SERIEs (2023) 14:503–553
https://doi.org/10.1007/s13209-023-00289-9

ORIGINAL ARTICLE

The differential impact by gender of the Covid-19 pandemic on the labor outcomes of older adults

Domenico Depalo[1] · Santiago Pereda-Fernández[2]

Received: 28 October 2022 / Accepted: 27 July 2023 / Published online: 15 September 2023

Abstract
We study the effect of the COVID-19 pandemic during the first semester of 2020 on the labor market outcomes of elderly workers, using data from the Survey of Health, Ageing and Retirement in Europe. We measure the gender gap in the conditional mean of the probability of experiencing a job interruption, of changing the number of hours worked, and of working from home. We control for a rich set of observable characteristics, including several measures of cognitive and non-cognitive ability. We apply decomposition methods to distinguish, on the one hand, the part of the gap that is due to gender differences in the endowments of the determinants of the outcome in question and, on the other, to gender differences in the effects of these determinants. We find that there is no gender gap in the probability of experiencing a job interruption nor in the probability of working fewer hours than before the pandemic. In contrast, there were significant differences in the probability of increasing the amount of worked hours or working remotely, which were larger for females in both cases. For the latter variable, the difference is largely attributable to different endowments between men and women. However, the gap in the probability of working longer hours is mostly attributable to the coefficients component.

We would like to thank Antonio dalla Zuanna, Giuseppe de Luca, Francesco d'Amuri, Eliana Viviano, seminar participants in Banca d'Italia, the Guest Editor Laura Hospido and two anonymous referees for useful comments. This work is part of the I+D+i project Ref. TED2021-131763A-I00 financed by MCIN/AEI/10.13039/501100011033 and by the European Union NextGenerationEU/PRTR. I gratefully acknowledge financial support from the Spanish Ministry of Universities and the European Union-NextGenerationEU (RMZ-18). The data that support the findings of this study are available from SHARE but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of SHARE. The codes to obtain the results in this paper are available at https://doi.org/10.5281/zenodo.8216737. The authors declare that they have no conflict of interest. All remaining errors are our own. I can be reached via email at santiagopereda@gmail.com.

✉ Santiago Pereda-Fernández
santiagopereda@gmail.com

[1] Banca d'Italia, Via Nazionale 91, 00184 Rome, Italy

[2] Facultad de Ciencias Económicas y Empresariales, Universidad de Cantabria, Avenida de los Castros 56, 39005 Santander, Spain

Keywords Cognitive and non-cognitive abilities · COVID-19 · Remote working · SHARE

JEL Classification J22 · J24 · J71 · J81

1 Introduction

In addition to the devastating effects on physical health and mortality, the COVID-19 pandemic had disruptive effects on labor markets. At the peak of the health emergency, several countries imposed lockdowns, preventing people from working in the offices or the stores, and encouraging the adoption of remote working. Simultaneously, the fall in economic activity prompted a reduction in the number of employees. This resulted in an increase in layoffs, partly mitigated by short-time work schemes and other country-specific policies (European Commission 2020). Additionally, the impact of the pandemic has been quite heterogeneous for different types of workers.

This is one of the very few papers, along with Brugiavini et al. (2022), which looks at the labor market outcomes of people aged 50 and above who were still active at the beginning of the health emergency, focusing on countries in the European Union (EU). Workers in this age range merit a specific analysis because they have several distinctive characteristics that are not common to the entire workforce. First, for a few months after the outbreak of the pandemic they have been considered the age group most at risk of infection and death by the virus (Zhang 2020).[1] Second, they are the age group closest to retirement and therefore leaving the labor force. As such, a nontrivial number of workers in this age group were eligible for early retirement, which the outbreak of the virus may have prompted. This is particularly relevant for those who lost their job during the pandemic, as their employability when they lose their jobs may have deteriorated significantly. Third, they represent about one third of the population between 15 and 64 years old (i.e., the active population) and their relative share will increase in the EU over the next 10–15 years, according to the projections of the UN (2019). Thus, their labor supply may have a substantial impact on GDP growth and the reallocation of workers to different jobs.

In this paper, we make the following contributions. First, we study how the COVID-19 pandemic affected a variety of labor market outcomes of European elderly workers, extending the results found in the literature. Specifically, we study the impact of the health emergency on the probability of experiencing a job interruption (extensive margin), on the number of hours worked (intensive margin), and on the probability of working from home (which we refer to as organizational margin). Second, we explore whether the pandemic had a differential effect on men and women of this age group. Third, using the detailed data at our disposal, we relate the labor market outcomes to cognitive and non-cognitive ability, highlighting which factors can help explain the differential impact of the pandemic between male and female workers.

[1] For example, in Italy, for which we have detailed administrative data, of the almost 250,000 cases reported in the first semester of 2020, over 70% of them referred to individuals above 50 years old. Moreover, less than 4% of the 35,000 deaths were people younger than 50 years old.

With respect to the first contribution, we estimate the probability of experiencing a job interruption during the first semester of 2020. We consider temporary interruptions, including those caused by the health emergency, after which the worker kept working in the same firm once the firm resumed its activity, or permanent ones, such as going into early retirement or becoming unemployed (Bauer and Weber 2020; Chodorow-Reich and Coglianese 2021). This outcome is particularly relevant, as several workers became unemployed, and the probability of finding another job may have been smaller for workers in this age group than for their younger counterparts. We also estimate the probability that these workers experienced either an increase or a decrease in the number of worked hours. This intensive margin may have long-run consequences in terms of expenditure power or from a labor market perspective, especially if this represents a structural change (Faberman et al. 2022). Additionally, we assess the change in the probability of working from home. Because it is likely that a non-negligible share of actual work will be performed remotely in the future (Ceurstemont 2020; Barrero et al. 2021), we consider the response of the elderly with respect to time arrangements as a key policy indicator for their inclusion in the labor force.

We focus on the gender gaps in these margins of adjustment. In regular times, gender gaps for the eldest active cohort could have been larger than for the population as a whole, given that participation rates have steadily converged only in the latest decades. Bearing and raising children is one of the factors behind the existing gaps (Goldin 2014), and the COVID-19 pandemic may have exacerbated this gender divide (Del Boca et al. 2020). However, workers at this stage of their lives are less likely to have young children. Therefore, this factor should have played a minor role in explaining differences that arose as a consequence of the pandemic. This feature allows us to isolate more precisely in which manner the response to the health emergency for elderly workers differed between both genders. In particular, the evidence of channels responsible for a "shecession" (Alon et al. 2020, 2022) for old age workers could be indicative of discrimination against women.

In addition, we carefully analyze the role of cognitive and non-cognitive abilities to explain the impact of the pandemic on workers of both genders. In recent years, there has been an ever-growing literature relating labor market outcomes to both types of abilities,[2] In this respect, a distinctive feature of our approach is that we take into account two different types of intelligence, coherently with the most recent models of human capital, which emphasize the role of heterogeneous dimensions of human capital (Sanders and Taber 2012). Adopting the taxonomy of Pietschnig and Voracek (2015), we consider crystallized intelligence, which consists of knowledge-based questions that cannot be solved by reasoning (e.g., naming the capital of a certain country), and fluid intelligence, which consists of reasoning-based tasks that can be solved with (virtually) no prior knowledge (e.g., providing the next number in a series such as 2, 4, 6,...). On the one hand, crystallized intelligence may become relatively more important over time, reflecting the increasing accumulation of culture (Pietschnig and Voracek 2015). On the other hand, fluid intelligence may be essential in some sectors and more generally to tackle new challenges, which are likely to be relatively more

[2] see, e.g., Heckman et al. (2006), Lindqvist and Vestman (2011), or Lin et al. (2018), for related works that analyze the role of cognitive ability, and Brunello and Schlotter (2011), Fletcher (2013), Flinn et al. (2020), or Alderotti et al. (2023), for analyses of the role of non-cognitive ability.

important at younger ages. While several papers distinguish between cognitive and non-cognitive abilities, Hermo et al. (2022) claim to be the first to make the distinction between crystallized and fluid intelligence in economics, focusing on Sweden. The present paper makes a further improvement considering different EU countries with a harmonized indicator and focusing on older workers.

To study the impact of the COVID-19 pandemic on the labor market participation of old age workers, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE). This is a survey informative on several dimensions, including the labor market, which is conducted in most EU countries since 2004 on individuals no younger than 50 years old. At the outbreak of the health emergency, wave 8 of the survey was in the field and had to be suspended. Therefore, the organizers integrated the existing questionnaire with new questions specifically related to the COVID-19 pandemic. This gives us the unique opportunity to evaluate how the health emergency affected specific dimensions of the respondents during the early stages of the pandemic.

We assess the gender gaps in the extensive, intensive and organizational margins using decomposition methods. We perform the Oaxaca-Blinder decomposition for our linear estimates (Oaxaca 1973; Blinder 1973), dividing the gender gap into an endowments and a coefficients component. The former relates the gaps to differences in the distribution of covariates between men and women; the latter captures differences that cannot be explained by the covariates. These admit several interpretations, including discrimination (i.e., a penalty or premium), differences in preferences, and the average marginal treatment effect, where the treatment and control are each group (Kline 2011).

