time series has a length of 27 days, but the first break date becomes stable at day 27 (i.e., March 22) when the sample counts at least 28 days. Therefore, the identification of the day from which LD1 became effective could have been spotted through our model selection procedure already from 28 days after February 24 (i.e., March 23).

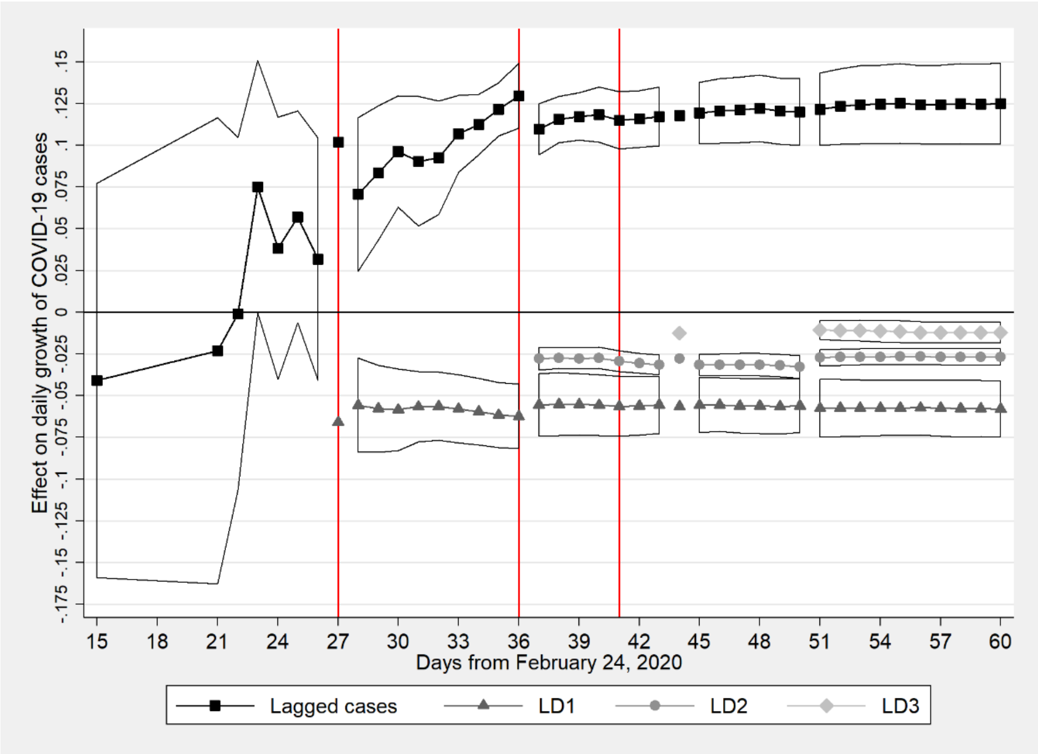
Moving to the identification of the second structural break, our second condition (i.e., structural breaks nested by number of breaks considered) starts to be satisfied in estimates based on 37-day-long time

[18] https://www.internazionale.it/opinione/roberta-carlini/2020/03/24/lista-chiusura-fabbriche-lavoratori

[19] For the sake of clarity, we do not illustrate in Fig. A2 estimated coefficients for lagged cases when the lowerbound value of their confidence intervals exceeds − 0.175 (e.g., estimates on samples with 18 or 19 days).

series, where the second break date is on day 36.[20] Thus, both LD1 and LD2 could have been clearly identified the day after their effectiveness day. Conversely, this is not the case for LD3. Although it became effective on the daily growth of COVID-19 cases on day 41 (see Section 5), LD3 is clearly identified from our model selection procedure only when samples with at least 51 days are considered (and only temporarily in estimates on time series counting 44 days from the beginning of the pandemic). The longer period needed to identify LD3 may be related to its lower alleviation effect on the daily growth of cases. Estimates based on reduced samples, however, point out that the LD3 effectiveness day is on day 41 (i.e., April 5), thus confirming all dates identified in our main analysis.

Figure 5 – Effects of lockdowns on the daily growth of COVID-19 cases by time series length



Notes: Outlined areas represent confidence intervals at the five percent level. 'Lagged cases' refers to the COVID-19 cases at time t-1, while 'LD1', 'LD2' and 'LD3' stand for the three lockdown interaction terms in Table 1. The three vertical lines represent, respectively, the effectiveness days of the school lockdown, main lockdown and business lockdown, as shown in Section 5.

In conclusion, this ex post validation analysis highlights two important aspects. First, from the day the three lockdowns are identified through our model selection procedure, social distancing measures have an alleviation effect on the daily spread of the novel coronavirus that is quite stable and similar to the one estimated in the full time series. Second, the effectiveness of the school lockdown could have been spotted already on March 23 (and even earlier, although less clearly). This means that the business lockdown introduced on March 26 could perhaps have been avoided as its announcement and consequent discussion started on March 21. It should be noted that the period during which the introduction of LD3 was under debate was characterized by the highest growth rates of COVID-19 cases and deaths (Fig. 1), and a common perception was that something more had to be done to stop the

[20] Note that the second break date occurs 3 days in advance, on day 33 (i.e., March 28), for the 26 provinces listed in the Prime Ministerial Decree of the 8th of March 2020.

pandemic's rampage. Nonetheless, the slight alleviation effects reported by the business lockdown and its economic effects confirm the importance of verifying in advance the need for additional restrictive measures.

9. Conclusions

In this paper, we have proposed a machine learning procedure to identify structural breaks in the dynamics of the COVID-19 outbreak to assess the impact of social distancing measures. By considering the case of Italy, three structural breaks are identified, and they can be associated respectively with each one of the three main restrictive measures enforced at the national level.

Analyzing the coefficients of the best model selected, we show that the first lockdown was the most effective one. Descriptive evidence suggests that, together with the direct effect of school closure, this lockdown has also had a strong indirect announcement effect, making people more aware of the phenomenon at hand. The impact of the last measure, the shutdown of "non-essential" activities, appears to have been hardly relevant. This may be due to the fact that both the business lockdown and the transition to working from home were underway well before the closure was imposed, as the electricity data seems to suggest, but rather to a loose definition of essentiality.

The results also show that the time elapsing between the implementation of restrictive measures and their impact on the infection outbreak data varies significantly. Indeed, the detection delay was 17 days for the first measure, 19 days for the main lockdown restricting freedom of mobility and imposing the shutdown of leisure and retail activities, and 10 days for the third lockdown. The increase from the first to the second detection delay can be attributed to the saturation of health facilities since the same days following the second lockdown correspond to the peak of contagion, but also to possible mistakes in communication procedures that increased geographic mobility in the timespan between the announcement of the measure and its enforcement. The remarkable decrease in the third detection delay, while being partially rooted in the lower severity of hospitalization and infection conditions, can also be related to an improvement in testing procedures and technology, as well as to the greater ability of individuals to recognize the symptoms.

The variability of the detection delay, the saturation, and the communication effects can be a useful evidence to increase the effectiveness of feedback control strategies and they also suggest that widespread testing campaigns could also decrease the overall detection delay, avoiding the risk of such strategies to fail. Furthermore, they confirm the adequacy of the data-driven methodology, which avoids any prior assumption about the effectiveness and the time distribution of the structural changes.

By exploiting the huge spatial variation in the social, health, and economic features of Italian provinces, we have confirmed the interpretation of the results above and deepen the peculiarities of each restrictive measure.

The same methodology can also be used to detect early the structural breaks on daily updated data. If applied backward to our case study, the first two structural breaks could have been correctly identified just the day after they occurred, while the detection of the third one would have needed 2 days more. It is relevant to be noticed that the effectiveness of the school lockdown could have been spotted at the beginning of the political debate on the possible implementation of the business lockdown. This evidence reveals that important policy implications can emerge from methodologies being able to verify in advance the need for additional restrictive measures, because the slight alleviation effects reported by the business lockdown and its potential (massive) negative effects on the national GDP could perhaps be avoided. Results like this seem crucial, in particular, in relation to whether a second wave of COVID-19 cases will really occur in the near future.

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Appendix

Table A1 – Data and variable descriptions

Variable	Source	Definition	Mean	Std. Dev.
Daily growth in COVID-19 cases	Civil Protection Department (2020)	Dependent variable Difference between the overall COVID-19 cases at time t and the overall COVID-19 cases at time t-1 at the provincial level	30.07	61.97
Number of deaths	Civil Protection Department (2020)	Number of people deceased with COVID-19 infection at the provincial level. As this information is available at the regional level only, the variable is calculated for each province weighting regional COVID-19 deaths by its share of regional COVID-19 cases.	93.63	271.78
Number of recovered	Civil Protection Department (2020)	Number of people recovered from COVID-19 infection at the provincial level. As this information is available at the regional level only, the variable is calculated for each province weighting regional COVID-19 recoveries by its share of regional COVID-19 cases.	156.44	452.55
Population density	ISTAT (2019)	Ratio between total provincial population and total surface area (km^2)	270.13	380.48
Proximity to a hospital	Ministry of Economic Development (2014)	Share of provincial population living in a municipality with at least one 1st level DEA hospital (i.e. a hospital providing first aid, resuscitation, and general surgery services)	0.333	0.171
Proximity to a railway station	Ministry of Economic Development (2014)	Share of provincial population living in a municipality with at least one silver railway station (i.e. a station with more than 2,500 daily visitors on average)	0.456	0.180
Hospital dismissals by the elderly	ISTAT (2018)	Share of hospital dismissals of people aged 65 or above (average for 2016–2018) at the provincial level	0.460	0.049
Mortality for infectious diseases	ISTAT (2017)	Mortality rate for infectious diseases at the provincial level (x 10,000 inhabitants)	2.488	0.957
High-school students	ISTAT (2018)	Share of students attending upper secondary schools at the provincial level out of the total population aged 64 or below	0.058	0.007
University students	ISTAT (2017)	Number of students attending universities at the provincial level out of the total population aged 64 or below	0.025	0.026
Nursing homes	ISTAT (2011)	Number of nursing homes at the provincial level (x 10,000 inhabitants)	1.129	0.638
Unemployment rate	ISTAT (2019)	Unemployment rate among people aged 15–74 at the provincial level	0.104	0.057
Poverty rate	INPS (2018)	Share of households declaring an ISEE[a] lower than 6,000 euros out of the total provincial population of households	0.072	0.039

Notes: [a] The ISEE is an indicator combining household income and wealth and it is generally declared when applying for social benefits. It consists of the sum of household income and 20% of household wealth (in terms of both financial assets and property) divided by an ad hoc equivalence scale. The ISEE equivalence scale is equal to the number of household members raised to the power of 0.65.

Table A2 – Detection delay by lockdown and model specification

Lockdown	Effectiveness delay (number of days from introduction)				
	Model 3	Model 5	Model 6	Model 7	Model 8
School lockdown (LD1)	17	17	17	17	17
Main lockdown (LD2)	19	21	19	19	19
Business lockdown (LD3)	10	18	10	10	10

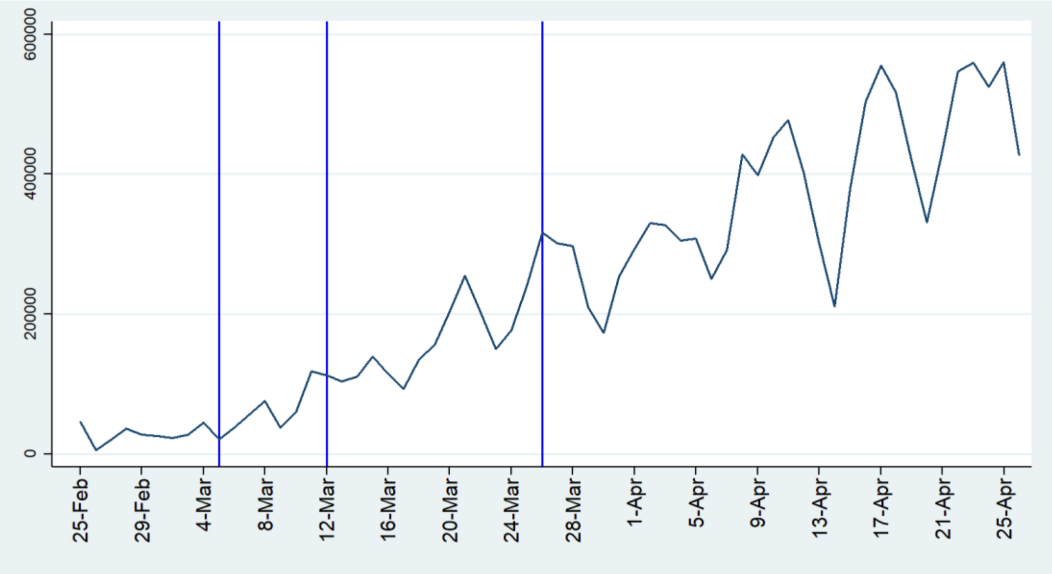
Notes: Unlike Model 3, Model 5 includes a quadratic polynomial of COVID-19 cases at time t-1 and its interactions with lockdowns variables, but there are no time dummies. Model 6 adds time dummies to Model 5. In contrast to Model 3, Model 7 includes the number of COVID-19 deaths and recovered at the regional level instead of the provincial one. Model 8 adds to Model 3 the number of swab tests undertaken at the provincial level. As this information is available at the regional level only, the variable is calculated for each province weighting regional COVID-19 swab tests by its share of regional COVID-19 cases.

Table A3 – Lockdown effects on the daily growth in COVID-19 cases by subsample and definition of dependent variable (fixed-effects panel model)

Variables	Model 3	Only even days	Only odd days	No Lombard provinces	No provinces listed in the Prime Ministerial Decree of March 8th, 2020	COVID-19 cases per every 10,000 inhabitants	No Lombard provinces and COVID-19 cases per every 10,000 inhabitants	No provinces listed in the Decree of March 8th, 2020 and COVID-19 cases per every 10,000 inhabitants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID-19 cases $_{t-1}$	0.125***	0.129***	0.121***	0.115***	0.126***	0.069***	0.081***	0.113***
	(0.012)	(0.016)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.029)
LD1 * COVID-19 cases $_{t-1}$	-0.058***	-0.060***	-0.056***	-0.055***	-0.068***	-0.038***	-0.052***	-0.080***
	(0.008)	(0.017)	(0.007)	(0.009)	(0.008)	(0.008)	(0.008)	(0.025)
LD2 * COVID-19 cases $_{t-1}$	-0.027***	-0.024***	-0.029***	-0.024***	-0.021***	-0.019***	-0.022***	-0.023***
	(0.002)	(0.004)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
LD3 * COVID-19 cases $_{t-1}$	-0.012***	-0.012***	-0.013***	-0.018***	-0.025***	-0.007**	-0.015***	-0.021***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Number of deaths	0.011	-0.029	0.054	0.149**	0.246***	0.05	0.206**	0.295**
	(0.040)	(0.040)	(0.044)	(0.061)	(0.058)	(0.038)	(0.103)	(0.113)
Number of recovered	-0.052**	-0.047*	-0.059***	-0.056***	-0.056***	-0.019	-0.018	-0.019
	(0.021)	(0.026)	(0.018)	(0.013)	(0.014)	(0.014)	(0.015)	(0.016)
Constant	0.178	0.172	1.979	0.367	0.105	0.008	0.01	0.004
	(1.636)	(1.709)	(1.908)	(1.040)	(0.761)	(0.026)	(0.022)	(0.017)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,313	3,210	3,103	5,605	4,779	6,313	5,605	4,779
R-squared	0.463	0.461	0.475	0.391	0.410	0.250	0.241	0.210
Number of provinces	107	107	107	95	81	107	95	81