Our findings show that changes in the labor market outcomes varied by job and individual characteristics. We find that there is no gender gap in the probability of experiencing a job interruption nor in the probability of working fewer hours than before the pandemic. For the former outcome, both components of the decomposition are significant: the endowments component reflects a positive differential for males, while the coefficients component is negative and of the same magnitude as the endowment effect. This implies a higher, unexplained, probability of experiencing a job interruption for women. In contrast, there were significant differences in the probability of increasing the number of worked hours or working remotely, which were larger for females in both cases. For the latter, the difference is largely attributable to different endowments between men and women. In particular, it was mainly driven by the possibility of performing tasks remotely (Dingel and Neiman 2020). However, the gap in the probability of working longer hours is mostly attributable to the coefficients component. These findings imply that much of the burden from COVID-19 was borne by elderly women. Our results suggest that a shecession may also arise for reasons unrelated to childbearing.

The closest related paper to ours is Brugiavini et al. (2022), who studied the impact from COVID-19 on elderly workers in European countries. Their main focus was on the probability of experiencing a job interruption and its length. They found that job characteristics were major determinants of the probability of experiencing work interruptions. In addition, they found this probability was larger for female, self-employed and, less educated workers. Relative to their work, our focus is on decomposition methods to analyze the differential impact of the pandemic on male and female workers. Moreover, we consider a wider array of outcomes and we include several relevant variables in the analysis, namely measures of cognitive and non-cognitive ability.

Other related works include Bui et al. (2020) and Goda et al. (2023), which studied the impact of the pandemic on elderly workers' in the USA. They found that their fall in employment was more severe than would have otherwise been predicted. Moreover, the majority of those who lost their jobs became unemployed or exited the labor force, with a non-negligible share retiring. Bertoni et al. (2021) used similar data to estimate the effect of working from home during COVID-19 on mental health, and they found negative effects for respondents with children at home, but positive effects for men and for those not living with children. Finally, Bertoni et al. (2021) found that those who retired earlier during the first wave of the health emergency limited their mobility more and adopted stricter preventive behavior in public. These limitations affected the mental health of retired singles.

The rest of the paper is organized as follows. Section 2 describes the SHARE dataset. The empirical strategy is described in Sect. 3, whereas the results are presented in Sect. 4. Finally, Sect. 5 concludes.

2 The SHARE dataset

2.1 Dataset description

This paper uses data from SHARE, a multidisciplinary panel database of micro data on health, socioeconomic status, and social networks of representative samples of individuals aged 50 and above, in 28 European countries. The data collection of wave 8 was gradually suspended, country by country, in March 2020 because of the COVID-19 pandemic and the subsequent lockdown measures enforced by the national governments of the various countries. Since returning to the regular face-to-face Computer-Assisted Personal Interview (CAPI) mode was unlikely, the central coordination team of SHARE designed a new survey which was fielded between June and August 2020 using a Computer-Assisted Telephone Interview (CATI) mode (Scherpenzeel et al. 2020). Here we shall describe briefly the key features of the two surveys that are important for our study.[3] We define the initial CAPI mode as the "standard questionnaire" and the later CATI questionnaire implemented during the pandemic as the "COVID questionnaire."

As with the previous waves of SHARE, wave 8 of the standard questionnaire offers a broad picture of the life of respondents at the time of the interview, including demographic information, physical and mental health, cognitive and non-cognitive abilities, and labor market activities.

The COVID questionnaire contains information in 8 different areas: basic demographics; health (both physical and mental) and health behavior; Corona-related infection; quality of healthcare; work; economic situation; social networks; conclusive

[3] For additional information on their country-coverage, sampling procedures, fieldwork activities, and non-sampling errors we refer the reader to Bergmann and Börsch-Supan (2021).

questions. Note that individuals who were interviewed with the standard questionnaire were re-interviewed with the COVID questionnaire.

Our analysis uses the subsample of respondents who participated in both interviews and were employed at the beginning of the pandemic.[4] As argued by De Luca et al. (2022), this subsample exploits the full force of the two surveys fielded in wave 8 as it contains microdata collected immediately before and after the COVID-19 outbreak and can be merged with the previous waves of the SHARE panel. To avoid additional concerns about cross-country differences in the sampling procedures for certain population groups, we further restrict our analysis to respondents aged between 55 and 65 years in 2020.[5] Our sample thus consists of 10,392 respondents from 25 European countries.[6]

One key advantage of our SHARE database is that we can directly observe self-reported data about the effects of the COVID-19 pandemic on labor market outcomes. Specifically, respondents to the Corona survey who reported being employed or self-employed at the time when COVID-19 broke out were asked a set of questions concerning the occurrence of work interruptions due to the Corona crisis (our measure of extensive margin), whether they reduced/increased the number of working hours since the outbreak of Corona (intensive margin), and the usual workplace since the outbreak of Corona (organizational margin).[7]

The change in the intensive margin is measured by two binary variables that reflect an increase or a decrease in the number of hours worked, but not by how much these hours changed. Although the latter information would be more coherent with the ideal definition of the intensive margin, from an econometric perspective it would present some disadvantages. First, because these variables are self-reported, the change in worked hours would be more prone to measurement error than a binary variable. Second, the variables that were more likely to be correlated with either an increase or a decrease in worked hours may be different: this is easier to analyze using the binary outcomes considered in this paper.

4 Out of the 12,692 individuals interviewed in wave 8, 10,392 were re-interviewed with the COVID questionnaire, implying an attrition rate of 18.1%, which is roughly equal for both genders. We have checked if the predetermined variables were predictors of dropping out from the latter questionnaire, and only a few of them were significant. Moreover, because the goal of the paper is to perform decompositions for gender differences, we checked if, for any of these variables, there was a difference across genders, finding that none of them was significantly different between men and women. See Tables 12 and 13 in Appendix A.

5 In most of the participating countries, younger cohorts of respondents may be subject to coverage errors due to the lack of refreshment samples in the last two waves of the panel (see Bergmann and Börsch-Supan (2021), Chapters 2 and 7).

6 See Table 14 in Appendix A for the sample size across countries.

7 Specifically, the four questions upon which these variables are based are the following: “Due to the Corona crisis have you become unemployed, were laid off or had to close your business?”, “Did you reduce your working hours since the outbreak of Corona?”, “Did you increase your working hours since the outbreak of Corona? Please include overtime.”, and “Since the outbreak of Corona, some people worked at home, some at their usual workplace outside their home, some both. How would you describe your situation? If the respondent got unemployed, laid off, or had to close business since the outbreak, he should think of the remaining time he or she worked during the outbreak. None of these means that did not work at all, neither at the usual workplace nor at home.” Regarding the first question, note that it is not known if the individuals retired, neither regularly or early.

We did not consider individual characteristics from the COVID questionnaire because they may introduced a simultaneity bias in our analysis.[8] We therefore use the information from the standard questionnaire, the one conducted before the COVID was discovered. This way we know that the health status that we observe does not depend on the labor market outcomes (more formally, it is predetermined).

The standard questionnaire contains a rich set of items that are important to explain the labor market outcomes. First, it includes several individual and household socio-demographic characteristics, like age, educational attainment, marital status, and the presence of children. In addition, it provides a large array of health conditions. Some of these are objectively measured, like the number of chronic diseases, whereas others are subjectively reported, like the self-perceived health status. Moreover, it contains job characteristics, such as indicators for self-employment, working in the public sector, working part-time, and the sector of activity.

Following Dingel and Neiman (2020) and Yasenov (2020), we exploit the latest variable to build an indicator of whether the job can be done remotely. Potentially remote jobs are those in the following sectors: financial intermediation, real estate, renting, and business activities, public administration and defence, compulsory social security, education, health, and social work, and other community, social, and personal service activities. The most important advantage of this indicator is the readily availability to policymakers, who tried to target the population most in need, and to researchers, who needed to understand the labor market consequences of the virus. The most important disadvantage is that not all jobs within an occupation group can actually be done remotely. Because of the latter feature, one should be wary of drawing strong conclusions from this indicator only.

A distinctive feature of our data is that we can explore the relevance of specific skills, which are measured by tests carried out by the SHARE interviewers. In particular, we have the mathematical performance, which is based on non-natural but simple algebra: this is a proxy for fluid intelligence. We also observe the fluency test score, which is based on the number of well-known words, and a recall test based on the ability to remember information: these are proxies for crystallized intelligence (Pietschnig and Voracek 2015).

Non-cognitive abilities capture personality traits that are based on the five orthogonal dimensions known as “Big Five”: (1) openness is the attitude of being imaginative, creative, curious, and unconventional; (2) conscientiousness is the attitude of being self-disciplined, systematic, and goal-oriented; (3) extraversion is the attitude of being active, forthcoming, and desiring social relationships; (4) agreeableness is the attitude of being friendly, warm, and sensitive toward others; (5) neuroticism is the attitude of worrying, being nervous, and emotionally unstable. Like for the two dimensions of intelligence, these attitudes may be relatively more important in some occupations and they may also change over time. In a literature review on earnings and non-cognitive abilities, Alderotti et al. (2023) found a positive association between labor market outcomes and the openness, conscientiousness, and extraversion traits, and a negative relation with agreeableness and neuroticism. Flinn et al. (2020) estimated a job search

[8] Consider for example the health status of the respondents: for an individual who experienced a work interruption and whose health status deteriorated it would be impossible to tell which of the two outcomes affected the other, or if they were jointly determined by another factor.

model, finding that conscientiousness and agreeableness are two variables that can explain part of the gender wage gap.[9]

2.2 Descriptive statistics

In Table 1, we report some key descriptive statistics. For two of the outcomes, there were no differences between men and women: around 16% of them experienced a job interruption and 21% of them reported a decrease in worked hours. However, a larger number of women than men reported an increase in worked hours (14% vs 11%) and worked remotely (39% vs 32%).

Regarding the predetermined variables, male workers tend to be older, more likely to live in a couple, and be self-employed relative to female workers. On the other hand, female workers are more likely than males to be college educated, live with children, work part-time or in the public sector, use a computer at work, and work in jobs that are potentially remote. Females also tend to score higher than their male counterparts in the five non-cognitive indicators, as well as the recall indicator, but lower in the numeracy indicator. Given that aging causes a cognitive decline and men are older than women in our sample, we tested if this was the main source of cognitive differences in our sample. We found that even after controlling for age, the cognitive differences are statistically significant.[10]

Finally, Table 2 shows the sectorial distribution of our sample. Male workers constitute the majority of the employees in some sectors, such as mining, construction, transport, storage and communications, agriculture, or manufacturing. On the other hand, education, health and social work, or hotels and restaurants are female-predominant sectors.

2.3 Preliminary evidence

Before we carry out the main analysis, we first investigate how the explanatory variables at our disposal relate to the probabilities to be employed *before* the COVID-19 pandemic took place, as well as that of being infected with the virus. The estimates for the former are shown in Table 3. One of the main determinants of being employed before the outbreak of the health emergency is having bad health, which reduces its probability by over 20 percentage points for men and 13 for women. In addition, there is evidence that the utility function of the household is jointly determined, as men living in couples are about 8 percentage points more likely of being employed than those living alone, whereas for women this probability is 3 percentage points smaller. Another important factor is the education level: those with no college education are less likely to be employed, particularly women. Even though this variable may be correlated with different measures of ability, the latter still display some predictive power on the probability of being employed. Indeed, higher fluid or crystallized ability, as well as more conscientious people are more likely to be employed, while the opposite is true

[9] Note that Flinn et al. (2020) did not have information on whether workers were managers, or white/blue collar either, so their analysis shares some advantages and disadvantages with ours.

[10] Results available upon request.

Table 1 Descriptive statistics

Variable	Male	Female	Difference
Job interruption	0.159	0.157	0.002
	(0.366)	(0.364)	(0.011)
Decreased hours	0.209	0.213	−0.003
	(0.407)	(0.410)	(0.014)
Increased hours	0.115	0.146	−0.031***
	(0.319)	(0.353)	(0.011)
Worked remotely	0.318	0.394	−0.076***
	(0.466)	(0.489)	(0.016)
Age	6.089	5.680	0.409***
	(2.958)	(3.117)	(0.061)
Age^2	45.830	41.975	3.855***
	(33.314)	(33.503)	(0.668)
Low educ	0.698	0.674	0.024***
	(0.459)	(0.469)	(0.009)
Couple	0.820	0.762	0.059***
	(0.384)	(0.426)	(0.008)
Children	2.015	2.093	−0.078***
	(1.277)	(1.193)	(0.025)
Bad health	0.212	0.207	0.006
	(0.409)	(0.405)	(0.008)
Extraversion	3.467	3.546	−0.079***
	(0.903)	(0.909)	(0.019)
Agreeableness	3.595	3.679	−0.084***
	(0.825)	(0.815)	(0.017)
Conscientiousness	4.049	4.153	−0.104***
	(0.816)	(0.764)	(0.016)
Neuroticism	2.546	2.777	−0.231***
	(0.966)	(1.019)	(0.021)
Openness	3.297	3.377	−0.080***
	(0.926)	(0.943)	(0.020)
Low numeracy	0.515	0.598	−0.083***
	(0.500)	(0.490)	(0.010)
Recall	10.081	10.855	−0.775***
	(3.247)	(3.352)	(0.067)

Table 1 continued

Variable	Male	Female	Difference
Fluency	22.506	22.737	−0.232
	(7.861)	(7.818)	(0.158)
Public sector	0.158	0.242	−0.083***
	(0.365)	(0.428)	(0.008)
Self-employed	0.120	0.056	0.064***
	(0.325)	(0.230)	(0.005)
Part-time	0.099	0.170	−0.071***
	(0.298)	(0.375)	(0.009)
Potentially remote	0.360	0.678	−0.318***
	(0.480)	(0.467)	(0.011)
Use PC	0.571	0.628	−0.056***
	(0.495)	(0.484)	(0.011)
Sample size	4227	6165	

Difference denotes the difference between male and female workers; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; standard deviation in parentheses; Age and Age^2 are centered around 55

Table 2 Sectors of occupation

Variable	Male	Female
Agriculture, hunting, forestry, fishing	9.3	4.3
Mining and quarrying	1.2	0.2
Manufacturing	17.6	9.2
Electricity, gas and water supply	3.4	1.1
Construction	11.8	1.7
Wholesale and retail trade	8.2	9.1
Hotels and restaurants	2.1	4.0
Transport, storage and communication	10.3	2.6
Financial intermediation	3.8	3.4
Real estate, renting and business activities	1.3	1.7
Public administration and defence; compulsory social security	7.7	8.0
Education	5.6	16.5
Health and social work	4.7	21.8
Other community, social and personal service activities	12.9	16.5

Percentages of workers in each sector by gender; wholesale and retail trade also includes repair of motor vehicles, motorcycles and personal and household goods for more neurotic individuals. As already found by Hermo et al. (2022) cognitive and non-cognitive abilities are important determinants of labor market participation. However, we also found that the results are heterogeneous, as fluid intelligence is slightly more relevant for men at 15% confidence level, whereas crystallized intelligence is equally relevant for both genders at the same confidence level.

Regarding the probability of being infected (Table 4), the two most important predictors are whether the individual worked from home, and if the worker does not have college education. Both variables are associated with a smaller chance of being infected, which is more intense for men. Note, however, that less than 1% of our sample was infected during the first wave of the COVID-19 pandemic, so the estimates are not very precise. Despite this, some measures of cognitive and non-cognitive ability still display predictive power in addition to the usual demographic variables. Most notably, crystallized intelligence is associated with a higher chance of becoming infected for both genders, fluid intelligence is associated with a higher probability just for women, and conscientiousness is associated with a smaller probability, though the latter is barely significant in the pooled regression.

Our sample also displays some regional variability (Table 5). We divide the sample into four geographical areas, finding that those where there is a higher percentage of employed people in our sample, are those where there is a higher percentage of infections. Taken together, the probabilities of infection and the perfect rank correlation between shares of infections and employment provide some empirical evidence that the workplace was an important channel of contagion, and therefore it is important to study what happened there during the pandemic, as we do in the next sections.

3 Empirical strategy

The majority of the outcomes of interest are self-reported and they already account for the change that took place because of the COVID-19 pandemic. Additionally, the covariates that we use are all predetermined relative to the COVID-19 event. It follows that the coefficients that we estimate are not biased by confounding factors.

One of the goals of our analysis is to estimate whether the effects of the pandemic were different between men and women, decomposing the relative contribution of their characteristics from their coefficients. To this aim, the estimates are obtained separately for workers of each gender. This constitutes the basic building block for performing the decompositions. Formally, denote the outcome of interest by Y, the covariates by X, the error term by U, and the slope coefficients by β_D, where D is a dummy indicator that takes value one for male workers and zero for female workers.