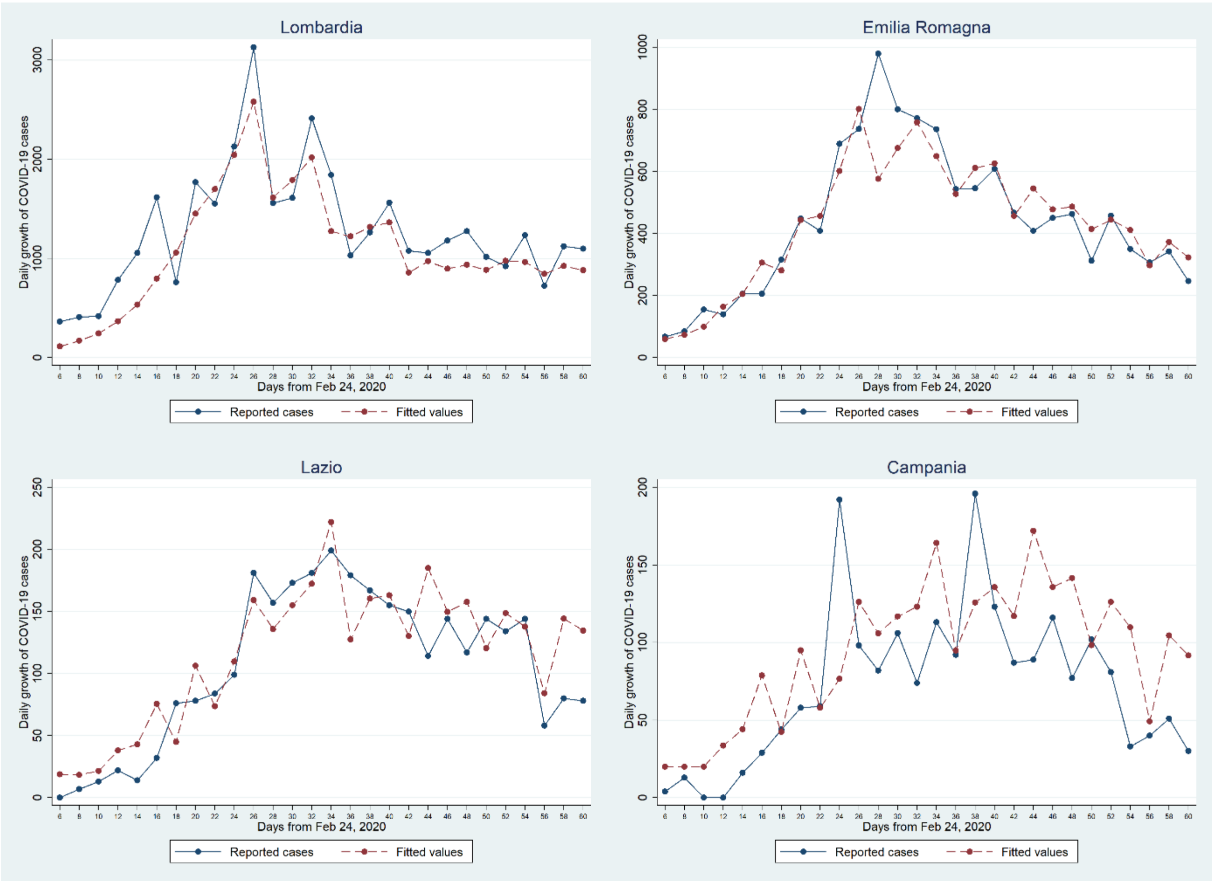
*Notes: Standard errors in parentheses are clustered by Italian province. *** p<0.01, ** p<0.05, * p<0.1. Column 6 replicates estimates in Model 3 but all COVID-19 cases are considered in relative terms with respect to the provincial population. Specifically, both the dependent variable and the "COVID-19 cases at time t-1" variable are divided by the number of inhabitants at the provincial level and then multiplied by 10,000. Column 7 is the same as Column 6 but replicates the analysis in a subsample excluding 12 Lombard provinces. Column 8 is the same as Column 6 but replicates the analysis in a subsample excluding 26 provinces listed in the Prime Ministerial Decree of the 8th of March, 2020.*

Figure A1 – Daily swabs performed at the national level



Source: Civil Protection Department (2020).

Figure A2 – Fitted values of the daily growth in COVID-19 cases at the regional level



Notes: Fitted values are based on our best model specification (Model 3).

Chapter 4 – Coronavirus pandemic, remote learning and emerging education inequalities[1]

1. Introduction

The coronavirus pandemic of 2020 forced countries to close schools and shift to distance learning almost overnight, without the time needed to prepare or evaluate its consequences on education. Several recent studies based on previous research on school interruptions predict that school closures will be followed by generalized declines in education levels (Burgess and Sievertsen, 2020; Haeck and Lefebvre, 2020; Kuhfeld et al., 2020; Psacharopoulos et al., 2020, Van Lancker and Parolin, 2020), but generalized distance schooling is a new phenomenon that can also exacerbate existing education inequalities and generate new ones. Differently from face-to-face schooling, it crucially depends on students being concretely able to attend virtual classes, and on schools and teachers effectively providing them. These unprecedented events spur scientists to provide new insights on the impact of remote teaching on students.

During distance schooling, the non-adequacy of ICT resources and related skills is particularly dramatic in developing countries but concerns also developed economies, where teaching relies on digital tools even during normal times. In them, the availability of ICT resources is more widespread, but digital inequalities still exist; some students lack the basic resources needed to learn remotely and some schools or teachers to provide online classes (Norris, 2001).[2] This study focuses on five European countries – France, Germany, Italy, Spain and United Kingdom – that were hit by the pandemic between the end of February and beginning of March 2020, and adopted similar measures concerning school closures and remote learning[3].

Due to the paucity of data on students' performance after the school closure, we use the 2018 wave of the Program for International Student Assessment (PISA), an international assessment implemented by the Organization for Economic Cooperation and Development (OECD) that measures 15-year-old students' reading, mathematics, and science literacy every three years and comprises data on ICT resources at home and at school. Thus, our analysis gauges the relationships between students' digital tools and education outcomes during times of traditional teaching, when these instruments are used but not essential. For this reason, while our results may underestimate the potential inequalities raising from remote learning, they nonetheless assess the importance of educational digital resources for students and schools even during normal times, when education is provided face-to-face.

Specifically, we test the relationships between students' scores in mathematics and reading and their possessions of a computer for schoolwork, an internet connection, a quiet place to study and their school's ICT resources. In our data, a proportion of fifteen-year-old students that ranges from more than

[1] This work is currently submitted for publication with the title "*Coronavirus pandemic, remote learning and emerging education inequalities*" (joint with Marina Murat). A working paper version can be found in the *GLO Discussion Paper* (n. 679/2020). It has been presented at XXXV National Conference of Labour Economics (Virtual online conference, 2020).

[2] We use the term 'distance schooling' when one or more technologies are used to deliver classes to students who are separated from the teacher and – with electronic technologies – support mutual interaction; 'remote learning', when ICT resources are used for education outside the physical school only temporarily; 'e-learning' when electronic resources permanently substitute education at the physical school.

[3] Some measures differed across the five countries. For example, school closures have been complete in Italy, while in the United Kingdom schools remained partially open for children with parents with specific jobs or from low-income households.

one third in France to more than 60 percent in Germany lacked at least one of the above digital factors needed to learn remotely.

Considering the longer run, we analyse whether the possibility of learning remotely is also associated with students' expectations on their future education. In particular, students unable to attend the virtual classes and lagging behind their peers may find the cognitive gap hard to close once back at school and, consequently, revise downwards their plans on future education. These negative choices may be exacerbated in countries where grades repetition is frequent and lagging behind increases the probability of repeating a grade once back at school. Hence, we test whether variations in the conditions for learning remotely are correlated with students' planned investments in education, the probability of repeating a grade, and the joint probabilities of these two events. To our knowledge, this is the first attempt to investigate the relationship between digital disparities and students' outcomes through a large cross-country database. It contributes to the research on education and offers a novel perspective on the essential role of home and school ICT resources and related skills in the formation of human capital.

Our main findings are that the lack of ICT resources at home, particularly a computer for schoolwork, are strongly correlated with students' negative score gaps in mathematics and reading in all five countries, but cognitive losses emerge also when digital resources at school are scarce. These cognitive losses have long run implications; students unable to learn remotely are more likely to revise downwards their plans on future education, especially where lagging behind increases the probability of repeating grades. We also find that negative gaps and long run implications are associated with countries' educational systems, school locations and families' socio-economic conditions. Our results are robust to the use of different specifications and covariates.

Although estimates are not causal relationships, our results are robust to the use of different specifications, covariates and a rich set of fixed effects. The policy implication of our findings are clear and urgent: all students and schools must be connected to the internet and able to participate in distant learning. Schools must count on efficient online platforms and students must own their own ICT devices and be guaranteed a quiet place to study. These measures may alleviate important educational disparities that, as our study shows, exist in normal times and are likely to have expanded during the school closures of the coronavirus pandemic. Whether and how much these inequalities have effectively grown or been avoided with appropriate policies in each country will be shown by the next wave of PISA data, to be collected in year 2021, as well as by other surveys and researches.

The rest of this paper is structured as follows, Section 2 discusses the related literature, Section 3 presents the data and some descriptive statistics, Section 4 shows the adopted methodology, results are provided in Section 5 and Section 6 concludes.

2. Main facts and literature.

2.1. Facts

Between March 5 and March 20 2020, schools in Italy, Spain, France, Germany and the United Kingdom closed and adopted distance teaching. During the second part of March, all European countries took similar measures (Viner et al., 2020). In our five countries, teaching was provided mostly online, but in France TV and radio transmissions were also utilized (UNESCO, 2020; Center for Global Development, 2020). After several weeks, when eventually the number of people infected by the coronavirus fell at sufficiently low levels, schools reopened in Germany, France and the United Kingdom, while in Italy and Spain they were kept closed until the autumn.

The still scant and fragmentary evidence available while we research on this topic suggests that the percentage of students who could not learn remotely, or could only partially learn, may be higher than expected when the advanced level of digital development of the five countries is considered. The OECD (2020) data on home computer possessions and internet connections in our countries show that between 85 and 90 percent households have access to the internet and between 72 percent and 93 percent have a computer at home, but these data concern pre-pandemic times, when most learning and working activities take place outside home; they focus on households rather than individuals, and do not provide information on the level of efficiency of the ICT devices. During school closures and the lockdown of most economic activities, almost all people in the household are very likely to need to use the ICT resources more than usual and simultaneously. All this suggests that when considered at individual – rather than household – level and during closures of schools and economic activities, the above figures should be substantially revised downwards.[4] At the same time, for remote learning to take place, ICT resources must be available and efficiently used also at school, and teachers must possess the skills needed to teach online. The preliminary and partial evidence available suggests that because of deficiencies in households' possessions and school shortages of ICT devices, digital platforms and skilled teachers, remote learning in our five countries was lower than expected. This especially applies to Germany; Conrads et al. (2017), European commission (2019), Kerres (2020) and UNESCO (2020) show German schools are on average less digitalized than in other developed countries.

Surveys conducted in some of the countries considered provide preliminary and partial evidence on remote learning during school closures. In England, between 10 percent and 12 percent of students had no devices at all (Andrew et al., 2020). A survey on distance learning in Italy evidences that only 40 percent of students could fully participate in remote learning; 10 percent could not participate at all and 20 percent could attend only occasionally (Autorità Garante per le Comunicazioni, 2020). In Germany, a survey of students in their graduation and pre-graduation years, shows that less than 50 percent of respondents received digital learning opportunities or material through online platform, email or video conferencing, and only about 15 percent of them had videoconferencing (such as Skype) interactions with teachers (Anger et al., 2020). There are no data on the proportion of German students that were entirely disconnected from remote learning, but consistently with the available evidence on schools, they are likely to be, also in this case, not less than 10 to 15 percent of all students. If this preliminary evidence from the United Kingdom, Italy and Germany applies also to the other two countries, then, overall, only between 30 percent to 50 percent of students could attend school online. The PISA 2018 dataset we use for this study reveal even higher figures in the five countries considered: a proportion of fifteen-year-old students ranging from more than 30 percent in France to more than 60 percent in Germany lacked at least one of the necessary conditions needed to learn remotely: an internet connection, a computer for school work or a school with sufficient digital resources (Figure 1-b).

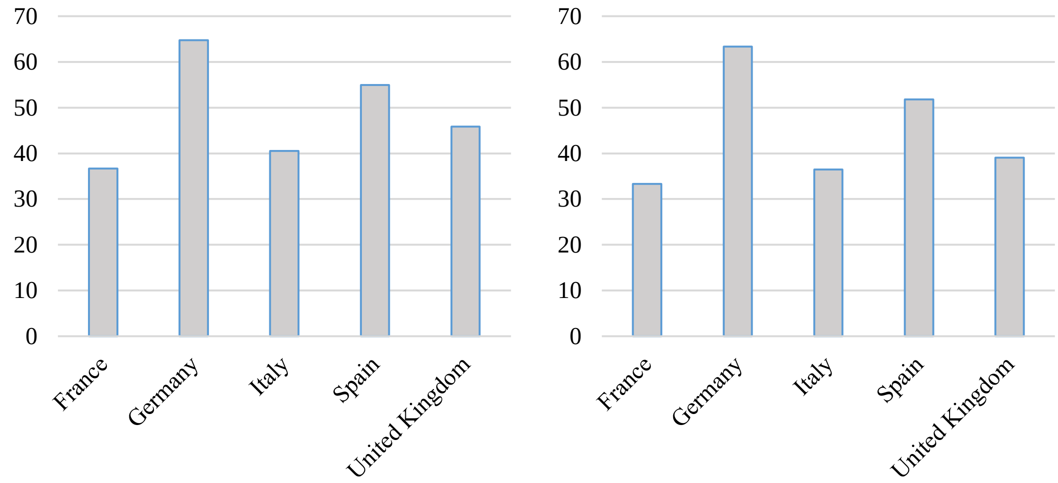
2.2. Literature

Several very recent researches trying to gauge the effects of the pandemic on education are based on the very scant data collected during and after the periods of school closures or on previous findings on

[4] Data from the Italian Institute of Statistics show that, during the schools and economy lockdown of 2020, households without people able to use ICT resources were about 24.2 percent of the total, with higher than average percentage for households with lower income levels, higher median age, the country's South and small towns (ISTAT, 2020).

school vacations or interruptions due to unexpected events.[5] Kuhfeld et al. (2020) predict that students in the United States "are likely to return in fall 2020 with approximately 63-68 percent of the learning gains in reading relative to a typical school year and with 37-50 percent of the learning gains in math" (pg. 1). Moreover, they estimate that losing ground will not be generalized, but the top third of students may make gains in reading. Several studies find that summer vacations are followed by sizable and significant cognitive losses, which often concern mathematics more than reading, and are higher for students from lower socio-economic conditions (Downey et al., 2004; Quinn et al., 2017; Atteberry and McEachin 2020; Carvalho et al., 2020). Van Lancker and Parolin (2020) find that summer vacation cognitive losses in the United States are significant for children of low-income families, but not for others. However, in other studies' results, cognitive losses due to school vacations are mostly temporary or negligible (Von Hippel and Hamrock, 2019).

Figure 1 - Percentage of fifteen-year-old students unable to learn remotely



(a) (b)

Note: In Figure (a) students lacking a computer, an internet connection, a quiet place to study at home or attending a school with few ICT. In Figure (b), a quiet place to study is not included.

Absenteeism has also been found to negatively influence cognitive outcomes. Students skipping school experience significant and negative cognitive gaps relatively to their peers, which increase with the days of absence (Chang and Romero, 2008; Gottfried, and Kirksey, 2017; Liu et al., 2020). Gottfried (2009 and 2011) and Aucejo and Romano (2016) find that losses associated with absenteeism tend to be higher in mathematics than in reading.