Table 3 Probability of employment before COVID-19

Variable	Pooled	Male	Female
Age	0.0008	0.0049	−0.0035
	(0.0054)	(0.0091)	(0.0066)
Age^2	−0.0048***	−0.0052***	−0.0045***
	(0.0005)	(0.0008)	(0.0006)
Low educ	−0.1176***	−0.0573***	−0.1505***
	(0.0107)	(0.0171)	(0.0138)
Couple	0.0053	0.0819***	−0.0311**
	(0.0114)	(0.0195)	(0.0140)
Children	0.0016	0.0085	−0.0052
	(0.0038)	(0.0058)	(0.0050)
Bad health	−0.1607***	−0.2064***	−0.1318***
	(0.0118)	(0.0186)	(0.0151)
Extraversion	0.0057	−0.0071	0.0102
	(0.0054)	(0.0085)	(0.0070)
Agreeableness	0.0010	0.0087	−0.0038
	(0.0060)	(0.0094)	(0.0078)
Conscientiousness	0.0298***	0.0301***	0.0284***
	(0.0062)	(0.0094)	(0.0082)
Neuroticism	−0.0307***	−0.0303***	−0.0315***
	(0.0050)	(0.0082)	(0.0063)
Openness	0.0083	0.0148*	0.0030
	(0.0051)	(0.0081)	(0.0066)
Low numeracy	−0.0323***	−0.0436***	−0.0229*
	(0.0099)	(0.0156)	(0.0127)
Recall	0.0057***	0.0068**	0.0037*
	(0.0017)	(0.0026)	(0.0021)
Fluency	0.0032***	0.0019*	0.0039***
	(0.0007)	(0.0011)	(0.0009)
Women	−0.0961***		
	(0.0096)		
Intercept	0.6605***	0.6288***	0.6059***
	(0.0524)	(0.0846)	(0.0678)
Sample size	9161	3689	5472

Estimates from a linear probability model; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; standard errors in parentheses

Table 4 Probability of being infected with COVID-19 if employed

Variable	Pooled	Male	Female
Age	0.0004	0.0020	−0.0005
	(0.0017)	(0.0023)	(0.0024)
Age^2	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)
Low educ	−0.0095***	−0.0104**	−0.0083
	(0.0035)	(0.0046)	(0.0051)
Couple	0.0009	−0.0017	0.0010
	(0.0038)	(0.0056)	(0.0053)
Children	0.0007	0.0014	0.0005
	(0.0013)	(0.0016)	(0.0020)
Bad health	0.0063	0.0016	0.0093
	(0.0047)	(0.0062)	(0.0067)
Extraversion	0.0016	0.0011	0.0015
	(0.0017)	(0.0022)	(0.0026)
Agreeableness	−0.0028	−0.0011	−0.0046
	(0.0020)	(0.0026)	(0.0030)
Conscientiousness	−0.0039*	−0.0029	−0.0044
	(0.0021)	(0.0026)	(0.0031)
Neuroticism	−0.0007	0.0013	−0.0027
	(0.0017)	(0.0023)	(0.0025)
Openness	−0.0026	−0.0034	−0.0021
	(0.0017)	(0.0022)	(0.0025)
Low numeracy	−0.0044	0.0021	−0.0099**
	(0.0032)	(0.0042)	(0.0046)
Recall	−0.0007	0.0000	−0.0014*
	(0.0005)	(0.0007)	(0.0008)
Fluency	0.0007***	0.0006*	0.0009***
	(0.0002)	(0.0003)	(0.0003)
Public sector	0.0043	0.0059	0.0037
	(0.0034)	(0.0047)	(0.0049)
Self-employed	0.0078	0.0025	0.0165*
	(0.0051)	(0.0056)	(0.0090)
Part-time	−0.0054	−0.0038	−0.0060
	(0.0052)	(0.0078)	(0.0071)
Use PC	0.0000	0.0018	0.0012
	(0.0039)	(0.0049)	(0.0058)

Table 4 continued

Variable	Pooled	Male	Female
Worked from home	−0.0091**	−0.0142***	−0.0058
	(0.0036)	(0.0049)	(0.0051)
Women	0.0052		
	(0.0033)		
Intercept	0.0499***	0.0246	0.0770***
	(0.0182)	(0.0243)	(0.0269)
Sample size	3612	1578	2034

Estimates from a linear probability model; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; standard errors in parentheses

Table 5 Percentage infected by COVID-19, by area

Area	Infected	Employed
North	1.0	71.3
Central	0.9	54.1
South	0.3	41.0
East	0.3	46.7

The outcome is modeled linearly as,[11]

$$Y_D = X'_D \beta_D + U_D \tag{1}$$

We are interested in the following decomposition:

$$\begin{aligned} \mathbb{E}\left[Y_1 - Y_0\right] &= \mathbb{E}\left[X'_1\beta_1 + U_1 - X'_0\beta_0 - U_0\right] \\ &= \underbrace{\mathbb{E}\left[X_1 - X_0\right]'\beta_1}_{Endowments\ component} + \underbrace{\mathbb{E}\left[X_0\right]'(\beta_1 - \beta_0)}_{Coefficients\ component} \end{aligned} \tag{2}$$

where we have added and subtracted $\mathbb{E}\left[X'_0\beta_1\right]$, and used the fact that, under ignorability, $\mathbb{E}\left[U_D|X_D\right] = 0$.

Equation 2 denotes the Oaxaca-Blinder decomposition which, in a linear framework and under exogeneity, allows to decompose total differences between both genders into an endowments and a coefficients component.[12] The former relates differences

[11] We are not considering models with joint decisions for married couples. Such framework could be statistically incoherent (Chesher and Rosen 2012), i.e., there exist some values of the regressors and the unobservables that yield no feasible value of the dependent variable. Alternatively, if the joint behavior is modeled using game theoretical assumptions, it could result in a multiplicity of equilibria (De Paula 2013). Moreover, it is not clear how to do decompositions when the outcome of a member of the couple is a regressor for the other one.

[12] It would also be possible to do the alternative decomposition $\mathbb{E}\left[Y_1 - Y_0\right] = \mathbb{E}\left[X_1 - X_0\right]'\beta_0 + \mathbb{E}\left[X_1\right]'(\beta_1 - \beta_0)$. The magnitude of each component is generally different from those of the presented distribution. Fortin et al. (2011) emphasize that the group taken as the reference depends on the preference of the researcher. In our analysis, qualitative conclusions are not affected by this decision.

in the observed covariates to differences in the outcomes, whereas the latter captures structural differences that are not related to the observable characteristics. These are typically interpreted in terms of premium or penalty, depending on the context. Alternatively, Kline (2011) shows that the coefficients component can be interpreted as a reweighting estimator of the average treatment effect.

An advantage of the linear model is that the detailed decomposition, i.e., decomposing each of the components into the contributions by each variable used in the regression, is straightforward to implement. This follows by the linearity of both the expectation operator and Eq. (1). To implement it, it is sufficient to sequentially change the average of each covariate from group 1 to group 0 for the endowments component, and the coefficient of each covariate from group 1 to group 0 for the coefficients component:

$$\mathbb{E}\left[Y_1 - Y_0\right] = \underbrace{\sum_{k=1}^{K} \mathbb{E}\left[X_{1k} - X_{0k}\right]' \beta_{1k}}_{Endowments\ component} + \underbrace{\sum_{k=1}^{K} \mathbb{E}\left[X_{0k}\right]' \left(\beta_{1k} - \beta_{0k}\right)}_{Coefficients\ component} \tag{3}$$

Despite the advantages of linear methods, they are prone to be biased when the estimated probabilities lie outside the unit interval for some of the individuals (Horrace and Oaxaca 2006). This problem can be overcome by using nonlinear methods, at the cost of making the decomposition slightly more convoluted. Assume that the nonlinear model represents a probability, such that $\mathbb{E}\left[Y_D | X_D\right] = \pi\left(X_D, \beta_D\right)$. Following Fairlie (2005) and Bauer and Sinning (2008), the decomposition in 2 can be extended to this model as follows:

$$\mathbb{E}\left[Y_1 - Y_0\right] = \underbrace{\mathbb{E}\left[\pi\left(X_1, \beta_1\right)\right] - \mathbb{E}\left[\pi\left(X_0, \beta_1\right)\right]}_{Endowments\ component} + \underbrace{\mathbb{E}\left[\pi\left(X_0, \beta_1\right)\right] - \mathbb{E}\left[\pi\left(X_0, \beta_0\right)\right]}_{Coefficients\ component} \tag{4}$$

Because the expectation operator is linear, it is possible to add and subtract the term $\mathbb{E}\left[\pi\left(X_0, \beta_1\right) | X_D\right]$, which is interpreted as the counterfactual average probability for a male when the distribution of the covariates is swapped to that of females. Regardless of the different expression, the interpretation carries through.[13]

4 Results

Tables 6, 7, 8, and 9 report the OLS estimates of a linear probability model for both genders, the difference between them, as well as the individual contribution of each

[13] The detailed decomposition of nonlinear models is feasible, although it is more complicated, and presents some practical disadvantages. For example, Yun (2004) proposed to linearize the decomposition, using some weights such that the sum of the estimated contribution of each variable to each of the effects does not add up to the overall components. Alternatively, Fairlie (2005) proposed another decomposition that is path-dependent, which with many variables makes the estimated individual contributions particularly sensitive to the ordering. We therefore use these nonlinear methods to compare the overall decompositions, but not the detailed ones. See Fortin et al. (2011) for further details.

variable to each of the components of the Oaxaca-Blinder decomposition. We control for a quadratic polynomial of age, the big five personality traits, the intelligence measures, distinguishing between the fluid (numeracy) and crystallized (recall and fluency) dimensions, as well as indicator variables for low educational attainment, living in couple, living with children, having bad health, working part-time, being self-employed, using the PC at work, working in the public sector, having a job that can be done potentially remotely and four geographical regions. We assess the robustness of the results to alternative models and methods in Sect. 4.4.