School interruptions due to abnormal events, such as teachers' strikes (Belot and Webbink, 2010; Johnson, 2011), natural disasters or pandemics, are also found to affect education levels. Skidmore and Toya (2002), McDermott (2012), Noy and duPont (2016), Meyers and Thomasson (2017) Cerqua and Di Pietro (2017), Di Pietro (2018), find that natural disasters have important consequences on students' decisions to leave education early (Imberman et al., 2012). In Pane et al (2008) Redlener et al. (2010), after Hurricanes Katrina and Rita in 2005, one over three students in the United States repeated grades, and a significant number of them never returned to school. Dorn et al. (2020) estimate the potential

[5] Hanushek and Woessmann (2020) and Azevedo et al. (2020) consider potential economic losses at individual and country levels. They are expected to be stronger for disadvantaged students and to have long-lasting effects.

impact of school closures of year 2020 in the United States; they predict increased drop-out rates and long run negative effects on education.

A parallel debate concerns the impact of using ICT resources in teaching and studying. Governments' and experts' opinions on e-learning vary widely, and empirical studies on the effects of providing students with ICT resources remain inconclusive (Banerjee et al., 2004; Fairlie, 2005; Machin et al., 2007; Yanguas, 2020). The evidence suggests that not just computers and the internet, but the software and how ICT devices are used play an important role in the cognitive process (a very complete review is in Escueta et al., 2020). The choices countries made in the past on the use of digital resources for education proved to be crucial in 2020, when schools were suddenly forced to adopt distance teaching. The survey of the European Commission (2019) and the above mentioned data from PISA 2018 show that even European countries differed substantially in their readiness for teaching remotely.

3. Data and descriptive statistics

We use the data from the 2018 wave of PISA assessment concerning students' test scores in mathematics and reading (except for Spain, from which data are only available on mathematics). To save space, we present most results on reading in Appendix A. We omit our results on science, the third field of PISA surveys, because they are very similar to those in mathematics and reading, but they are available from the authors upon request. Overall, we consider 73,305 students enrolled in over 2,577 schools in the five countries. The PISA dataset is the result of a two-stage stratified design, where, first, individual schools are sampled, and secondly, students are randomly sampled within schools. Given that each participating student in PISA survey answers a limited amount of questions taken from the total test item pool, OECD provides ten test scores (known as plausible values), which can be interpreted as multiple imputed values of students' performance based on students' answers to the test and their background questionnaires. The difficulty of each item represents a weight, used to compute the weighted averages of correct responses. This approach allows having a measure of an individual's proficiency for each student in each subject area, regardless of the questions actually answered. We employ the recommended OECD strategy for estimation of coefficients and their variances, making use of all ten plausible values all throughout the main analysis (OECD, 2018, provides detailed technical information). In each country, the sample represents about 95 percent of the population of 15-year-old students.

Regarding the availability of ICT resources at home and at school and of a quiet place to study, we select from the PISA Student's Questionnaire the answers to the following questions: *Which of the following are in your home*: *A computer you can use for school work*, *A quiet place to study*, *A link to the internet*, responses can be 'yes' or no', and from the School's Questionnaire: *To what extent do you agree with the following statements about your school's capacity to enhance learning and teaching using digital devices? The number of digital devices connected to the internet is sufficient*; answers vary from 'Strongly disagree' to 'Strongly agree'. Concerning the planned length of students' education, the question we consider is: *Which of the following do you expect to complete?* answers range from lower secondary to advanced tertiary and research education programs. We build a dummy variable with values equal to one if the student expects to complete at most the lower secondary or the upper secondary studies that do not lead to tertiary education (ISCED levels 2, 3A or 3B) and 0 if the student plans to complete higher levels. Our control variables are gender, age (year and months), higher level of education of parents (HISCED), immigration status (which includes first and second generation immigrant students), age of arrival into the country, whether the student has repeated one or more school years and the school location in a rural or urban area.

Descriptive statistics are summarised in Table A1. Overall, the proportions of students lacking at least one of the four essential factors needed to learn at home – a computer, an internet connection, a quiet place to study at home, a school providing online classes – are about 36 percent of all students in France, 46 percent in the United Kingdom, 41 percent in Italy, 55 percent in Spain and 65 percent in Germany. If only the ICT devices for remote learning are considered (*No quiet place to study* is excluded), these percentages decrease only slightly (Figure 1-a, 1-b).

Grade repetition is unusual in the United Kingdom and frequent in the other four countries, especially Spain and Germany, where it concerns respectively 29 and 20 percent of students. Educational systems also differ in the degree of tracking between schools: the age at which students are tracked for the first time is 10 in Germany, 14 in Italy, 15 in France and 16 in Spain and the United Kingdom (Woessmann, 2009). The proportion of students planning to leave education early varies from about 30 percent in Germany (where vocational school can be attended while working part-time) to six percent in Italy, but secondary studies can be completed at different ages in each of the five countries.[6]

4. Empirical strategy

To gauge the links between remote learning and education outcomes, we test, separately for each country, the relationships between the students' scores in mathematics or reading and the lack of the resources needed to learn remotely with the following specification:

$$\text{Test scores}_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + X_{ij}\Pi + \lambda_j + v_j + \varepsilon_{ij} \quad (1)$$

where *Test score* is the weighted test score in mathematics or reading of student *i* in school *j*, *No computer*, *No internet*, *No quiet place*, *Few school ICT* are the variables of interest. X_{ij} is the set of covariates, which comprise gender (a dichotomous variable, with value one if female and zero otherwise), age, the highest level of education of parents (HISCED in PISA), the student's status of immigration (a dichotomous variable), age of arrival at the country, and whether the student has repeated one or more school years, λ_j are school fixed effects and v_j and ε_{ij} are error terms at school and student levels.

In a further set of tests, we use Probit specifications to test the correlations between the probability of leaving education early and our four variables of interest regarding the resources needed to learn remotely. The dependent variable, concerning the students' plans on the length of their future education, is a binary variable with value one when students expect to complete at most the lower secondary or upper secondary studies not leading to tertiary education, and zero otherwise. We also test the correlation between the probability of repeating a school year and our variables of interest in all countries except the United Kingdom, where grades repetition is not frequent. Afterwards, we use a Bivariate Probit

[6] Secondary studies are typically completed after 10 years of schooling in Spain, 11 in the United Kingdom, 12 in Italy and Spain, and 13 in Germany. Children start compulsory education when they are five years old in the United Kingdom and six years in the other four countries. Therefore, the age at which secondary education is completed also depends on the age of starting compulsory education.

specification to test the joint probabilities of leaving school early and repeating a school year. The Probit and Bivariate Probit specifications on leaving school early and repeating a school year are:

$$\text{Leaving education early}^{*}_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{1ij} \quad (2)$$

$$\text{Repeated grade}^{*}_{ij} = \alpha_1 + \beta_1 \text{No computer}_{ij} + \beta_2 \text{No internet}_{ij} + \beta_3 \text{No quiet place}_{ij} + \beta_4 \text{Few school ICT}_j + W_{ij}\Pi + v_j + \varepsilon_{2ij} \quad (3)$$

With Leaving education early:

$$\begin{cases} \text{Leaving education early}_{ij} = 1 \text{ if Leaving education early}^{*}_{ij} > 0 \\ \text{Leaving education early}_{ij} = 0 \text{ if Leaving education early}^{*}_{ij} \leq 0 \end{cases}$$

And Repeated grade:

$$\begin{cases} \text{Repeated grade}_{ij} = 1 \text{ if Repeated grade}^{*}_{ij} > 0 \\ \text{Repeated grade}_{ij} = 0 \text{ if Repeated grade}^{*}_{ij} \leq 0 \end{cases}$$

The error terms ε_{1ij} and ε_{2ij} are assumed to be independently and identically distributed as bivariate normal. The vector W_{it} comprises the above covariates, except for *Repeated grade*, which is now one of the two dependent variables.

5. Results.

5.1. ICT resources at home and at school and a quiet place to study.

The results of estimating equation (1) in the field of mathematics are in Figure 2; negative values are the differences between the scores of students unable to learn remotely and those of their peers. They are the coefficients on our variables of interest, which derive first base regressions that include only the four variables *No computer*, *No internet*, *No quiet place to study* and *Few school ICT*, and, second, from regressions comprising all covariates and school fixed effects (except, to avoid collinearities, for Figure 2-d, regarding *Few school ICT*, where the full regression controls for all covariates, including school types). Coefficient values are easier to interpret by considering that, in the average of OECD countries, 40 score points (on a mean of about 500) correspond to the cognitive content of about one school year

(OECD; 2019). Table A2 in Appendix A reports all coefficients in mathematics while Figure A1 and Table A4 in Appendix A reports coefficients on reading.

In the base regressions of Figure 2, all coefficients on the four variables of interest are strongly negative and significant. Specifically, *not having a computer at home* is correlated with a negative gap of about 1.7 of a school year in Germany, 1.5 year in France, and more than one year in Italy, Spain and the United Kingdom; significance is at the one percent level in all cases. Moreover, coefficients are robust to the inclusion of all control variables. Interestingly, some coefficients shrink when covariates are included into the regressions, but these changes, when they are statistically significant, take place in relation to different covariates in each country. In particular, more than 50 percent of the negative gap in France is explained by the types of schools attended by students (lyceums, technical or vocational, and private or public); in Italy, one third of the gap is explained by the tracking between schools; in Spain, two thirds is explained by grades repetition; in Germany, by school types, grades repetition and social conditions at home; in the United Kingdom, social conditions explain about 23 percent of the gap (Table A2).[7] We find very similar results when analysing the scores in reading (Table A4 in Appendix A).

Hence, in France, Italy and Germany, the type of school students attend explains part of the gap associated with the unavailability of a computer at home, which suggests that these students are more concentrated in technical and vocational schools, where average scores are lower than in lyceums and general schools. In France, the distinction between private and public schools also matters; private schools are more frequent among lyceums and provide higher education standards. As said above, however, part of the negative gaps is explained by other factors, but they remain strong and significant even after these factors have been taken into account. In the full regressions, the cognitive losses in mathematics associated with not having a computer at home are more than half of a school year in France, Germany and the United Kingdom, and more than a fourth of a year in Italy and Spain (Figure 2).

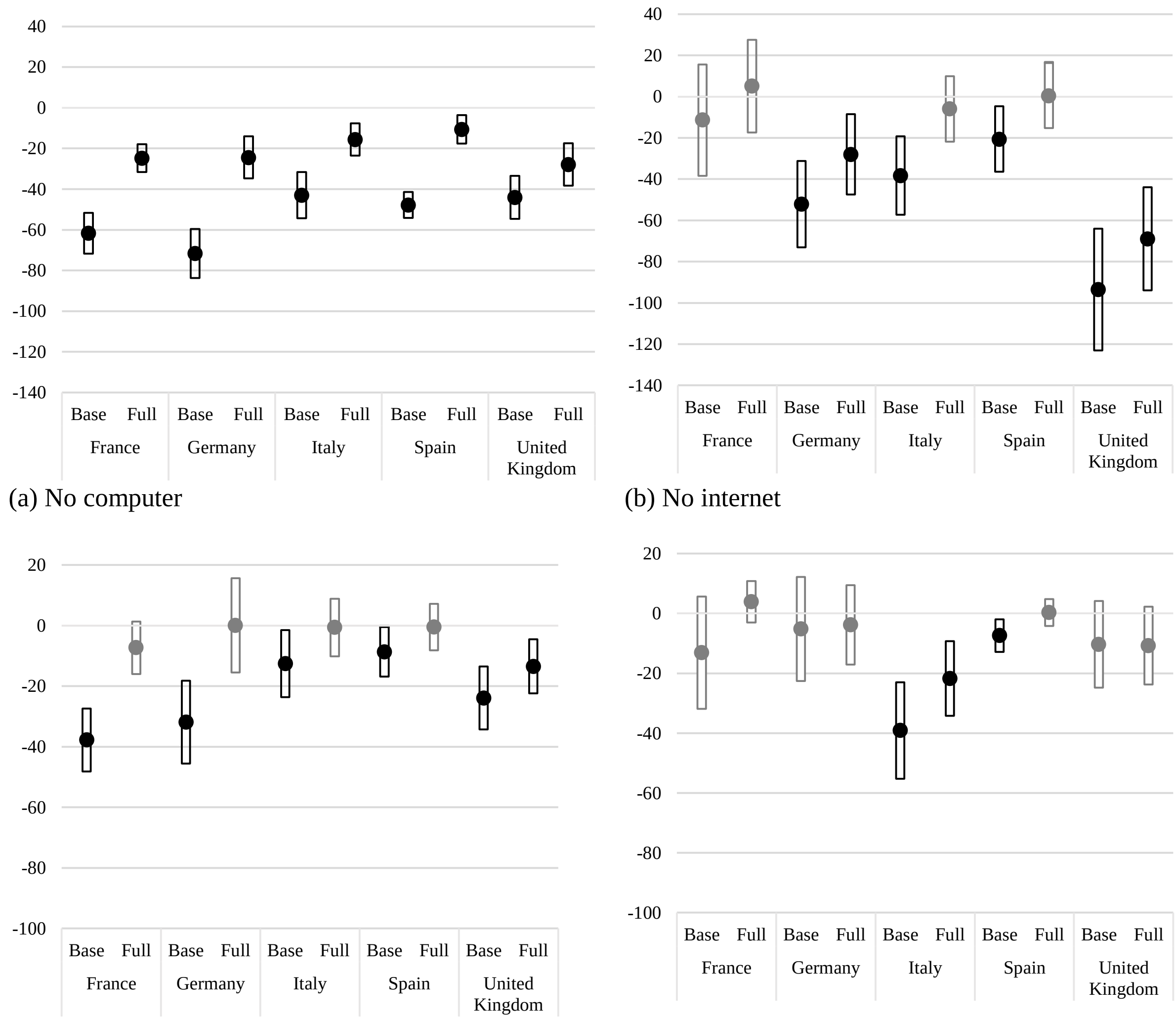
Negative gaps in mathematics associated with *unavailability of an internet connection at home* in the base model are negative in all countries and, except for France, also significant (Figure 2). In Italy, the coefficient loses significance when school fixed effects are included into the regression, evidencing that students without internet at home are unevenly distributed across schools, while in Spain the gap is explained by family socioeconomic conditions and grade repetition. Negative gaps in Germany and the United Kingdom are robust to all specifications and, in the full regressions, equal two thirds of a school year in Germany and almost two years in the United Kingdom (column 35, Table A2). It is interesting to note that, among the five countries, the United Kingdom is characterized by both the lowest percentage of families without internet (Table A1) and, everything else given, the largest negative score gaps of students in this households. Hence, the share of these students is smaller than in the other four countries but they appear to be more marginalized. This may be due to digital network effects. Where the use of internet is more widespread, schools and students have more incentives to use it for teaching and learning, and the disadvantages of non-users increase.

Not having a quiet place to study at home matters especially in France and the United Kingdom. In France, about half of the negative gap is explained by the type of school attended by the students. With everything else given, it equals about a fourth of a school year. In the full model concerning the United Kingdom, where the cognitive losses correspond to about a third of a school year (Figure 2 and Table A2). Coefficients are smaller but also negative and significant in Italy and Spain. In Italy they are

[7] Measures of statistically significant interactions between the coefficients of variables of interest and cofactors are available from the authors upon request.

explained by the social conditions at home and the school type attended, in Spain by the social conditions and grade repetition. [8]

Figure 2 - Gaps in mathematics. ICT resources and a quiet place to study



(a) No computer (b) No internet

(c) No quiet place to study (d) Few school ICT

Note: Dependent variable: mathematics score. Values in the y-axes are the differences in scores between students without and with the resources for learning remotely at home or at school. The base regression includes only the four variables of interest; the full regression includes all the covariates of equation (1), except for Figure (d), where school fixed effects are not included to avoid collinearities. Grey denotes significance below five percent.