Some potentially relevant missing variables, such as whether the worker is a manager or white/blue collar or sectorial dummies, could be major determinants of the outcomes.[14] Part of their impact on the outcome variables is captured by either the intercept or the coefficients of the variables that are correlated to the missing variables. This is the same argument of Flinn et al. (2020), from which we took the model specification. Therefore, the decompositions are sensitive to the choice of covariates, and one should not conclude that the coefficients components necessarily reflect discrimination.[15]

Regarding the interpretation of the effects, note that several policies were introduced by the European Governments during the studied period, notably incentivizing working from home and strengthening the short-time work schemes.[16] Both of them limited individual circulation, preventing the spread of contagion. The former allowed workers in potentially remote jobs to work without interruption (Dingel and Neiman 2020), and in principle, it should not affect their income levels. The latter prevents the job loss, at the cost of public spending and possibly reducing workers' income. Therefore, our results can be interpreted as the effects produced by COVID-19, either directly or indirectly.

4.1 Probability of experiencing a job interruption

Job interruptions, i.e., the extensive margin, depend on some variables that are relevant for both genders and some that are relevant only for men or women (Table 6). For both genders, those who work in the private sector and those in either Southern or Central Europe have a higher probability of experiencing a job interruption, as well as

14 The potentially remote indicator relies on the sector of occupation, so it is not possible to control for both potentially remote jobs and sector of occupation, because they are collinear. Because being employed in a job that lent itself to working remotely is a potentially crucial channel for the outcomes in this study, we prefer to include this indicator in the regressions. In contrast, white/blue collar is not present in the dataset.

15 Oaxaca (1973) emphasized that "a researcher's choice of control variables implicitly reveals his or her attitude toward what constitutes discrimination in the labor market": while controlling for few characteristics increases the weight of discrimination with respect to the total difference, controlling for many characteristics increases the weight of endowment component. For this reason, a reference theoretical background for the interpretation of the results is extremely important. We paid much attention to this step. While we would have liked to have the information about the position of the employee, all the variables that we control for are rooted in the most recent literature on human capital (Sanders and Taber 2012). It follows that our "attitude toward what constitutes discrimination in the labor market" is remarkably smaller than in the existing literature.

16 For example, Italy and Germany imposed lockdowns within the first 10 days of March, whereas France and Spain did it a week later (Hale et al. 2020).

low educated men (columns 1–2). The latter are more exposed to the business cycle, coherently with the Mincer (1974) equation because their investment in human capital is lower.[17] Workers in the public sector are less subject to the business cycle either because of the nature of their tasks, which are always required, or the preferences of the policy maker (Lamo et al. 2013). Finally, Southern Europe was the hardest-hit region by the first wave of the pandemic, which explains why workers from other regions were significantly less affected by the pandemic via fear of contagion (Aum et al. 2021; Depalo and Viviano 2021), or drop in economic activity.

Several variables are relevant for only one of the two genders. Some of these are related to job characteristics and some to cognitive and non-cognitive abilities. Among the former, women are more likely to experience a job interruption if they are self-employed or if they do not use a computer in their jobs. As for the cognitive and non-cognitive ability measures, male workers who scored higher in the agreeableness and neuroticism personality traits and female workers who scored lower in the fluency test were more likely to experience a job interruption. Interestingly, gender differences in job characteristics and non-cognitive ability (column 3 of Table 6) are statistically significant, whereas most of the other coefficients are not statistically different. We thus conclude that there is a gender divide along these dimensions.

Even though the probability of experiencing a job interruption in the early months after the pandemic was the same for men and women (see Table 1), the Oaxaca-Blinder decomposition uncovers a sizable amount of heterogeneity. In particular, both components are of about the same magnitude in size (4.7 and 4.5 percentage points, respectively), although with reverse signs: the endowments component is positive, meaning that male workers had on average some observed characteristics that would make them more likely to experience a job interruption, whereas the coefficients component is negative, meaning that if both genders had the same distribution of observables, a job interruption would have been more likely for female workers.

The type of job and its characteristics contributed to both components. Specifically, about two thirds of the endowments component can be attributed to differences in self-employment and working in the public sector, which are more prevalent for men and women, respectively. The coefficients component determined a higher probability of suffering a job interruption for women who were self-employed. In contrast, this probability was smaller if they used the computer at work.

Individual characteristics played a smaller role in the determination of both components. On the one hand, differences in the endowment of educational level and in fluency led to a higher probability of a job interruption for men. On the other hand, differences in the returns to agreeableness and neuroticism contributed positively to the coefficients component, thus mitigating its overall size. This result supports the relevance of personality traits as determinants of labor market outcomes (Lindqvist and Vestman 2011).

Finally, we do not find significant differences related to household characteristics, such as living in couple or having children. This result, which is likely due to the specific age group that we consider, is coherent with recent papers on the pandemic,

[17] The non-significant effect of the age profile is coherent with (standard extensions of) the Mincer (1974) equation, because it captures the concavity of the age-earning profile (Borjas and Van Ours 2010). This flattening behavior is extremely important for the age group of this paper.

Table 6 Regression and decomposition for probability of experiencing a job interruption

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Age	−0.0104	0.0095	−0.0199	−0.0059	−0.0911
	(0.0098)	(0.0077)	(0.0124)	(0.0056)	(0.0571)
Age^2	0.0010	−0.0007	0.0017	−0.0039	0.0592
	(0.0009)	(0.0008)	(0.0012)	(0.0042)	(0.0430)
Low educ	0.0490**	0.0250	0.0241	0.0055**	0.0125
	(0.0193)	(0.0162)	(0.0249)	(0.0023)	(0.0131)
Couple	−0.0100	0.0022	−0.0122	0.0002	−0.0104
	(0.0249)	(0.0171)	(0.0313)	(0.0019)	(0.0259)
Children	−0.0001	−0.0053	0.0052	−0.0000	0.0108
	(0.0069)	(0.0063)	(0.0098)	(0.0002)	(0.0195)
Bad health	−0.0054	0.0271	−0.0325	−0.0003	−0.0042
	(0.0256)	(0.0212)	(0.0335)	(0.0004)	(0.0043)
Extraversion	−0.0024	0.0068	−0.0092	0.0003	−0.0334
	(0.0097)	(0.0085)	(0.0129)	(0.0014)	(0.0466)
Agreeableness	0.0314***	0.0067	0.0246*	−0.0006	0.0898*
	(0.0112)	(0.0096)	(0.0148)	(0.0009)	(0.0537)
Conscientiousness	0.0033	0.0042	−0.0009	−0.0003	−0.0036
	(0.0112)	(0.0100)	(0.0144)	(0.0011)	(0.0630)
Neuroticism	0.0221**	−0.0022	0.0243*	0.0004	0.0584*
	(0.0098)	(0.0080)	(0.0133)	(0.0016)	(0.0304)
Openness	0.0061	0.0125	−0.0064	−0.0008	−0.0224
	(0.0092)	(0.0079)	(0.0121)	(0.0012)	(0.0422)
Low numeracy	0.0154	−0.0136	0.0290	0.0013	0.0133
	(0.0178)	(0.0150)	(0.0234)	(0.0014)	(0.0107)
Recall	−0.0023	0.0023	−0.0045	0.0024	−0.0530
	(0.0031)	(0.0026)	(0.0040)	(0.0033)	(0.0470)
Fluency	0.0000	−0.0027**	0.0027	0.0036**	0.0641
	(0.0013)	(0.0011)	(0.0017)	(0.0016)	(0.0390)
Public sector	−0.0838***	−0.0526***	−0.0312	0.0168***	−0.0142
	(0.0227)	(0.0178)	(0.0270)	(0.0047)	(0.0131)
Self-employed	0.0049	0.2029***	−0.1980***	0.0163***	−0.0322***
	(0.0242)	(0.0278)	(0.0447)	(0.0031)	(0.0062)
Part-time	0.0143	0.0209	−0.0067	−0.0009	−0.0009
	(0.0334)	(0.0222)	(0.0425)	(0.0022)	(0.0054)

Table 6 continued

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Potentially remote	−0.0262	−0.0310*	0.0048	0.0102*	0.0018
	(0.0205)	(0.0186)	(0.0299)	(0.0061)	(0.0102)
Use PC	0.0165	−0.0979***	0.1144***	−0.0011	0.0810***
	(0.0204)	(0.0182)	(0.0295)	(0.0014)	(0.0194)
Central	−0.0398	−0.0307	−0.0091	0.0003	−0.0025
	(0.0290)	(0.0278)	(0.0466)	(0.0005)	(0.0109)
North	−0.1865***	−0.0972***	−0.0893*	−0.0008	−0.0140*
	(0.0337)	(0.0317)	(0.0477)	(0.0021)	(0.0073)
East	−0.1486***	−0.1243***	−0.0243	0.0046**	−0.0103
	(0.0271)	(0.0262)	(0.0430)	(0.0022)	(0.0161)
Intercept	0.1032	0.2472***	−0.1439		
	(0.0972)	(0.0843)	(0.1343)		
Total				0.0474***	−0.0453***
				(0.0128)	(0.0166)

The first two columns report the OLS estimates for each gender, the third column reports their difference, and the last two columns report the two components from the Oaxaca-Blinder decomposition between male and female workers; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

finding that childcare was an important channel of the gender differences in the labor market outcomes (Alon et al. 2020, 2022). Relative to the existing literature, our results show that such differences can exist even after netting out the childcare channel.

4.2 Probability of a change in the amount of worked hours

The probability of an increase in weekly worked hours, related to the intensive margin, has been associated with different workers' individual and job characteristics according to their gender, as shown in Table 7. In particular, men were more likely to work more hours if they were older, single, with children, if they could work remotely, or if they had a high level of fluid intelligence, as measured by numeracy (column 1). On the other hand, women were more likely to work more hours if they worked in the public sector, or had children (column 2). In contrast, this probability was smaller if they had a low level of education or if they had bad health. The coefficients that are most significantly different across genders are age, marital status, having low numeracy, and working in the public sector.

The average difference in the probability of working more weekly hours, has been equal to 11% and 14% for males and females, respectively (Table 1). Only the coefficients component is significant, which is slightly above four percentage points, signaling an unexplained effect against women for the intensive margin. This was mainly determined by family and individual demographic characteristics, i.e., living

Table 7 Regression and decomposition for probability of more hours worked

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Age	0.0261***	−0.0001	0.0262**	0.0141**	0.1197**
	(0.0092)	(0.0083)	(0.0111)	(0.0056)	(0.0568)
Age^2	−0.0024***	−0.0004	−0.0021*	−0.0018	−0.0713*
	(0.0009)	(0.0009)	(0.0011)	(0.0043)	(0.0426)
Low educ	−0.0052	−0.0492***	0.0441*	−0.0006	0.0215*
	(0.0183)	(0.0175)	(0.0240)	(0.0021)	(0.0123)
Couple	−0.0844***	0.0104	−0.0948***	0.0011	−0.0812***
	(0.0237)	(0.0185)	(0.0330)	(0.0020)	(0.0258)
Children	0.0130**	0.0120*	0.0010	0.0004	0.0021
	(0.0066)	(0.0068)	(0.0099)	(0.0006)	(0.0198)
Bad health	−0.0099	−0.0429*	0.0329	0.0008	0.0038
	(0.0254)	(0.0233)	(0.0299)	(0.0006)	(0.0040)
Extraversion	0.0111	0.0083	0.0027	−0.0016	0.0099
	(0.0091)	(0.0090)	(0.0127)	(0.0013)	(0.0465)
Agreeableness	0.0089	−0.0166	0.0256*	0.0014	0.0937*
	(0.0107)	(0.0104)	(0.0151)	(0.0010)	(0.0545)
Conscientiousness	−0.0130	0.0033	−0.0163	0.0012	−0.0682
	(0.0106)	(0.0107)	(0.0151)	(0.0011)	(0.0630)
Neuroticism	−0.0003	−0.0125	0.0122	0.0025	0.0290
	(0.0094)	(0.0087)	(0.0128)	(0.0018)	(0.0305)
Openness	−0.0070	0.0058	−0.0128	0.0009	−0.0447
	(0.0087)	(0.0084)	(0.0124)	(0.0011)	(0.0423)
Low numeracy	−0.0296*	0.0164	−0.0460**	−0.0016	−0.0201*
	(0.0171)	(0.0161)	(0.0231)	(0.0016)	(0.0103)
Recall	0.0021	0.0005	0.0016	−0.0021	0.0183
	(0.0029)	(0.0028)	(0.0041)	(0.0031)	(0.0476)
Fluency	0.0005	0.0004	0.0001	−0.0005	0.0025
	(0.0012)	(0.0011)	(0.0016)	(0.0016)	(0.0401)
Public sector	−0.0182	0.0396**	−0.0578**	0.0038	−0.0272**
	(0.0214)	(0.0191)	(0.0283)	(0.0045)	(0.0135)
Self-employed	0.0190	−0.0137	0.0327	−0.0012	0.0052
	(0.0230)	(0.0317)	(0.0371)	(0.0028)	(0.0062)
Part-time	−0.0097	−0.0423*	0.0325	0.0005	0.0040
	(0.0325)	(0.0250)	(0.0406)	(0.0018)	(0.0050)
Potentially remote	0.0370*	0.0155	0.0216	−0.0051	0.0082
	(0.0195)	(0.0204)	(0.0269)	(0.0067)	(0.0107)

Table 7 continued

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Use PC	0.0143	0.0190	−0.0047	−0.0012	−0.0035
	(0.0199)	(0.0204)	(0.0249)	(0.0017)	(0.0211)
Central	0.0205	0.0978***	−0.0773*	−0.0001	−0.0211*
	(0.0290)	(0.0309)	(0.0411)	(0.0015)	(0.0116)
North	0.0588*	0.0380	0.0209	0.0007	0.0035
	(0.0324)	(0.0345)	(0.0477)	(0.0009)	(0.0079)
East	−0.0290	−0.0034	−0.0256	0.0001	−0.0110
	(0.0274)	(0.0293)	(0.0351)	(0.0012)	(0.0172)
Intercept	0.0745	0.0902	−0.0157		
	(0.0937)	(0.0912)	(0.1318)		
Total				0.0118	−0.0426**
				(0.0127)	(0.0168)

The first two columns report the OLS estimates for each gender, the third column reports their difference, and the last two columns report the two components from the Oaxaca-Blinder decomposition between male and female workers; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

in couple, age, and the level of education. It is worth emphasizing that if we net out the effect associated with the marital status, the sign of the coefficients component is reversed to almost 4 percentage points. Cognitive and non-cognitive ability make a smaller contribution to the coefficients component. Among these, the most relevant variable was agreeableness, which mitigated the size of the overall coefficients component, i.e., highly agreeable male workers were more likely to increase their hours worked than their female counterparts.

In contrast, the probability of working less weekly hours was mostly driven by the job characteristics, the country of residence, and some personality traits (columns 1–2 in Table 8). More specifically, self-employed workers were more likely to work fewer hours, whereas those working in the public sector or Northern or Eastern Europe were less likely. These results stem from the heterogeneous severity of the first wave across countries, and the fact that the lockdowns affected self-employed and private sector workers more than other workers (Adams-Prassl et al. 2020; Kalenkoski and Pabilonia 2022). Regardless, it is also noteworthy that workers with a high value in the openness indicator were more likely of reducing their working hours, probably because they substituted their working time with their non-job-related activities.[18] As for the gender divide, notable differences are related to the use of PC on the job and having a potentially remote job. The former reduced significantly the probability to work fewer hours for women, but not for men: as we condition on cognitive and non-cognitive abilities, this result can be attributed to differences in tasks, which we do not observe. The possibility to work remotely increased the probability to reduce

18 Another possibility, not in contrast with this explanation, is that more open individuals have less time to spend with their colleagues and therefore they can conclude their tasks earlier.

the working time for women but not for men. We interpret this finding as confirming the previous argument that women spent more time doing family duties (Del Boca et al. 2020).

As was the case for the overall probability of going through a job interruption, the gender differential of working fewer hours (about 21% for both men and women) was not significantly different from zero. The endowments and coefficients components were equal to 1.2 and −1.6 percentage points, respectively, although neither of them is significant. For the endowments component, the type of job mattered more than individual characteristics: the main contributors were being self-employed and working in the public sector. These were only partially compensated by the openness trait. Hence, because male workers are more likely to be self-employed and less likely to work in the public sector, they were more likely to work fewer hours than women with respect to the pre-pandemic period. On the other hand, two variables were significant explanatory variables for the coefficients component: being self-employed, which reduced the probability of working more hours by a larger margin for women than for men, and using the computer at work, which operated in the opposite direction.

Overall, the results concerning the coefficients components of the intensive margin for older workers unveil important differences between workers who increased their working hours and those who decreased them. Regarding the increase of the intensive margin, living with a partner constituted the most important penalty for women (Del Boca et al. 2020; Profeta 2021), thus representing an important channel for the shecession at older ages. Job characteristics were instead more important for the reduction of the intensity of labor market participation.

4.3 Probability of working remotely

Working remotely, i.e., the organizational margin, was strongly determined by workers' levels of education and types of intelligence, as well as some job characteristics (Table 9). Specifically, workers with either a higher level of education, who use the computer on the job, or those with a potentially remote job, were more likely of working remotely (columns 1–2). The intelligence, both fluid (higher numeracy) and, at least for women, crystallized (recall and fluency) increased the probability to work remotely. Public employees, male workers in part-time jobs and, self-employed females, were also more likely of working remotely. Additionally, workers in the countries less affected by the first wave were less likely to work remotely.