A scarce availability of ICT devices at school is significantly correlated with negative score gaps in mathematics in the base regressions in all countries, significance is under 5 percent only in Italy and Spain (Figure 2 and Table A2). Results are similar with reading as the dependent variable, in Table A4. They shrink when school types are controlled for in Italy and private schools in Spain. Hence, a higher availability of ICT resources in lyceums in Italy and in private schools in Spain explains part of the negative gaps. However, among the four variables of interest, this appears to be the

[8] We use the variable on parents' education as a proxy of the family social conditions, but results do not change significantly if, instead of education, we consider the level of parents' employment. Obviously, we cannot use SES index (i.e. the socio-economic status) because it includes our variables of interest.

less correlated with students' scores.[9] Given its crucial role for remote learning to actually take place, this is an unexpected result. Since the variable has several missing observations (about 3 percent in Spain and Italy, but 18 percent in the United Kingdom, Table A1), we checked whether results were robust to the imputation of missing values. Regressions on the sample with imputed values showed that coefficients do not change significantly (results are in Tables C1, C2, C3 and C4 in Appendix C). The distribution of cognitive losses across the five countries, and their correlations with other explanatory variables are similar when reading is taken as the dependent variable (Figure A1 and Table A4 in Appendix A).

The low explanatory value of this variable might also be driven by heterogeneity in coefficients at a more disaggregated level. In particular, as cities are generally better endowed with internet and broadband infrastructures than rural areas, it can be reasonably expected that schools in urban areas make more use of digital resources than those in rural locations. If this is so, the negative score gaps of students in cities and towns attending schools with scarce ICT resources should be larger than those of students in rural areas also attending schools with few ICT resources. In the first case the digital network effects, and the corresponding losses of outsiders, should be stronger. To test this hypothesis, we use the answers to the question in the School Questionnaire: *Which of the following definitions best describes the community in which your school is located?* to build a categorical variable, denominated *Location*, where rural areas (with fewer than 3,000 people) take value zero, towns (between 3,000 and 100,000 people) value one, and cities (with more than 100,000 people) value two. Then, we interact *Location* with *Few school ICT*.

Results in Table 1 show that the coefficients on the interactions of the two variables regarding cities and towns (rural areas are in the intercept) are negative and significant in France, Germany and Italy. More specifically, in France gaps lose significance when the variable *School types* is added to the regression (not shown to save space), which suggests that students in cities and towns attending technical and vocational schools, and public schools, with few ICT resources experience the higher cognitive losses. In Italy, the type of school attended explain part of the negative gaps (also in this country, lyceums are more concentrated in urban areas and make more use of digital devices), but they remain robust to all specifications. In Germany, the negative gaps of students attending urban schools with scarce digital resources are very strong and robust to all controls. This supports our expectation that, everything else given, students attending schools that make a scarce use of ICT resources for teaching in locations where the use of digital devices is more widespread experience larger cognitive losses. On the other hand, in Spain and the United Kingdom locations appear to be non-significant; the correlations between the use of digital devices by schools and students' scores are unaffected by schools' locations. In Spain, as said above, the cognitive losses of attending a school with scarce digital devices is explained by the distinction between private versus public schools. We find very similar results regarding reading scores, which are not shown to save space.

[9] We obtained similar results with other variables in the School Questionnaire concerning the availability at school of computers, digital platforms and other ICT resources.

Table 1 – Few school ICT resources and school locations. Dependent variable: students' scores in mathematics.

	France		Germany		Italy		Spain		United Kingdom	
	Base model	Full model	Base model	Full model	Base model	Full model	Base model	Full model	Base model	Full model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No computer	-60.810***	-25.892***	-69.941***	-39.661***	-42.936***	-24.399***	-47.680***	-12.740***	-43.709***	-33.247***
No internet	-13.469	-7.315	-51.866***	-28.715***	-35.868***	-20.398**	-19.753**	-0.187	-92.735***	-74.714***
No quiet place	-39.348***	-9.389**	-32.446***	-9.997	-12.852**	1.068	-8.804**	-1.823	-23.563***	-18.855***
(Few school ICT)*(Town)	-38.436**	-9.92	-113.500***	-136.197***	-92.164*	-49.496**	-1.671	-5.421	5.859	3.978
(Few school ICT)*(City)	-32.704	-6.15	-138.865***	-134.872***	-118.420**	-65.532***	-8.244	-11.02	28.873	20.881
Few school ICT	23.791**	12.425	114.612***	131.151***	59.663	31.626	-2.379	7.899	-24.789*	-20.874*
Town	70.414***	-7.998	55.179***	103.942***	40.03	17.711	1.508	-3.175	0.77	6.631
City	78.945***	-4.109	67.509***	87.696***	60.158	27.203	16.225**	7.039	-11.395	-0.594
Constant	440.230***	483.027***	459.915***	-64.002	460.021***	354.371***	483.440***	318.870***	520.361***	166.434
Covariates	no	yes	no	yes	no	yes	no	yes	no	yes
Observations	5,381	5,247	4,024	3,728	11,029	10,779	34,072	32,915	10,689	9,680
R^2	0.075	0.449	0.076	0.302	0.084	0.280	0.035	0.300	0.050	0.109

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of the variable Location is "Rural area". Covariates are: gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private).*

5.2 Leaving education early and repeating grades.

Not being able to learn remotely may have longer run consequences than the score gaps seen above, which, in principle, could be at least partly reversed once back at school.[10] Students not learning remotely for weeks and months and foreseeing their scores will fall considerably below those of their peers may choose to shorten the length of their planned future education. They may drop out of school altogether, or stop studying when completing their compulsory schooling cycle or secondary school. As already seen, we use the question *Which of the following do you expect to complete*? and, as said above, set equal to one the answers indicating lower and upper secondary education to not leading to tertiary studies, the expectation of completing education at the lower secondary or at upper secondary levels not leading to tertiary studies, and zero for higher levels. Moreover, if falling behind may reduce students' planned investments in education, the concrete possibility of repeating grades may reinforce this decision. Hence, we expect students unable to attend remote learning to cut their planned investments in education and to reduce them even more if they are also likely to repeat grades.

We test whether our four variables indicating the lack of ICT resources at home or at school and of a quiet place to study are correlated with the probabilities of leaving school early and of repeating grades (the latter, except for the United Kingdom). Then, we test whether these two probabilities are significantly correlated. As in equations (2) and (3) above, we use Probit specifications for the first two tests and Bivariate probit regressions for the latter. In the Probit specification, the coefficients of the marginal probabilities on each variable of interest are in columns 1 to 4 of Table 2. The base regressions include only our four variables of interest, while the full regressions control for all covariates in equations (2) and (3). The results on the Bivariate probit regressions are in columns 5 and 6. The *Rho* coefficients report the correlation between the residuals of the regressions having *Leaving education early* and *Repeated grade* as dependent variables. Other than for the United Kingdom, Bivariate probit coefficients are not reported for France because both the raw correlation coefficient between y_1 and y_2 (Table A3 in Appendix A) and the *Rho* coefficient for this country are non-significant.

Results from the separate Probit regressions show that, in all countries, the lack of ICT resources, especially of a computer at home, significantly increases the two probabilities of leaving education early and, except for the United Kingdom, of repeating grades. In the full regressions (column 2 of Table 2), not having a computer at home increases the probability of leaving education early by 15 percent in Germany (where the average frequency of leaving education early is the predicted mean of y_1: 19 percent in Germany), 11 percent in the United Kingdom, 10 percent in Spain, and three percent in Italy. Not having an internet connection at home rises the probability of leaving education early by two percent in Spain. Not having a quiet place to study is correlated with a higher probability of leaving education early by two percent in Spain and six percent in United Kingdom. Everything else given, not having a computer is also correlated with a higher probability of repeating a grade, it increases by 24 percent in Spain, six percent in Germany, four percent in Italy and two percent in France (column 4). Not having a quiet place to study is positively correlated with a higher probability of repeating a grade in Germany (six percent) and in Italy (three percent). The unavailability of an internet connection at home rises to probability of repeating almost a grade by 10 percent in Spain. A scarce availability of ICT devices at school increases the probability of repeating a grade by three percent in Italy and by two percent in Spain.

The correlation between our variables of interest and the probability of leaving education early can be at least partially mediated by students' scores which, as seen in the Session 5.1, are strongly correlated with

[10] von Hippel and Hamrock (2019), find that cognitive losses deriving from summer vacations are reversed after variable lengths of time once back at school.

them. In this case, there would be a direct and an indirect (thorough scores) link between the availability of the resources needed for remote learning and students' probabilities of leaving school early. In order to control for this possibility, we include students' scores among covariates. Table A5, in the Appendix, shows that adding the scores in mathematics to our regressions does not modify our main results. Coefficients shrink but remain significant. Regarding the probability of leaving education early, the only two exceptions are the lack of a computer at home in Germany and an internet connection in Spain, which lose significance. Regarding the probability of repeating grades, coefficients on the lack of a computer at home and a quiet place to study lose their significance in Germany, and the lack of computers both at home and at school lose significance in Italy. Other coefficients do not change substantially. We repeated these tests using the scores in reading rather than in math and found very similar results. They are not presented to save space, but are available upon request.

The Bivariate Probit regressions add interesting insights on the joint probabilities of the two events. The *Rho* coefficients are strong and highly significant for Spain, Germany and Italy, indicating that the use of the Bivariate Probit specifications on these countries' data is appropriate. Their positive signs show that the two outcomes, repeating grades and leaving education early, reinforce each other. For example, as seen in the Probit specifications, not having a computer at home in Spain increases the probability of leaving education early by 10 percent and the probability of repeating grades by 24, while in the Bivariate probit regressions, not having a computer at home increases the joint probability of leaving education early and repeating a grade by 13 percent (column 6 of Table 2). In Spain, similar results apply to the other three variables of interest: not having an internet connection at home, not having a quiet place to study and attending a school with scarce ICT resources. The joint probabilities of repeating grades and leaving school early are all significantly correlated with the lack of the factors needed to learn remotely. In Section 5.1 above was seen that, in Spain, the negative score gaps associated with schools having few ICT resources were explained by the distinction between private and public schools, and the lower digitalization of the latter. Here, we see that even controlling for all cofactors, attending a school with few ICT resources significantly increases the joint probabilities of repeating a grade and leaving education early.

Analogous outcomes derive from the lack of computer at home in Germany and Italy. In the Bivariate Probit regressions, it significantly increases the joint probabilities of repeating grades and leaving education early by 14 percent in Germany and by three percent in Italy (column 5). Controlling for all covariates, coefficients shrink but remain significant at the one and five percent levels, respectively (column 6). Not having a quiet place to study in Germany, and a scarcity of ICT resources at school in Italy also increase the joint probabilities of repeating grades and leaving education early (column 5). In Italy, most of the correlation between the joint probabilities and *Few school ICT* resources is explained by the school types attended (Column 4, Table A6).

Moreover, to control for the sensitivity of our results, we used an alternative indicator for the lack of schooling experienced by only a subset of students: the absence from school. We tested the correlations between scores in mathematics and reading and the days of absence from school. Results are in Appendix B. As expected, these negative gaps are bigger than those related to the lack of each of the four factors needed to learn remotely considered above, but follow the same general patterns within and across countries. Also in this case, results are robust to different covariates and specifications. Further robustness controls, based on the imputation of missing observations are in Appendix C.

As mentioned above, this study's results are correlations between variables, not causal relationships. The lack of a time dimension in our data and of potentially valid instruments do not allow us to test for causality or to exclude endogeneity and omitted variables. However, our coefficients are robust to different specifications, covariates, fixed effects and missing observations. They show that, even during normal times, students unable to learn remotely suffer strong and significant cognitive losses with respect to their peers and tend to leave education earlier. This lack of ICT resources becomes crucial during school closures, when the impossibility of distant schooling is likely to strongly deepen the education inequalities we find in our study.

Table 2 – Marginal probabilities: Leaving education early and repeating grades

		Probit				Bivariate probit	
Dependent variable:		Leaving education early (y_1) = 1		Repeated grade (y_2) = 1		$y_1 = 1$ & $y_2 = 1$	
		Base	**Full**	**Base**	**Full**	**Base**	**Full**
		(1)	(2)	(3)	(4)	(5)	(6)
France	No computer	0.05**	0.02	0.17***	0.02***		
	No internet	0.01	0.00	0.02	0.03		
	No quiet place to study	0.02	0.00	0.12***	0.01		
	Few school ICT	0.03**	0.02	0.08*	0.01		
	Observations	5,168	5,067	5,370	5,247		
	Predicted mean y_1, y_2	0.13	0.16	0.12	0.07		
Germany	No computer	0.24***	0.15***	0.13***	0.06*	0.14***	0.06***
	No internet	0.17**	0.10	0.07	0.05	0.08	0.04
	No quiet place to study	0.08**	0.04	0.09***	0.06**	0.06***	0.03
	Few school ICT	0.00	0.02	0.01	0.13	0.00	0.00
	Observations	3,778	3,554	4,017	3,752	3,770	3,549
	Rho					*0.42****	*0.26****
	Predicted mean y_1, y_2	0.31	0.19	0.18	0.12	0.10	0.05
Italy	No computer	0.06***	0.03**	0.08***	0.04**	0.03***	0.01**
	No internet	0.01	0.00	0.03	0.00	0.03***	0.00
	No quiet place to study	0.02*	0.01	0.07***	0.03*	0.01	0.00
	Few school ICT	0.02**	0.01	0.05***	0.03**	0.01**	0.00
	Observations	10,482	10,287	11,010	10,779	10,473	10,278
	Rho					*0.50****	*0.40****
	Predicted mean y_1, y_2	0.07	0.13	0.04	0.09	0.03	0.01
Spain	No computer	0.15***	0.10***	0.31***	0.24***	0.15***	0.13***
	No internet	0.04***	0.02**	0.15***	0.10***	0.05***	0.04***
	No quiet place to study	0.03***	0.02*	0.04***	0.02	0.02***	0.02***
	Few school ICT	0.02***	0.00	0.06***	0.02**	0.02***	0.01**
	Observations	33,178	32,074	34,144	32,970	33,166	32,066
	Rho					*0.90****	*0.82****
	Predicted mean y_1, y_2	0.08	0.25	0.09	0.28	0.07	0.08
United Kingdom	No computer	0.14***	0.11***				
	No internet	0.13*	0.13				
	No quiet place to study	0.07***	0.06***				
	Few school ICT	0.01	0.01				
	Observations	10,260	9,400				
	Predicted mean y_1, y_2	0.15	0.03				

*Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. Leaving education early and Repeated grade are dichotomous variables taking, respectively, value one when the student plans to leave education early and zero otherwise, and value one when grades are repeated and zero otherwise. Full regressions of columns 2, 4 and 6 include all covariates of equations (2) and (3). Margins are computed at mean values of covariates.*

6. Discussion and conclusions

Several recent empirical investigations on school closures due to the coronavirus pandemic predict negative effects on overall education levels, but they can also exacerbate education inequalities. In this study, we used PISA 2018 data to test the extra cognitive loses of students lacking the factors needed to make remote learning actually possible: a computer for schoolwork, an internet connection, a quiet place to study, or a school with enough ICT resources. In the five European countries we consider, the proportion of fifteen-year-old students lacking at least one of them ranges from more than 30 percent in France to more than 60 percent in Germany.

We found that the scores in mathematics and reading of these students are strongly and significantly lower than those of their peers; and most of these cognitive gaps remain strong and significant after controlling for individual and family characteristics, school types and school fixed effects. In particular, everything else equal, the lack of a computer at home is correlated with negative gaps in mathematics that range from a fourth of a school year in Spain to 70 percent of a school year in the United Kingdom, Germany and France. Differently from several empirical studies on school interruptions, we find very similar results in mathematics and reading and, in some cases, even higher cognitive losses in reading (Gottfried, 2009 and 2011; Quinn and Polikoff, 2017; Aucejo and Romano, 2016).

Moreover, in the longer run, students unable to learn remotely are more likely to drop out from school or end their education earlier. This relationship is stronger in countries such as Spain, Germany and Italy, were students falling behind their peers are also more likely to repeat grades. In these countries, and especially in Spain, the two probabilities, of repeating grades when going back at school and of dropping out are significantly and strongly correlated.