The overall probability of working remotely was about 7.5 percentage points higher for women (39.5%, as opposed to 32% for men), and the decomposition indicates that about three quarters can be accounted for by differences in covariates, most notably job characteristics, the type of job and some individual demographics. In particular, about two thirds of the endowments components can be attributed to using the computer at work and working at a potentially remote job (Blinder and Krueger 2013; Dingel and Neiman 2020; Basso et al. 2022). The probability to work remotely increased more for female workers because they were more likely to be employed in the public sector, although it was partially counteracted because they were less likely to be self-employed. Another major contributor was the educational level, which accounted for

Table 8 Regression and decomposition for probability of fewer hours worked

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Age	−0.0080	0.0106	−0.0186	−0.0043	−0.0852
	(0.0117)	(0.0096)	(0.0144)	(0.0064)	(0.0693)
Age^2	0.0008	−0.0009	0.0017	−0.0043	0.0585
	(0.0011)	(0.0010)	(0.0014)	(0.0049)	(0.0517)
Low educ	0.0132	0.0256	−0.0123	0.0015	−0.0060
	(0.0232)	(0.0201)	(0.0308)	(0.0027)	(0.0149)
Couple	0.0278	−0.0098	0.0376	−0.0011	0.0323
	(0.0301)	(0.0213)	(0.0364)	(0.0023)	(0.0316)
Children	−0.0031	−0.0027	−0.0005	−0.0001	−0.0010
	(0.0084)	(0.0079)	(0.0110)	(0.0003)	(0.0239)
Bad health	−0.0051	−0.0372	0.0321	0.0007	0.0037
	(0.0323)	(0.0268)	(0.0407)	(0.0007)	(0.0048)
Extraversion	−0.0030	0.0026	−0.0057	0.0004	−0.0206
	(0.0116)	(0.0104)	(0.0156)	(0.0017)	(0.0565)
Agreeableness	0.0085	−0.0032	0.0117	0.0003	0.0430
	(0.0135)	(0.0120)	(0.0183)	(0.0010)	(0.0662)
Conscientiousness	−0.0042	−0.0073	0.0031	0.0004	0.0128
	(0.0135)	(0.0123)	(0.0182)	(0.0013)	(0.0763)
Neuroticism	0.0243**	0.0066	0.0177	−0.0013	0.0420
	(0.0120)	(0.0101)	(0.0160)	(0.0020)	(0.0372)
Openness	0.0307***	0.0220**	0.0088	−0.0039**	0.0306
	(0.0110)	(0.0097)	(0.0139)	(0.0017)	(0.0513)
Low numeracy	0.0099	−0.0186	0.0285	0.0019	0.0125
	(0.0217)	(0.0186)	(0.0285)	(0.0019)	(0.0125)
Recall	−0.0035	0.0034	−0.0069	0.0037	−0.0813
	(0.0037)	(0.0032)	(0.0049)	(0.0039)	(0.0578)
Fluency	−0.0001	−0.0006	0.0005	0.0008	0.0124
	(0.0016)	(0.0013)	(0.0020)	(0.0019)	(0.0488)
Public sector	−0.0680**	−0.0492**	−0.0188	0.0142**	−0.0089
	(0.0272)	(0.0221)	(0.0348)	(0.0058)	(0.0165)
Self-employed	0.0994***	0.1976***	−0.0982*	0.0174***	−0.0156**
	(0.0292)	(0.0368)	(0.0539)	(0.0039)	(0.0075)
Part-time	−0.0049	0.0287	−0.0336	0.0003	−0.0041
	(0.0411)	(0.0288)	(0.0514)	(0.0023)	(0.0061)
Potentially remote	0.0378	0.0390*	−0.0012	−0.0129*	−0.0004
	(0.0247)	(0.0235)	(0.0356)	(0.0078)	(0.0129)
Use PC	0.0355	−0.0432*	0.0787**	−0.0030	0.0582**
	(0.0253)	(0.0235)	(0.0348)	(0.0022)	(0.0255)

Table 8 continued

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Central	−0.0403	−0.0493	0.0091	0.0000	0.0025
	(0.0368)	(0.0357)	(0.0575)	(0.0007)	(0.0139)
North	−0.1635***	−0.1620***	−0.0015	−0.0019	−0.0002
	(0.0412)	(0.0398)	(0.0588)	(0.0021)	(0.0096)
East	−0.1533***	−0.0914***	−0.0619	0.0036*	−0.0265
	(0.0348)	(0.0337)	(0.0526)	(0.0020)	(0.0208)
Intercept	0.1386	0.2131**	−0.0745		
	(0.1190)	(0.1052)	(0.1606)		
Total				0.0124	−0.0159
				(0.0152)	(0.0201)

The first two columns report the OLS estimates for each gender, the third column reports their difference, and the last two columns report the two components from the Oaxaca-Blinder decomposition between male and female workers; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

around 40% of the endowments component. Some indicators of cognitive and non-cognitive ability were also significant, but of different signs: men were more likely to work remotely because they tend to have higher fluid intelligence (numeracy), and the opposite is true for women because they tend to have higher crystallized intelligence (fluency and recall).

The difference due to the coefficients component is smaller (1.7 percentage points) and not statistically significant. Other things equal, extraversion or self-employment increased the probability of working remotely more for women than for men. In contrast, working part-time or in a potentially remote job increased the probability more for men than for women. Overall, no penalty is estimated for either gender with respect to the organizational margin.

To sum up, the results of the extensive and the intensive margin are coherent with a shecession hypothesis at older ages, related to workload at home. Women were more likely to work more hours, i.e., the intensive margin, mostly because of family characteristics: the coefficients components indicate an unexplained larger probability for them, which was partially offset by the individual characteristics. In contrast, they were more likely to work remotely due to differences in endowments. In particular, they worked more often in jobs that had the characteristics that allowed them to work remotely, which explains about half of the difference. A broader view of the results is in Table 10.

4.4 Robustness of the results

We assess the sensitivity of the baseline results by reporting the decomposition for several alternative specifications and estimators. We show the results when: we exclude the cognitive and non-cognitive ability variables; we use sectorial dummies; we use

Table 9 Regression and decomposition for probability of working remotely

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Age	0.0222*	0.0042	0.0181	0.0120*	0.0826
	(0.0115)	(0.0106)	(0.0150)	(0.0066)	(0.0715)
Age^2	−0.0020*	−0.0009	−0.0010	−0.0047	−0.0355
	(0.0011)	(0.0011)	(0.0015)	(0.0055)	(0.0536)
Low educ	−0.2133***	−0.1972***	−0.0162	−0.0245***	−0.0079
	(0.0227)	(0.0222)	(0.0336)	(0.0044)	(0.0155)
Couple	0.0122	0.0211	−0.0089	0.0023	−0.0077
	(0.0295)	(0.0235)	(0.0379)	(0.0025)	(0.0323)
Children	0.0040	−0.0213**	0.0253**	0.0001	0.0526**
	(0.0082)	(0.0087)	(0.0117)	(0.0003)	(0.0249)
Bad health	−0.0459	−0.0427	−0.0032	0.0007	−0.0004
	(0.0315)	(0.0296)	(0.0396)	(0.0007)	(0.0050)
Extraversion	−0.0168	0.0167	−0.0335**	0.0024	−0.1215**
	(0.0114)	(0.0115)	(0.0164)	(0.0017)	(0.0586)
Agreeableness	0.0179	0.0207	−0.0028	−0.0018	−0.0102
	(0.0133)	(0.0132)	(0.0186)	(0.0013)	(0.0686)
Conscientiousness	−0.0127	−0.0098	−0.0029	0.0012	−0.0121
	(0.0132)	(0.0135)	(0.0187)	(0.0013)	(0.0793)
Neuroticism	0.0006	0.0105	−0.0098	−0.0021	−0.0233
	(0.0118)	(0.0111)	(0.0160)	(0.0023)	(0.0384)
Openness	0.0140	0.0181*	−0.0041	−0.0018	−0.0144
	(0.0109)	(0.0107)	(0.0154)	(0.0014)	(0.0532)
Low numeracy	−0.0502**	−0.0670***	0.0168	0.0067***	0.0073
	(0.0213)	(0.0204)	(0.0297)	(0.0023)	(0.0129)
Recall	0.0058	0.0077**	−0.0019	−0.0061	−0.0222
	(0.0037)	(0.0036)	(0.0050)	(0.0039)	(0.0598)
Fluency	0.0000	0.0034**	−0.0034	−0.0047**	−0.0810
	(0.0015)	(0.0015)	(0.0021)	(0.0022)	(0.0505)
Public sector	0.0563**	0.0556**	0.0007	−0.0117**	0.0003
	(0.0267)	(0.0243)	(0.0369)	(0.0056)	(0.0170)
Self-employed	0.0084	0.0956**	−0.0872	0.0084**	−0.0139*
	(0.0287)	(0.0403)	(0.0531)	(0.0037)	(0.0079)
Part-time	0.0806**	−0.0154	0.0960*	−0.0044*	0.0117*
	(0.0404)	(0.0318)	(0.0523)	(0.0024)	(0.0063)
Potentially remote	0.1228***	0.0563**	0.0666*	−0.0185**	0.0253*
	(0.0243)	(0.0259)	(0.0363)	(0.0086)	(0.0135)
Use PC	0.2050***	0.2110***	−0.0060	−0.0174***	−0.0044
	(0.0248)	(0.0259)	(0.0318)	(0.0038)	(0.0265)