More generally, we found that the cognitive inequalities arising from the lack of the resources needed to learn remotely are less explained by students' and families' characteristics than by countries' educational systems. Negative gaps in mathematics and reading associated with the lack of remote learning follow each country's type of differentiation between types of schools. Where tracking starts earlier, such as in Germany and Italy, students unable to learn remotely are more concentrated in technical and vocational schools and are also more likely to drop out early. When tracking interacts with schools being private or public, such as in France, students unable to learn remotely are more concentrated in vocational and technical schools that are also public (Le Donné, 2014). Where the distinction between private and public schools matters more, such as in Spain and the United Kingdom, these negative cognitive gaps are more concentrated in public schools. A further line of demarcation, which involves both types of models, is grades repetition: in countries where it is more frequent, such as Spain, Germany and Italy, digital negative gaps and an early termination of studies is more frequent among repeaters.

In turn, the segmentation between types of schools – with tracking or the private-public distinction – and the existence of digital network externalities can reinforce each other. Students attending schools with scarce ICT resources that are located in urban areas – where the use of digital resources is more widespread – tend to experience the biggest cognitive losses. These schools are typically vocational or technical in French, Italian and German cities and towns; and, in France, they are mostly public rather than private. Similarly, students not having an internet connection at home or a computer for schoolwork experience the highest losses in countries, such as the United Kingdom, where the use of digital resources is more widespread. Hence, our results show that digital divides in countries and their educational systems are interrelated phenomena. This is a crucial issue in the field of education. When countries are forced to close schools and adopt distance learning, existing education inequalities are exacerbated and digital ones emerge. Policymakers should develop targeted policies addressing the needs of disadvantaged students and schools, tailored in accordance with countries' educational systems and digital divides.

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Appendix A. Figures and Tables.

Table A1 – Descriptive statistics

	France				Germany				Italy				Spain				United Kingdom			
	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing	Obs.	Mean	Std. Dev.	Missing
Math score	6,308	495.41	92.57	0.0	5,451	500.04	95.39	0.0	11,785	486.59	93.78	0.0	35,943	481.39	88.40	0.0	13,818	501.77	93.02	0.0
Reading score	6,308	492.61	101.18	0.0	5,451	498.28	105.75	0.0	11,785	476.28	96.87	0.0		-			13,818	503.93	100.21	0.0
Leave educ. early (%)	5,930	11.98	0.32	6.0	4,408	31.02	0.46	19.1	10,943	5.57	0.23	7.1	34,406	8.85	0.28	4.3	12,750	12.85	0.33	7.7
Repeated grade (%)	6,215	16.56	0.37	1.5	4,674	19.63	0.40	14.3	11,495	13.21	0.34	2.5	35,449	28.71	0.45	1.4	13,306	2.52	0.16	3.7
No computer (%)	6,193	9.22	0.29	1.8	4,711	7.98	0.27	13.6	11,485	9.96	0.30	2.5	35,391	8.58	0.28	1.5	13,250	8.06	0.27	4.1
No internet (%)	6,203	1.54	0.12	1.7	4,721	2.03	0.14	13.4	11,491	2.84	0.17	2.5	35,371	2.12	0.14	1.6	13,262	0.82	0.09	4.0
No quiet place to study (%)	6,186	6.31	0.24	1.9	4,723	4.85	0.21	13.4	11,491	8.73	0.28	2.5	35,372	7.34	0.26	1.6	13,204	10.97	0.31	4.4
Few school ICT (%)	5,498	25.69	0.44	12.8	4,718	55.87	0.50	13.4	11,347	28.64	0.45	3.7	34,880	46.70	0.50	3.0	11,324	30.93	0.46	18.0
Days of absence	4,947			21.6	2,523			47.6	9,183			22.1	27,865			22.5	12,620			8.7
Days of absence: 0 (%)	4,947	83	0.38		2,523	87	0.34		9,183	45	0.50		27,865	72	0.45		12,620	78	0.42	
Days of absence: 1-2 (%)	4,947	10	0.31		2,523	9	0.28		9,183	39	0.49		27,865	22	0.41		12,620	17	0.38	
Days of absence 3-4 (%)	4,947	3	0.16		2,523	2	0.14		9,183	7	0.26		27,865	3	0.18		12,620	3	0.16	
Days of absence 5 + (%)	4,947	4	0.18		2,523	2	0.15		9,183	9	0.28		27,865	3	0.16		12,620	2	0.14	
Female (%)	6,308	49.33	0.50	0.0	5,451	46.22	0.50	0.0	11,785	48.26	0.50	0.0	35,943	49.37	0.50	0.0	13,818	51.45	0.50	0.0
Age	6,308	15.86	0.29	0.0	5,451	15.83	0.29	0.0	11,785	15.77	0.29	0.0	35,943	15.84	0.29	0.0	13,818	15.76	0.28	0.0
Parents' education	6,133	4.95	1.30	2.8	4,481	4.41	1.66	17.8	11,439	4.42	1.45	2.9	34,925	4.68	1.65	2.8	12,391	4.89	1.29	10.3
Immigrant status (%)	6,167	14.29	0.35	2.2	4,727	22.17	0.42	13.3	11,354	10.03	0.30	3.7	34,844	12.19	0.33	3.1	12,979	19.76	0.40	6.1
Age of arrival	6,177	0.51	2.29	2.1	4,798	0.71	2.81	12.0	11,479	0.43	1.95	2.6	35,419	0.66	2.48	1.5	13,293	0.84	2.86	3.8
School type	6,308			0.0	5,451			0.0	11,785			0.0	35,943			0.0	13,818			0.0
General school (%)	6,308	63.82	0.48		5,451	54.76	0.50		11,785	48.10	0.50		35,943	99.04	0.10		13,818	100.00	-	
Technical school (%)	6,308	30.22	0.46		5,451	38.10	0.49		11,785	31.46	0.46		35,943	-	0.01		13,818	-	-	
Vocational school (%)	6,308	5.96	0.24		5,451	7.14	0.26		11,785	20.43	0.40		35,943	0.95	0.10		13,818	-	-	
Public school (%)	5,602	80.03	0.40	11.19	4,690	96.09	0.19	13.96	11,575	96.38	0.19	1.78	34,911	67.68	0.47	2.87	11,888	34.01	0.47	13.97
Location of school	5,602			11.19	4,663			14.46	11,575			1.78	34,884			2.95	11,859			14.18
Location: Rural area (%)	5,602	2.50	0.16		4,663	1.14	0.11		11,575	3.75	0.19		34,884	4.44	0.21		11,859	7.09	0.26	
Location: Town (%)	5,602	75.17	0.43		4,663	71.80	0.45		11,575	71.79	0.45		34,884	59.22	0.49		11,859	61.51	0.49	
Location: City (%)	5,602	22.33	0.42		4,663	27.06	0.44		11,575	24.46	0.42		34,884	36.34	0.48		11,859	31.40	0.48	

Notes: All plausible values employed. All results are weighted and replication weights are taken into account.

Table A2 – Remote learning resources. Dependent variable: students' scores in mathematics.

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-61.665***	-62.454***	-54.039***	-28.222***	-41.431***	-25.841***	-24.816***	-71.654***	-72.331***	-51.245***	-57.527***	-59.858***	-42.608***	-24.381***
No internet	-11.409	-11.859	-2.028	-13.101	5.066	-7.114	5.066	-52.083***	-51.585***	-40.398***	-39.117***	-47.646***	-29.673***	-27.994***
No quiet place to study	-37.730***	-37.646***	-25.310***	-16.487***	-23.646***	-9.322**	-7.290*	-31.865***	-31.582***	-20.928**	-22.577***	-22.950***	-9.777	0.092
Few school ICT	-13.096	-13.484	-13.175	5.276	-3.594	3.879		-5.194	-4.805	-2.406	-6.866	-6.039	-3.816	
Female		-11.299***				-23.550***	-20.487***		-10.119***				-19.123***	-23.125***
Age		16.522***				3.966	4.151		23.042***				28.940***	31.463***
Parents' education			15.275***			6.151***	4.509***			12.828***			8.827***	2.575***
Immigrant status			-29.262***			-26.182***	-20.038***			-27.793***			-24.400***	-16.022***
Age of arrival			-2.450***			0.283	-0.293			-4.161***			-3.085***	-1.848***
Technical school				-106.168***		-90.068***					-57.263***		-41.867***	
Vocational school				-159.776***		-138.798***					-113.49***		-76.218***	
Public school				-27.021***		-21.324***					-14.135		-3.283	
Repeated grade					-112.327***	-32.927***	-47.036***					-65.722***	-47.832***	-38.773***
Constant	511.156***	254.832***	440.410***	560.092***	522.622***	476.964***	435.469***	517.389***	157.183	468.540***	558.381***	531.514***	67.782	27.422
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	5,381	5,381	5,251	5,381	5,370	5,247	5,247	4,077	4,077	3,819	4,049	4,017	3,752	3,779
R^2	0.063	0.069	0.135	0.407	0.242	0.448	0.510	0.067	0.075	0.158	0.202	0.138	0.284	0.507

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level for coefficients on School Type is "General school".*

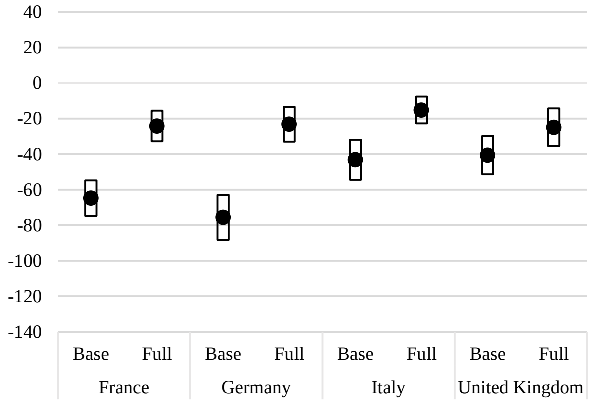
Table A2 – Remote learning resources. Dependent variable: students' scores in mathematics. Continued from previous page.

	Italy							Spain						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-42.997***	-42.869***	-36.175***	-29.858***	-36.798***	-24.348***	-15.621***	-47.796***	-48.504***	-35.001***	-44.512***	-16.909***	-12.792***	-10.671***
No internet	-38.255***	-37.975***	-28.375***	-26.188***	-35.493***	-21.079**	-5.986	-20.609**	-19.945**	-11.933	-17.474**	-5.965	-0.19	0.369
No quiet place to study	-12.559**	-12.935**	-7.766	-3.549	-7.386	1.225	-0.609	-8.648**	-8.521**	-3.775	-8.029*	-4.462	-1.79	-0.437
Few school ICT	-39.119***	-38.502***	-36.914***	-24.642***	-35.405***	-21.774***		-7.378***	-7.457***	-4.190*	-2.982	-2.05	0.274	
Female		-14.222***				-28.059***	-22.622***		-8.505***				-16.401***	-16.824***
Age		16.532***				10.288**	10.240***		19.486***				11.528***	10.970***
Parents' education			9.486***			3.638***	-0.808			10.695***			5.554***	3.606***
Immigrant status			-21.264***			-2.477	-13.657***			-17.487***			-6.401*	-5.831*
Age of arrival			-2.752***			-1.704*	-1.582*			-3.091***			-2.244***	-2.145***
Technical school				-38.475***		-38.404***								
Vocational school				-99.599***		-88.190***					-75.540***		-24.675**	
Public school				-14.011		-6.298					-23.167***		-6.372**	
Repeated grade					-72.036***	-50.653***	-42.139***					-98.301***	-90.676***	-89.502***
Constant	505.411***	251.503***	465.833***	543.225***	512.830***	375.655***	351.802***	490.590***	186.275***	443.601***	504.608***	513.130***	317.048***	330.016***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	11,029	11,029	10,790	11,029	11,010	10,779	10,779	34,174	34,174	33,056	34,099	34,144	32,970	33,044
R^2	0.073	0.082	0.103	0.226	0.140	0.278	0.525	0.031	0.037	0.089	0.055	0.273	0.298	0.376

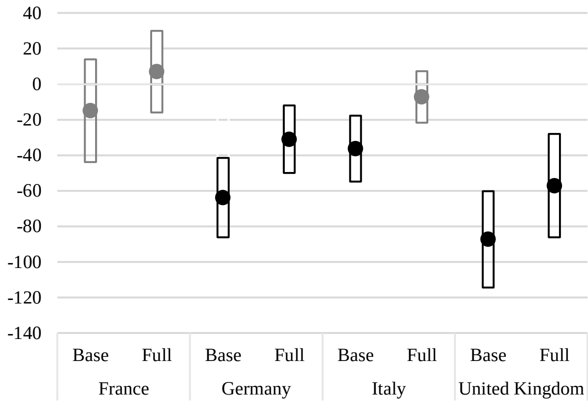
	United Kingdom						
	(29)	(30)	(31)	(32)	(33)	(34)	(35)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-44.061***	-44.231***	-34.099***	-42.996***	-43.967***	-33.605***	-27.918***
No internet	-93.525***	-95.301***	-82.958***	-93.147***	-84.543***	-74.200***	-68.881***
No quiet place to study	-23.916***	-23.307***	-19.925***	-24.021***	-22.759***	-19.055***	-13.452***
Few school ICT	-10.327	-10.472	-10.835	-9.807	-10.854	-10.76	
Female		-18.752***				-17.736***	-17.021***
Age		22.596***				20.185***	14.873**
Parents' education			13.221***			12.042***	4.389***
Immigrant status			-13.329**			-12.177**	-5.119
Age of arrival			0.478			0.785	0.556
Public school				-25.117***		-23.675***	
Repeated grade					-58.984***	-53.333***	-40.031***
Constant	516.184***	169.773	456.497***	524.617***	517.962***	162.418	269.686***
School FE	no	no	no	no	no	no	yes
Observations	10,718	10,718	9,724	10,689	10,670	9,680	9,704
R^2	0.046	0.061	0.072	0.063	0.055	0.107	0.280

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < Notes: Standard errors are clustered at 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level for coefficients on School Type is "General school".*

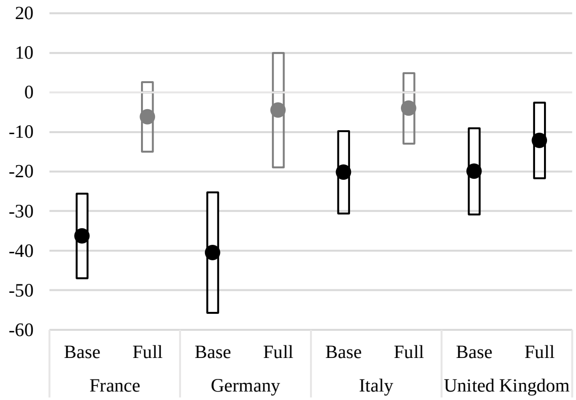
Figure A1 – Gaps in reading. ICT resources and a quiet place to study



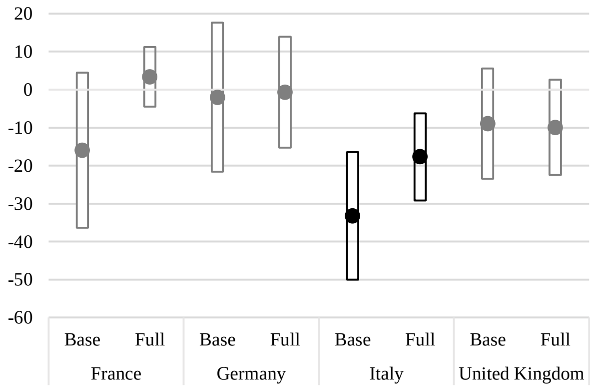
(a) No computer



(b) No internet



(c) No quiet place to study



(d) Few ICT at school

Note: Dependent variable: reading scores. Values in the y-axes are the differences in scores between students without and with the resources for learning remotely at home or at school. The base regressions include only the four variables of interest; the full regressions include all the covariates of equation (1): gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private) and school fixed effects, except for Figure (d), where fixed effects are not included to avoid collinearities. Grey denotes significance below five percent.

Table A3 – Main correlation coefficients

Variable 1	Variable 2	France	Germany	Italy	Spain	United Kingdom
Reading score	Math score	0.83 ***	0.82 ***	0.77 ***		0.77 ***
Reading score	Leave educ. Early	-0.18 ***	-0.46 ***	-0.23 ***		-0.30 ***
Reading score	Repeated grade	-0.43 ***	-0.26 ***	-0.29 ***		-0.11 ***
Reading score	No computer	-0.20 ***	-0.17 ***	-0.15 ***		-0.12 ***
Reading score	No internet	-0.04 *	-0.09 ***	-0.09 ***		-0.09 ***
Reading score	No quiet place to study	-0.11 ***	-0.09 ***	-0.07 ***		-0.08 ***
Reading score	Few school ICT	-0.07	0.01	-0.16 ***		-0.05
Reading score	Days of absence: 0	0.26 ***	0.21 ***	0.14 ***		0.15 ***
Reading score	Days of absence: 1-2	-0.16 ***	-0.15 ***	0.01		-0.10 ***
Reading score	Days of absence 3-4	-0.15 ***	-0.09 ***	-0.09 ***		-0.06 ***
Reading score	Days of absence 5 +	-0.14 ***	-0.12 ***	-0.17 ***		-0.11 ***
Math score	Leaving education early	-0.19 ***	-0.45 ***	-0.20 ***	-0.30 ***	-0.32 ***
Math score	Repeated grade	-0.45 ***	-0.27 ***	-0.27 ***	-0.51 ***	-0.10 ***
Math score	No computer	-0.21 ***	-0.18 ***	-0.14 ***	-0.15 ***	-0.14 ***
Math score	No internet	-0.04 *	-0.07 ***	-0.09 ***	-0.07 ***	-0.10 ***
Math score	No quiet place to study	-0.13 ***	-0.09 ***	-0.06 ***	-0.04 ***	-0.10 ***
Math score	Few school ICT	-0.06	-0.01	-0.19 ***	-0.04 **	-0.06
Math score	Days of absence: 0	0.22 ***	0.21 ***	0.16 ***	0.17 ***	0.19 ***
Math score	Days of absence: 1-2	-0.13 ***	-0.15 ***	-0.03	-0.09 ***	-0.13 ***
Math score	Days of absence 3-4	-0.11 ***	-0.09 ***	-0.09 ***	-0.10 ***	-0.10 ***
Math score	Days of absence 5 +	-0.14 ***	-0.10 ***	-0.15 ***	-0.11 ***	-0.11 ***
Leaving education early	Repeated grade	0.01	0.21 ***	0.23 ***	0.39 ***	0.09 ***
Leaving education early	No computer	0.06 ***	0.12 ***	0.10 ***	0.16 ***	0.14 ***
Leaving education early	No internet	0.01	0.05	0.03	0.06 ***	0.07 ***
Leaving education early	No quiet place to study	0.03	0.06 **	0.05 ***	0.04 ***	0.09 ***
Leaving education early	Few school ICT	0.05 **	-0.01	0.05 **	0.04 ***	0.02
Leaving education early	Days of absence: 0	-0.09 ***	-0.12 ***	-0.03 *	-0.11 ***	-0.12 ***
Leaving education early	Days of absence: 1-2	0.06 ***	0.08 ***	-0.02	0.06 ***	0.09 ***
Leaving education early	Days of absence 3-4	0.03	0.07 ***	0.02	0.06 ***	0.06 **
Leaving education early	Days of absence 5 +	0.05 ***	0.05 **	0.08 ***	0.07 ***	0.06 ***
Repeated grade	No computer	0.16 ***	0.07 **	0.08 ***	0.20 ***	0.01
Repeated grade	No internet	0.04 *	0.02	0.03	0.10 ***	0.05
Repeated grade	No quiet place to study	0.10 ***	0.03	0.07 ***	0.05 ***	0.02
Repeated grade	Few school ICT	0.09	0.01	0.06 ***	0.05 ***	-0.03 **
Repeated grade	Days of absence: 0	-0.10 ***	-0.12 ***	-0.08 ***	-0.15 ***	-0.03 *
Repeated grade	Days of absence: 1-2	0.06 ***	0.08 ***	0.02	0.09 ***	0.01
Repeated grade	Days of absence 3-4	0.06 ***	0.04	0.02	0.08 ***	0.00
Repeated grade	Days of absence 5 +	0.06 ***	0.08 **	0.10 ***	0.09 ***	0.08 ***
No computer	No internet	0.14 ***	0.13 ***	0.20 ***	0.27 ***	0.18 ***
No computer	No quiet place to study	0.18 ***	0.26 ***	0.20 ***	0.11 ***	0.14 ***
No computer	Days of absence: 0	-0.08 ***	-0.10 ***	-0.06 ***	-0.04 ***	-0.11 ***
No computer	Days of absence: 1-2	0.03 **	0.09 ***	-0.01	0.02	0.09 ***
No computer	Days of absence 3-4	0.02	0.04	0.04 **	0.04 ***	0.03
No computer	Days of absence 5 +	0.09 ***	0.02	0.08 ***	0.03 ***	0.05 ***
No internet	No quiet place to study	0.07 ***	-0.01	0.07 ***	0.06 ***	0.09 ***
No internet	Few school ICT	0.02	-0.04 *	0.05 **	0.02 **	0.04 **
No internet	Days of absence: 0	-0.07 ***	-0.03	-0.02	-0.03 **	-0.04 *
No internet	Days of absence: 1-2	0.03	0.02	0.00	0.02 *	0.02
No internet	Days of absence 3-4	0.03	-0.02 ***	0.00	0.01	0.00
No internet	Days of absence 5 +	0.07 ***	0.05	0.03	0.02	0.07 *
No quiet place to study	Few school ICT	0.02	0.03	0.07 ***	0.01	0.04 *
No computer	Few school ICT	0.03	-0.01	0.06 ***	0.02 *	0.01
No quiet place to study	Days of absence: 0	-0.09 ***	-0.05 *	-0.04 **	-0.04 ***	-0.08 ***
No quiet place to study	Days of absence: 1-2	0.02	0.02	0.01	0.03 ***	0.07 ***
No quiet place to study	Days of absence 3-4	0.04 ***	0.04	0.00	0.00	0.02
No quiet place to study	Days of absence 5 +	0.11 ***	0.05	0.04 *	0.05 ***	0.03 **
Few school ICT	Days of absence: 0	-0.01	-0.02	-0.05 **	-0.01	-0.01
Few school ICT	Days of absence: 1-2	0.00	0.03	0.00	0.01	0.00
Few school ICT	Days of absence 3-4	0.03	-0.01	0.05 ***	0.02 *	0.01
Few school ICT	Days of absence 5 +	0.00	-0.01	0.04 **	-0.02	-0.01

Notes. All plausible values employed. All results are weighted and replication weights are taken into account.

Table A4 – Remote learning resources. Dependent variable: student scores in reading

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-64.732***	-62.744***	-57.614***	-28.896***	-43.504***	-25.674***	-24.151***	-75.504***	-74.150***	-52.564***	-59.597***	-63.610***	-41.884***	-23.130***
No internet	-14.939	-13.557	-4.413	-16.666	-6.675	-7.593	7.061	-63.841***	-62.881***	-48.034***	-49.197***	-59.217***	-34.707***	-30.961***
No quiet place to study	-36.272***	-36.189***	-22.735***	-13.913***	-21.478***	-6.803	-6.181	-40.495***	-38.693***	-26.004***	-29.941***	-31.686***	-14.032*	-4.470
Few school ICT	-15.905	-14.671	-15.507	3.424	-5.938	3.394		-2.002	-2.284	0.818	-3.643	-2.745	-0.652	
Female		20.993***				4.185***	2.536***		24.854***				9.192***	2.077**
Age		18.803***				-23.177***	-18.301***		16.639**				-22.054***	-13.193***
Parents' education			13.785***			-0.896	-1.647***			13.555***			-5.586***	-4.282***
Immigrant status			-26.300***			8.257***	10.174***			-25.602***			16.467***	9.765***
Age of arrival			-3.763***			6.286*	6.592*			-6.756***			23.334***	28.147***
Technical school				-117.524***		-99.393***					-67.932***		-49.598***	
Vocational school				-165.869***		-142.118***					-129.148***		-90.586***	
Public school				-23.196***		-17.309***					-4.881		7.754	
Repeated grade					-117.434***	-29.387***	-52.264***					-69.709***	-44.503***	-33.991***
Constant	509.784***	200.572**	446.737***	558.486***	521.783***	431.056***	390.221***	515.164***	240.138**	464.591***	551.784***	529.956***	129.132	66.100
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	5,381	5,381	5,251	5,381	5,370	5,247	5,247	4,077	4,077	3,819	4,049	4,017	3,752	3,779
R^2	0.058	0.072	0.113	0.394	0.223	0.408	0.473	0.067	0.083	0.167	0.213	0.131	0.292	0.519

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients of coefficients on School type is "General school".*

Table A4 – Remote learning resources. Dependent variable: student scores in reading. Continued from previous page

	Italy							United Kingdom						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
No computer	-43.131***	-41.625***	-36.336***	-27.733***	-36.227***	-22.098***	-15.123***	-40.546***	-40.269***	-30.262***	-39.594***	-40.836***	-29.535***	-24.823***
No internet	-36.301***	-37.648***	-28.302***	-23.740***	-33.301***	-22.346***	-7.153	-87.267***	-84.213***	-79.169***	-86.935***	-76.362***	-65.126***	-57.124***
No quiet place to study	-20.204***	-19.360***	-13.952***	-9.740*	-14.450***	-3.524	-4.041	-19.950***	-20.164***	-16.480***	-19.949***	-18.757***	-16.205***	-12.137**
Few school ICT	-33.251***	-34.476***	-31.418***	-18.047***	-29.118***	-17.693***		-8.964	-9.096	-9.395	-8.384	-9.472	-9.935	
Female		25.493***				1.760*	-2.151**		14.529***				11.223***	4.013***
Age		17.625***				-7.268	-17.242***		21.997***				-13.341**	-6.750
Parents' education			7.887***			-2.039***	-2.373***			11.819***			-1.001	-1.403**
Immigrant status			-26.734***			8.524***	12.327***			-12.041*			16.528***	16.156***
Age of arrival			-3.267***			11.193**	12.543***			-1.530*			20.472***	13.796***
Technical school				-62.270***		-50.866***								
Vocational school				-112.726***		-95.923***								
Public school				-5.627		-4.011					-21.563***		-20.273***	
Repeated grade					-80.197***	-49.844***	-42.351***					-68.166***	-63.984***	-50.910***
Constant	494.614***	204.328**	463.197***	533.470***	502.932***	344.849***	295.794***	517.697***	163.604*	466.834***	524.790***	519.778***	146.740*	275.850***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	11,029	11,029	10,790	11,029	11,010	10,779	10,779	34,174	34,174	33,056	34,099	34,144	32,970	33,044
R^2	0.062	0.082	0.090	0.263	0.140	0.294	0.496	0.033	0.042	0.054	0.044	0.044	0.082	0.234

*Notes. Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "General school".*

Table A5 – Dependent variable: Marginal probabilities of leaving education early and repeating grades. Probit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Leaving education early					Dependent variable: Grade repetition			
	France	Germany	Italy	Spain	United Kingdom	France	Germany	Italy	Spain
No computer	0.05**	0.24***	0.06***	0.15***	0.14***	0.17***	0.13***	0.08***	0.31***
No internet	0.01	0.17**	0.01	0.04***	0.13*	0.02	0.07	0.03	0.15***
No quiet place	0.02	0.08**	0.02*	0.03***	0.07***	0.12***	0.09***	0.07***	0.04***
Few school computers	0.03**	0	0.02**	0.02***	0.01	0.08*	0.01	0.05***	0.06***
No computer	0.05**	0.24***	0.05***	0.14***	0.14***	0.17***	0.13***	0.08***	0.31***
No internet	0.01	0.16**	0.02	0.05***	0.12*	0.02	0.07	0.04	0.16***
No quiet place	0.02	0.08**	0.02*	0.03***	0.07***	0.12***	0.09***	0.06***	0.04***
Few school computers	0.03**	0	0.02**	0.02***	0.01	0.08*	0.01	0.05***	0.06***
Covariates: Female, age									
No computer	0.04*	0.171***	0.05***	0.11***	0.11***	0.15***	0.08**	0.06***	0.26***
No internet	-0.01	0.12	0	0.02*	0.14*	0.01	0.06	0.01	0.11***
No quiet place	0.01	0.07	0.02	0.02*	0.06***	0.08***	0.07**	0.05***	0.02
Few school ICT	0.03**	0	0.02*	0.01**	0	0.08*	0.01	0.05***	0.04***
Covariates: Parents' education, immigrant status, age of arrival									
No computer	0.02	0.2***	0.03**	0.13***	0.14***	0.02***	0.09***	0.05**	0.30***
No internet	0.01	0.12	0	0.03**	0.13*	0.03	0.05	0.01	0.13***
No quiet place	0	0.05	0.01	0.03***	0.07***	0.02*	0.07**	0.04**	0.04***
Few school ICT	0.02	0.01	0.01	0.01*	0.01	0.01	0.01	0.02*	0.03**
Covariates: Type of school, and private/public									
No computer	0.04*	0.17***	0.05***	0.10***	0.11***	0.15***	0.07**	0.06***	0.25***
No internet	0	0.12	0	0.03**	0.13*	0.01	0.06	0.01	0.11***
No quiet place	0.01	0.06	0.02	0.02**	0.06***	0.08***	0.07**	0.05**	0.02
Few school ICT	0.03**	0	0.02**	0.01**	0.01	0.08*	0.01	0.05***	0.04***
Covariates: Female, age, parents' education, immigrant status, age of arrival									
No computer	0.02	0.15***	0.03**	0.1***	0.11***	0.02***	0.06*	0.04**	0.24***
No internet	0	0.1	0	0.02**	0.13	0.03	0.05	0	0.10***
No quiet place	0	0.04	0.01	0.02*	0.06***	0.01	0.06**	0.03*	0.02
Few school ICT	0.02	0.02	0.01	0	0.01	0.01	0.13	0.03**	0.02**
Covariates: Female, age, parents' education, immigrant status, age of arrival, school types									
No computer	0	0.04	0.02*	0.04***	0.06***	0.01*	0.01	0.02	0.16***
No internet	-0.01	0.02	-0.01	0.01	0.03	0.01	0.01	-0.02	0.07**
No quiet place	-0.01	0.02	0.01	0.01*	0.04**	0.01	0.05	0.03*	0.02
Few school ICT	0.03	0.01	0	0	0	0.01	0.01	0.01	0.03**
Covariates: Female, age, parents' education, immigrant status, age of arrival, school types, math score									

*Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account.*

Table A6 – Marginal probabilities of Leaving education early and Grade repetition. Bivariate Probit

	(1)	(2)	(3)	(4)	(5)	(6)
	Early & not repeating	Early & repeating	Early & not repeating	Early & repeating	Early & not repeating	Early & repeating
	Germany		Italy		Spain	
No computer	0.12***	0.14***	0.03**	0.03***	0.00	0.15***
No internet	0.09	0.08	0.01	0.03***	0.00	0.05***
No quiet place	0.02	0.06***	0.01	0.01	0.01*	0.02***
Few school ICT	0.00	0.00	0.01	0.01**	0.00	0.02***
	Rho =0.42; p value = 0.00		*Rho =0.50; p value = 0.00*		*Rho =0.90; p value = 0.00*	
No computer	0.12***	0.13***	0.03**	0.03***	0.00	0.14***
No internet	0.09	0.07	0.01	0.01	0.00	0.05***
No quiet place	0.02	0.06***	0.01	0.01**	0.01*	0.02***
Few school ICT	0.00	0.00	0.01*	0.01***	0.00	0.02***
	Rho =0.41; p value = 0.00		*Rho =0.48; p value = 0.00*		*Rho =0.89; p value = 0.00*	
Covariates: Female, age						
No computer	0.09***	0.08***	0.025**	0.02***	0.01*	0.11***
No internet	0.06	0.06	0.01	0.00	0.00	0.02***
No quiet place	0.02	0.04*	0.01	0.01*	0.00	0.01**
Few school ICT	0.00	0.00	0.01	0.01***	0.00	0.01**
	Rho =0.38; p value = 0.00		*Rho =0.48; p value = 0.00*		*Rho =0.86; p value = 0.00*	
Covariates: Parents' education, immigrant status, age of arrival						
No computer	0.11***	0.10***	0.02**	0.01**	0.00	0.13***
No internet	0.07	5.00	0.01	0.00	0.00	0.04***
No quiet place	0.01	0.04**	0.01	0.01	0.01*	0.02***
Few school ICT	0.01	0.00	0.01	0.00	0.00	0.01**
	Rho =0.29 p value = 0.00		*Rho =0.41; p value = 0.00*		*Rho =0.87; p value = 0.00*	
Covariates: School type, private/public						
No computer	0.09***	0.06***	0.01**	0.01**	0.01*	0.09***
No internet	0.06	0.04	0.00	0.00	0.00	0.02**
No quiet place	0.01	0.03	0.00	0.00	0.01*	0.01**
Few school ICT	0.01	0.00	0.00	0.00	0.00	0.01
	Rho =0.26; p value = 0.00		*Rho =0.40; p value = 0.00*		*Rho =0.82; p value = 0.00*	
Covariates: Female, age, parents' education, immigrant status, age of arrival, school types, private/public						

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account.*

Appendix B. Absence from school.

To predict the potential relationships between not attending school, either physical or virtual, and scores, we use a variable concerning the days of absence from school, which is an ordinal variable built from answers to the question, in the Students' Questionnaire: *In the last two full weeks of school, how often did [you] skip a whole school day*; answers vary from 'never' to 'more than five days'. Control variables are as in equation (1).[11]

$$\text{Test scores}_{ij} = \alpha_1 + \beta_1 \text{Days of absence}_{ij} + X_{ij}\Pi + \lambda_j + v_j + \varepsilon_{ij} \qquad \text{(SA1)}$$

More specifically, the variable *Days of absence* takes four values, each corresponding to the days of absence: 'zero days' is 'absorbed' into the intercept, and the other values correspond to, respectively, one or two days, three or four days, and five or more days. Figure B1 below depict the results of these tests. The main findings are that not attending school is correlated with strong, negative and significant score gaps in both mathematics and reading, which substantially grow with the days of school missed. Moreover, losses in reading tend to be slightly bigger than those in mathematics. As in Section 5.1, this result differs from previous findings of the empirical literature on vacations and school interruptions. (Cooper et al., 1996; Gottfried, 2009 and 2011; Quinn and Polikoff, 2017). Additionally, all coefficients are robust to the inclusion of covariates and school fixed effects, showing that students who miss school days lose ground with respect to their peers even when all other factors are equal.

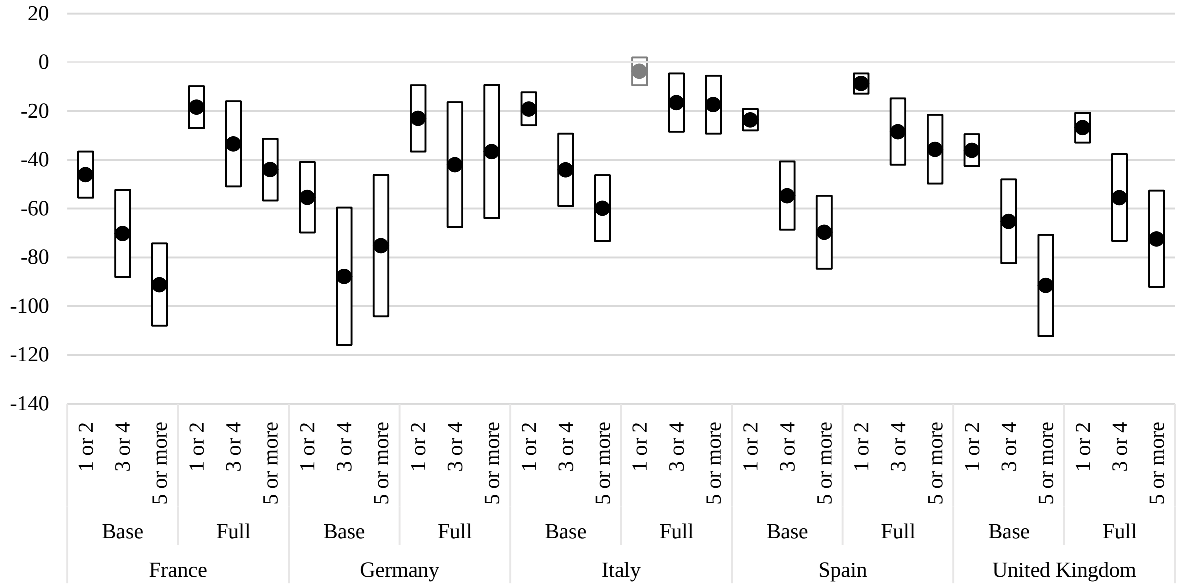
Because of the ordinal character of the variable *Days of absence*, with unequally spaced intervals between values and not upper bound (five or more days), we cannot compute and predict the potential cognitive losses of students who did not attend remote learning during the school closures of year 2020. However, because of the long duration of school closures during year 2020, we can reasonably hypothesise that they are as large as or larger than those of skipping five or more days of the physical school in two weeks. In the first case, the interruption in learning is continuous and lasts for weeks and months, while in the second it can be sporadic and distributed along the school year. Hence, regarding the scores in mathematics, the coefficients on 'skipping five or more days' that in the full models range from almost one school year in Italy to almost two years in the United Kingdom (Figure B1, Table B1), should be read as the smallest predicted negative gaps of students unable to learn remotely.

It may be noted that these negative gaps are larger than those of Section 5.1. This could be expected, given that Days of absence registers an interruption in learning due to any reason or group of reasons, while each of the four variables of interest in Section 5.1 were specific, and its correlation with scores was always tested controlling for the other three. Moreover, some motives for being absent from school can be correlated. For example, regarding remote schooling, it may be noted that the variables No internet and No computer at home are positively and significantly correlated in all five countries (Table SA1).

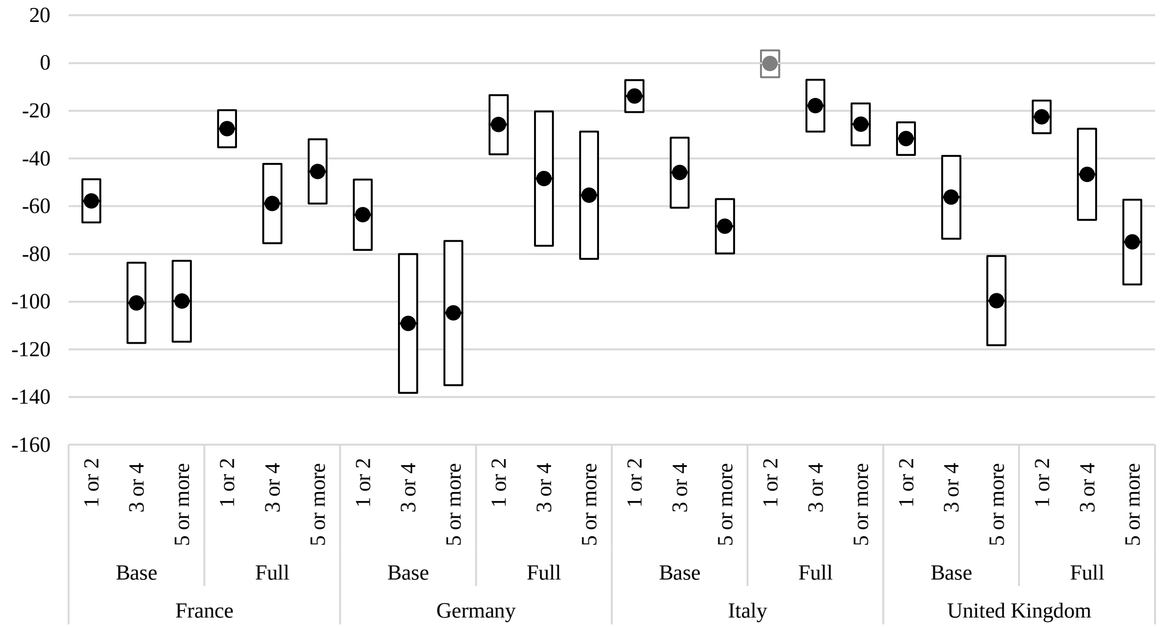
As in Section 5.1, most coefficients on our variables of interest are robust to the introduction of the control variables but can vary significantly with some of them. In France, coefficients shrink significantly when the types of schools attended are controlled for (columns 1 and 4 in Table SA1); in Italy, they vary when controlling for the types of schools and grades repetition; in Spain, they vary with grades repetition.10F These results, as those of Section 5.1, provide support to the findings of the literature on the relationships between inequalities in students' cognitive outcomes and countries' school systems (Checchi et al., 1999; Hanushek and Woessmann, 2006; Brunello and Checchi, 2007; Ammermueller, 2013; Murat and Frederic, 2014; Woessmann, 2016).

[11] A student can skip remote schooling because of a lack of ICT resources at home or at school or a quiet place to study. Since they can be alternative explanations of the same phenomenon, equation (1) does not control for absence from school, and equation (SA1) does not control for the lack of ICT resources or a quiet place to study. The question concerns the last two full weeks of school, but can be interpreted as a proxy for the student's general behavior during the school year. Moreover, this variable is more appropriate for our analysis than an indicator of summer or winter vacations when all students are out of school. Some studies find that part of the concepts learnt at school are forgotten during summer, especially concerning mathematics (Cooper et al., 1996; Quinn and Polikoff, 2017).

Figure B1 – Absence from school. Student scores in mathematics and reading



(a) Days of absence - Math score



(b) Days of absence - Reading score

Note: Dependent variable: (a) mathematics score; (b) reading score. Coefficients on days of absence in the y-axis (base: no days of absence). The base regression includes only the four variables of interest; the full regression includes all the covariates of equation (SA1) gender, age, repeated grade, immigrant status, age of arrival, highest parents' level of education, school types (general, technical, vocational), public school (versus private) and school fixed effects. Grey denotes significance below five percent.

Table B1 – Absence from school. Dependent variable: Students' scores in mathematics.

	France							Germany						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
Days of absence: 1-2	-46.098***	-47.203***	-38.982***	-19.423***	-38.617***	-20.122***	-18.392***	-55.351***	-55.581***	-49.426***	-48.971***	-48.897***	-40.497***	-23.009***
Days of absence: 3-4	-70.258***	-71.619***	-63.651***	-31.616***	-52.233***	-35.290***	-33.471***	-87.753***	-87.846***	-78.399***	-79.600***	-77.065***	-66.699***	-41.986***
Days of absence: 5 +	-91.166***	-94.313***	-81.159***	-46.620***	-72.238***	-49.214***	-44.005***	-75.230***	-77.126***	-66.694***	-59.951***	-60.375***	-52.007***	-36.627***
Female		-13.594***				-25.272***	-21.764***		-8.922**				-14.857***	-25.516***
Age		18.536***				4.524	2.725		21.318**				28.872***	28.798***
Parents' education			16.695***			7.352***	5.427***			13.680***			10.338***	3.597***
Immigrant status			-30.724***			-27.363***	-25.014***			-29.130***			-20.915***	-16.396***
Age of arrival			-1.917**			0.496	-0.008			-4.733***			-3.753***	-1.455
Technical school				-105.227***		-85.643***					-61.434***		-46.629***	
Vocational school				-159.500***		-131.944***					-94.507***		-78.911***	
Public school				-26.924***		-20.766***					-9.089		0.058	
Repeated grade					-114.059***	-38.465***	-46.929***					-68.965***	-44.519***	-36.117***
Constant	509.438***	222.381***	431.249***	561.208***	524.477***	464.059***	456.225***	521.411***	187.983	469.254***	554.346***	532.968***	57.296	69.424
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	4,947	4,947	4,834	4,455	4,940	4,368	4,831	2,523	2,523	2,374	2,202	2,489	2,065	2,370
R^2	0.063	0.072	0.142	0.403	0.255	0.455	0.522	0.054	0.060	0.147	0.172	0.128	0.269	0.538

	Italy							Spain						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE	Base	Female-Age	Social conditions	School types	Repeated grade	Full	Full - FE
Days of absence: 1-2	-19.082***	-19.088***	-18.183***	-16.429***	-16.306***	-15.133***	-3.697	-23.560***	-23.710***	-20.499***	-22.295***	-12.221***	-11.466***	-8.698***
Days of absence: 3-4	-44.113***	-43.943***	-44.325***	-27.999***	-40.667***	-28.993***	-16.576***	-54.656***	-55.167***	-50.992***	-52.086***	-33.654***	-33.709***	-28.440***
Days of absence: 5 +	-59.820***	-60.944***	-57.499***	-40.407***	-49.802***	-37.420***	-17.359***	-69.657***	-70.642***	-63.674***	-64.672***	-40.633***	-40.512***	-35.631***
Female		-16.606***				-28.421***	-22.461***		-7.455***				-15.538***	-16.872***
Age		23.701***				14.358***	13.220***		20.339***				11.651***	11.348***
Parents' education			10.375***			4.009***	-0.354			11.108***			5.503***	3.432***
Immigrant status			-20.991***			-1.490	-12.646**			-20.530***			-7.242**	-6.387*
Age of arrival			-2.687**			-1.750*	-1.580			-3.214***			-2.209***	-2.259***
Technical school				-40.444***		-40.815***								
Vocational school				-103.905***		-92.031***					-82.226***		-27.909**	
Public school				-17.415		-9.092					-22.820***		-5.327*	
Repeated grade					-69.921***	-47.619***	-41.165***					-98.603***	-89.857***	-89.220***
Constant	505.496***	139.885*	463.173***	551.219***	512.242***	317.725***	305.641***	494.372***	176.048***	447.042***	509.645***	516.965***	318.689***	329.055***
School FE	no	no	no	no	no	no	yes	no	no	no	no	no	no	yes
Observations	9,183	9,183	8,993	9,019	9,176	8,826	8,988	27,865	27,865	27,014	27,105	27,845	26,262	27,004
R^2	0.040	0.054	0.080	0.208	0.103	0.264	0.523	0.037	0.043	0.103	0.061	0.276	0.300	0.388

*Notes. Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "General school".*

Appendix C. Robustness check: missing observations.

Table A1, on descriptive statistics, shows that observations are missing for some of the variables used in this study. While the problem is minor at the single variable level, it can become more serious in the full regressions, comprising several variables. Dropping all student observations that have a missing value on at least one variable could mean a substantial reduction in sample size that, in itself, could lead to biased results. Therefore, to control for the robustness of our results, we impute the missing values by using the 'mean imputation method' described in Little and Rubin (1987) and adapted to the PISA data by Woessmann et al. (2007) and Puma et al. (2009).

This method predicts the conditional mean for each missing observation on the explanatory variables using non-missing values of the specific variables and a set of explanatory variables observed for all students. It addresses the problem of missing values consistently with the multilevel analysis of estimation with PISA data (Puma et al., 2009).

More specifically, for each student *i* with missing data on a specific variable *M*, a set of 'fundamental' explanatory variables *E* with data available for all students is used to impute the missing data in the following way. Let *S* denote the set of students *z* with available data for *M*. Using the students in S, the variable *M* is regressed on *E*. Following Woessmann et al. (2007), the set of fundamental variables, *E*, includes gender, age, five grade dummies and five dummies for the number of books at home.[12]

$$M_{z\in S} = E_{z\in S}\theta + \varepsilon_{z\in S}$$

Then, the coefficients from these regressions and the data on E_i are used to impute the value of *Mi* for the students with missing data.

$$\widetilde{M}_{i\notin S} = E_{i\notin S}\theta$$

Furthermore, to account for the possibility of non-randomly missing observations, and to avoid results being driven by imputed data, we include a vector of imputation dummy variables as controls in the estimation. This vector contains one dummy for each variable of the model that takes the value of one for observations with missing and thus imputed data and zero for observations with original data. The vector allows the observations with missing data on each variable to have their own intercepts. Also, we include interaction terms between each variable and the corresponding imputation dummy, which allows observations with missing data to also have their own slopes for the respective variable. These imputation controls make the results robust against possible bias arising from imputation errors in the variables (Woessmann et al., 2007).

We run OLS regressions with continuous or ordinal dependent variables and Probit or Bivariate Probit regressions with binary dependent variables. In the first case, missing observations are substituted by predicted values, in the second, by the values with the highest predicted probability.

We find that almost all coefficients from the regressions run with the sample comprising the imputed missing data are not significantly different from those obtained with the original sample. Results on data from Germany evidence

[12] We substituted the very few missing observations regarding the number of books at home with the median imputation of the lowest available value of the variable in either school or country.

a minor variation in the coefficient on *No computer* at home in the full biprobit regression; it loses significance (Table B1, in the Appendix). Results on the United Kingdom show the coefficient that the coefficient on *Few school ICT* is now significant in the full regression. Other coefficients do not differ significantly from those obtained with the regressions on the original data, which supports the robustness of this study's results.

Table C1 – Remote learning resources. Imputed values. Dependent variable: student scores in mathematics.

	France			Germany			Italy			Spain			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
No computer	-59.628***	-22.588***	-21.200***	-75.415***	-42.305***	-26.493***	-43.112***	-24.741***	-16.018***	-47.712***	-12.976***	-10.931***	-45.418***	-36.917***	-29.689***
No internet	-25.275**	-18.757*	-3.565	-47.625***	-26.727***	-24.359***	-36.248***	-19.703**	-6.486	-21.078***	-0.884	0.066	-90.690***	-80.475***	-69.929***
No quiet place to study	-34.927***	-8.891**	-5.635	-33.515***	-11.444*	-0.632	-12.775**	0.217	-0.193	-8.269**	-1.527	-0.358	-24.743***	-20.531***	-13.627***
Few school ICT	-13.234	3.820		-3.966	-3.369		-39.999***	-21.725***		-7.218***	0.183		-10.667	-11.377*	
Female		-22.721***	-19.554***		-14.782***	-19.961***		-28.804***	-23.227***		-15.845***	-16.395***		-13.251***	-14.578***
Age		2.653	3.397		32.172***	33.567***		10.293**	9.607***		11.729***	11.158***		18.521***	14.842***
Parents' education		5.722***	4.041***		8.816***	3.165***		3.307***	-0.940		5.509***	3.532***		11.313***	4.917***
Immigrant status		-25.372***	-20.585***		-24.026***	-16.294***		-1.299	-12.462***		-6.106*	-4.934		-10.698**	-3.991
Age of arrival		0.006	-0.278		-2.984***	-1.985***		-1.612*	-1.632*		-2.375***	-2.342***		0.800	0.716
Technical school		-90.421***			-41.056***			-41.364***			127.433				
Vocational school		-142.423***			-80.405***			-92.156***			-27.502***				
Public school		-22.165***			1.877			-5.524			-6.548***			-25.244***	
Repeated grade		-31.466***	-45.061***		-49.002***	-37.180***		-50.626***	-43.253***		-90.535***	-89.726***		-56.686***	-46.333***
Constant	510.594***	499.580***	444.879***	516.701***	8.185	-5.817	505.478***	377.900***	369.105***	490.384***	313.813***	329.524***	516.010***	189.506**	265.303***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	35,943	35,943	35,943	13,818	13,818	13,818
R^2	0.075	0.469	0.530	0.098	0.350	0.541	0.076	0.299	0.533	0.042	0.317	0.392	0.049	0.129	0.284

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "general school". Regressions on sample with imputed values.*

Table C2 – Remote learning resources. Imputed values. Dependent variable: student scores in reading

	France			Germany			Italy			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
No computer	-62.433***	-22.008***	-20.572***	-80.717***	-43.102***	-26.919***	-42.202***	-21.840***	-14.683***	-43.323***	-34.158***	-27.708***
No internet	-28.441**	-21.092**	-5.942	-58.807***	-33.578***	-28.778***	-35.007***	-20.099***	-6.974	-82.179***	-66.431***	-56.234***
No quiet place to study	-34.369***	-8.332**	-5.851	-40.708***	-14.123*	-2.160	-20.551***	-5.620	-5.160	-21.011***	-17.478***	-11.501**
Few school ICT	-15.825	3.094		-1.445	-0.502		-34.390***	-17.565***		-9.660	-11.024*	
Female		7.787***	9.744***		17.982***	10.583***		8.173***	11.874***		19.119***	16.684***
Age		5.385	6.246*		25.706***	28.329***		9.551**	10.197***		17.271***	13.423***
Parents' education		3.815***	2.150**		8.941***	2.426***		1.432	-2.411***		10.897***	4.874***
Immigrant status		-22.720***	-19.748***		-22.283***	-14.705***		-6.872	-16.459***		-11.777**	-5.384
Age of arrival		-0.986*	-1.483***		-5.715***	-4.656***		-1.931***	-2.333***		-0.878	-1.059*
Technical school		-99.295***			-46.062***			-53.751***				
Vocational school		-145.384***			-89.696***			-99.824***				
Public school		-18.477***			10.130			-4.276			-21.126***	
Repeated grade		-29.183***	-51.874***		-46.756***	-33.344***		-49.084***	-42.968***		-59.941***	-49.086***
Constant	509.180***	447.886***	393.965***	515.041***	87.767	66.936	494.699***	373.638***	340.275***	517.736***	196.797***	276.992***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	13,818	13,818	13,818
R^2	0.075	0.438	0.502	0.097	0.351	0.548	0.066	0.313	0.507	0.041	0.116	0.255

*Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "general school". Regressions on sample with imputed values.*

Table C3 – Absence from school. Imputed values. Dependent variable: student scores in mathematics

	France			Germany			Italy			Spain			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
Days of absence: 1-2	-46.098***	-19.309***	-17.847***	-55.351***	-41.961***	-23.997***	-19.082***	-14.224***	-2.606	-23.560***	-11.012***	-8.601***	-36.014***	-30.865***	-25.238***
Days of absence: 3-4	-70.258***	-32.629***	-31.828***	-87.753***	-65.461***	-45.455***	-44.113***	-27.555***	-14.462**	-54.656***	-32.600***	-27.274***	-65.262***	-62.114***	-53.037***
Days of absence: 5 +	-91.166***	-49.286***	-44.647***	-75.230***	-55.612***	-42.126***	-59.820***	-36.800***	-14.965**	-69.657***	-40.422***	-36.775***	-91.505***	-80.210***	-68.337***
Female		-23.777***	-20.343***		-15.747***	-20.520***		-30.039***	-23.280***		-15.853***	-16.443***		-13.538***	-14.638***
Age		2.954	3.776		32.436***	33.517***		10.356**	10.119***		12.108***	11.420***		18.090***	14.943***
Parents' education		6.217***	4.321***		9.772***	3.753***		3.519***	-0.921		5.709***	3.695***		11.984***	5.333***
Immigrant status		-26.054***	-21.060***		-24.545***	-15.854***		-0.021	-12.424***		-6.935**	-5.511*		-10.006**	-4.618
Age of arrival		-0.011	-0.253		-3.509***	-2.349***		-1.751**	-1.678*		-2.323***	-2.311***		0.684	0.650
Technical school		-87.818***			-42.300***			-41.286***			84.376**				
Vocational school		-139.841***			-81.041***			-95.177***			-27.969***				
Public school		-20.555***			3.246			-9.356			-6.085**			-23.164***	
Repeated grade		-34.697***	-45.705***		-51.031***	-38.403***		-49.103***	-42.268***		-89.926***	-89.014***		-57.192***	-48.218***
Constant	509.438***	493.673***	439.148***	521.411***	1.392	-17.758	505.496***	384.318***	353.856***	494.372***	311.017***	324.366***	513.717***	192.163**	261.105***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	35,943	35,943	35,943	13,818	13,818	13,818
R^2	0.059	0.472	.0.534	0.040	0.344	0.538	0.064	0.297	0.534	0.030	0.323	0.396	0.052	0.138	0.292

*Notes: Standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "general school". The base level of the days of absence is no days. Regressions on sample with imputed values.*

Table C4 – Absence from school. Imputed values. Dependent variable: student scores in reading.

	France			Germany			Italy			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE	Base	Full	Full - FE
Days of absence: 1-2	-57.775***	-28.822***	-26.908***	-63.560***	-47.933***	-27.068***	-13.878***	-9.281***	0.853	-31.715***	-27.296***	-21.774***
Days of absence: 3-4	-100.495***	-56.730***	-56.465***	-109.104***	-78.958***	-54.718***	-45.943***	-28.197***	-16.911***	-56.252***	-54.678***	-46.469***
Days of absence: 5 +	-99.803***	-50.915***	-46.404***	-104.759***	-79.614***	-63.764***	-68.396***	-42.493***	-22.916***	-99.557***	-83.372***	-70.724***
Female		6.389***	8.624***		16.932***	9.970***		7.093**	11.734***		18.569***	16.405***
Age		5.802*	6.762*		25.828***	28.307***		9.650**	10.556***		16.604***	13.350***
Parents' education		4.172***	2.384***		9.935***	3.057***		1.729*	-2.250***		11.519***	5.291***
Immigrant status		-23.110***	-20.183***		-22.391***	-14.210***		-5.717	-16.593***		-10.863**	-5.786
Age of arrival		-0.838	-1.291**		-6.253***	-5.024***		-2.130***	-2.451***		-0.991	-1.129**
Technical school		-94.986***			-47.292***			-53.992***				
Vocational school		-140.306***			-90.081***			-101.823***				
Public school		-15.868***			11.429			-7.315			-18.855***	
Repeated grade		-32.147***	-51.168***		-48.517***	-34.364***		-47.309***	-41.991***		-59.958***	-50.812***
Constant	511.736***	443.192***	389.969***	522.872***	85.553	54.102	494.983***	378.395***	326.514***	516.464***	203.720***	275.230***
Vector of imputation dummy and interaction	yes	yes	yes	yes	yes	Yes	yes	yes	yes	yes	yes	yes
School FE	no	no	yes	no	no	Yes	no	no	yes	no	no	yes
Observations	6,308	6,308	6,308	5,451	5,451	5,451	11,785	11,785	11,785	13,818	13,818	13,818
R^2	0.084	0.449	0.511	0.045	0.350	0.548	0.069	0.318	.0509	0.053	0.130	0.265

*Notes: Standard errors are clustered at the school level. *** p < 0.01, ** p < 0.05, * p < 0.1. All plausible values employed. All results are weighted and replication weights are taken into account. The base level of coefficients on School type is "general school". The base level of the days of absence is no days. Regressions on sample with imputed values*

Acknowledgments

At the beginning of my PhD career, I was aware that the path I had chosen required a significant amount of self-study, as well as discussions and exchanges. Looking back at the past three years, I recognize all the people who deserve my gratitude and appreciation, as they prompted my curiosity and stimulated my critical thinking. All the people I have met throughout this path, all the people who wrote a book I read, all the people who enriched me with their views, simply deserve my deepest and sincerest thanks.

There are some people who intensely inspired me, guiding me towards this final achievement. Among these, my greatest gratitude goes to professor Baldini, who managed to share with me his passion for research and his incredible knowledge. He is the one who made me understand the relevance of details and of analysing society without any preconception.

I would like to thank all the professors I had the honour to meet during the past three years. Particularly, I would like to thank Fabrizio (also known as Robin Hood) and Majilinda, for supporting me with their altruism, making me live one of the most significant experiences of my life. Professor Murat, who engaged me in her projects. Her valuable help allowed me to conclude this thesis. Thanks to professor Addabbo, for including me in the European University Association network and for allowing me to manage and deliver PhD seminars. Her passion and devotion are the determinants for the growth of the Doctoral Research school.

Thanks to my DEMB colleagues: Giovanni, Eleonora, Francesco, Alessia, Giulia, Noemi and Matteo. We share not only the (extremely) small office in which we are working, but also some quality time, both inside and outside the academia. It is mainly due to them that I will remember these intense years as a constant stimulation to take a step forward.

A special thanks to my old pals, Davide B., Giovanni, Alessandro, Andrea e Davide M., because loneliness is never an option with them. They came all the way up to Luxembourg just to bring me a can of tuna. Their sincerity and authenticity is what makes our friendship unique. Thank Matteo for his quixotic battles and perseverance, as he constantly gives me new insights that I would otherwise miss.

Thank you to my parents, my brother, my cousins, my aunts and uncles, and my family as a whole, for their great support. I will always be grateful for the love and understanding you have blessed me with.

Last but not least, my greatest and deepest appreciation goes to Serena, the brightest part of me, whose support in my daily choices is what made me conclude this path. Thank you for standing by me both in calm and turbulent times. Your kindness is my inspiration. This thesis is also yours.

Ringraziamenti

Che il dottorato fosse un percorso di studio ma anche di continuo confronto e contaminazione mi era chiaro sin dall'inizio. Però soltanto adesso mi guardo dietro per cercare di trovare una sintesi, un filo conduttore di questi tre anni e mi rendo conto di quante persone meriterebbero almeno una riga di ringraziamento perché hanno contribuito a stimolare le mie curiosità e a permettermi di maturare un pensiero critico. A tutte le persone che ho incontrato, a tutte le persone che hanno scritto un libro che ho letto, a tutti coloro che mi hanno arricchito: semplicemente grazie.

E poi ci sono quelle persone per cui non puoi, in coscienza, esimerti dal citare in queste occasioni. Pertanto, grazie al professor Baldini per avermi sempre trasmesso la sua passione e per i suoi tantissimi insegnamenti. In particolare, per avermi fatto capire l'importanza della cura dei dettagli e dell'osservazione della realtà libera da preconcetti.

Grazie anche a tutti i professori che ho conosciuto in questi anni, in particolare grazie a Fabrizio (alias Robin Hood) e a Majilinda per avermi sostenuto con così tanto altruismo e avermi permesso di svolgere una delle esperienze più belle della mia vita. Alla professoressa Murat, per avermi coinvolto nei suoi progetti e l'enorme aiuto per terminare questa tesi. Grazie alla professoressa Addabbo, per avermi coinvolto nella collaborazione con l'*European University Association*, nell'organizzazione dei seminari per i dottorandi e per la dedizione con cui sta facendo crescere la scuola di dottorato.

Grazie ai ragazzi del DEMB, in particolare Giovanni, Eleonora, Francesco, Alessia, Giulia, Noemi, Matteo con cui sto condividendo un piccolo ufficio provvisorio (che poi così provvisorio non è), ma soprattutto tanti momenti importantissimi dentro e fuori l'università. È soprattutto grazie a loro se ricorderò questi tre anni come un incessante pungolo alla curiosità e all'approfondimento.

Grazie ai miei amici, a Davide B., Giovanni, Alessandro, Andrea e Davide M., perché con loro non mi sono mai sentito solo, per essere venuti a portarmi una scatoletta di tonno in Lussemburgo, per la sincerità e la genuinità della nostra amicizia. Vorrei poi ringraziare Matteo per il suo contagioso amore per le battaglie donchisciottesche e per le lunghe (lunghissime) chiacchierate grazie alle quali capisco che, ancora una volta, non avevo ancora capito nulla.

Grazie ai miei genitori, a mio fratello, ai miei cugini e ai miei zii (siete davvero troppi per elencarvi tutti). Grazie per l'enorme sostegno e comprensione che mi avete sempre dimostrato. Voi siete stati l'ingrediente basilare perché io avessi la possibilità e la fortuna di scegliere questo arduo e magnifico percorso.

Infine, un ringraziamento a Serena che da anni mi incoraggia a essere la versione migliore di me. Grazie per esserci sempre e per aver condiviso con me i (tanti) momenti belli e quelli difficili. Questa tesi è anche tua.