Table 9 continued

Variable	Regressions			Oaxaca-Blinder	
	β_{Men}	β_{Women}	$\beta_{Men} - \beta_{Women}$	Endowments	Coefficients
Central	0.0553	−0.0834**	0.1387**	0.0000	0.0378***
	(0.0361)	(0.0393)	(0.0569)	(0.0013)	(0.0146)
North	−0.0090	−0.1543***	0.1453**	−0.0001	0.0242**
	(0.0404)	(0.0439)	(0.0629)	(0.0005)	(0.0100)
East	−0.1214***	−0.1325***	0.0111	0.0054**	0.0047
	(0.0342)	(0.0372)	(0.0527)	(0.0027)	(0.0216)
Intercept	0.1791	0.0886	0.0906		
	(0.1168)	(0.1159)	(0.1654)		
Total				−0.0587***	−0.0170
				(0.0175)	(0.0211)

The first two columns report the OLS estimates for each gender, the third column reports their difference, and the last two columns report the two components from the Oaxaca-Blinder decomposition; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

objective health measures instead of self-reported health; the estimator is either a probit or a logit.[19]

Table 11 shows the decomposition results for each of the alternative specifications. The probability of experiencing a job interruption is the most robust result. When the ability measures are excluded, the results are slightly smaller in magnitude. When one uses the sectorial dummies, both components are roughly half of the magnitude in the baseline specification. As a consequence, the coefficients components would become statistically insignificant, although the sign would remain unchanged.

The decomposition of the probability of an increase in worked hours is robust to the change in variables, and the coefficients are slightly smaller in magnitude only when the ability variables are omitted. However, the results are slightly different when one uses nonlinear methods for the decomposition: the endowments component becomes negative and significant, whereas the coefficients component is much closer to zero and insignificant. In contrast, the decomposition of the probability of a decrease in worked hours is quite stable across specifications. Only the endowments component is significant at the 95% confidence level in one of the nonlinear specifications, while the coefficients component is never significant.

Lastly, the decomposition of the probability of working remotely does not change much across specifications. The endowments component is always statistically significant, whereas the coefficients components is not. Still, the magnitude of the endowments component is larger in the nonlinear decompositions.

[19] We report the detailed decomposition of OLS with different covariates in Tables 20, 21, 22 and 23. For comparability, the covariates in the decomposition are grouped into several categories. Additionally, we report the detailed decomposition of the nonlinear estimators in Tables 15, 16, 17, and 18. All these tables are located in Appendix A.

Table 10 Summary of results, baseline specification

	Job interruption		More hours worked		Fewer hours worked		Worked remotely	
	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients
Individual demographics	−0.0042	−0.0195	0.0117	0.0699***	−0.0071	−0.0327	−0.0172*	0.0392
	(0.0075)	(0.0254)	(0.0072)	(0.0251)	(0.0086)	(0.0305)	(0.0095)	(0.0314)
Family demographics	0.0002	0.0004	0.0016	−0.0791***	−0.0012	0.0313	0.0024	0.0450
	(0.0019)	(0.0288)	(0.0021)	(0.0289)	(0.0023)	(0.0352)	(0.0026)	(0.0363)
Health	−0.0003	−0.0042	0.0008	0.0038	0.0007	0.0037	0.0007	−0.0004
	(0.0004)	(0.0043)	(0.0006)	(0.0040)	(0.0007)	(0.0048)	(0.0007)	(0.0050)
Non cognitive ability	−0.0009	0.0887	0.0044	0.0196	−0.0041	0.1078	−0.0021	−0.1814
	(0.0027)	(0.1032)	(0.0028)	(0.1042)	(0.0034)	(0.1265)	(0.0036)	(0.1311)
Cognitive ability	0.0073*	0.0244	−0.0043	0.0007	0.0064	−0.0564	−0.0040	−0.0958
	(0.0040)	(0.0553)	(0.0039)	(0.0563)	(0.0048)	(0.0687)	(0.0052)	(0.0709)
Type of job	0.0322***	−0.0472***	0.0031	−0.0180	0.0319***	−0.0286	−0.0078	−0.0018
	(0.0062)	(0.0168)	(0.0056)	(0.0171)	(0.0075)	(0.0208)	(0.0072)	(0.0215)
Job characteristics	0.0091	0.0828***	−0.0063	0.0047	−0.0159*	0.0578**	−0.0360***	0.0209
	(0.0063)	(0.0216)	(0.0069)	(0.0234)	(0.0081)	(0.0283)	(0.0095)	(0.0294)
Geographic	0.0040*	−0.0268	0.0008	−0.0285	0.0017	−0.0243	0.0053**	0.0668
	(0.0023)	(0.0305)	(0.0020)	(0.0330)	(0.0021)	(0.0399)	(0.0024)	(0.0417)
Intercept		−0.1439		−0.0157		−0.0745		0.0906
		(0.1287)		(0.1308)		(0.1588)		(0.1645)
Total	0.0474***	−0.0453***	0.0118	−0.0426**	0.0124	−0.0159	−0.0587***	−0.0170
	(0.0128)	(0.0166)	(0.0127)	(0.0168)	(0.0152)	(0.0201)	(0.0175)	(0.0211)

Individual demographics contains the quadratic polynomial of age and low education, family demographics contains couple and children, health contains bad health, type of job contains public sector, self-employed and part-time, job characteristics contains potentially remote and use PC, geographic contains Central, North and East, cognitive ability contains low numeracy, recall and fluency, non-cognitive ability contains extraversion, agreeableness, conscientiousness, neuroticism and optimism; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 11 Decompositions for different specifications

	Job interruption		More hours worked		Fewer hours worked		Worked remotely	
	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients
Baseline	0.0474***	−0.0453***	0.0118	−0.0426**	0.0124	−0.0159	−0.0587***	−0.0170
	(0.0128)	(0.0166)	(0.0127)	(0.0168)	(0.0152)	(0.0201)	(0.0175)	(0.0211)
No ability	0.0412***	−0.0355**	0.0043	−0.0383**	0.0068	−0.0048	−0.0580***	−0.0214
	(0.0118)	(0.0155)	(0.0116)	(0.0156)	(0.0140)	(0.0188)	(0.0159)	(0.0197)
Sectors	0.0262**	−0.0242	0.0095	−0.0403**	0.0059	−0.0093	−0.0580***	−0.0177
	(0.0123)	(0.0160)	(0.0117)	(0.0161)	(0.0143)	(0.0192)	(0.0166)	(0.0202)
Health	0.0494***	−0.0460***	0.0105	−0.0414**	0.0043	−0.0068	−0.0512***	−0.0231
	(0.0133)	(0.0170)	(0.0131)	(0.0171)	(0.0158)	(0.0206)	(0.0179)	(0.0214)
Probit	0.0483***	−0.0463***	−0.019**	−0.0119	0.0183**	−0.0218	−0.0686***	−0.0071
	(0.0127)	(0.0157)	(0.0077)	(0.0124)	(0.0089)	(0.0175)	(0.0146)	(0.0164)
Logit	0.0461***	−0.044***	−0.0183**	−0.0125	0.0161*	−0.0196	−0.0689***	−0.0068
	(0.0131)	(0.0158)	(0.0081)	(0.0129)	(0.0092)	(0.0177)	(0.0148)	(0.0164)

"Baseline" denotes the baseline specification, "No ability" denotes the specification excluding and including the cognitive and non-cognitive ability variables, "Sectors" denotes the specification using sectorial dummies, "Objective health" denotes the specification with objective health measures, "Probit" and "Logit" denote the nonlinear specifications with the baseline covariates; in "Sectors", the variable potentially remote is dropped due to multicollinearity, and the sectorial dummies are included in type of job; in "Objective health" the variable bad health is substituted by the following objective health measures: having a problem that limits the amount of paid work, having difficulties for doing everyday activities, having been limited in activities due to a health problem in the previous six months, having too little energy in the previous month, and having been depressed in the previous month; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

5 Conclusion

In this paper, we study the impact of the COVID-19 pandemic during its early months on the labor market outcomes of elderly workers in Europe. This age group has received little specific attention, despite the fact that they constitute a notable share of the entire workforce, with certain characteristics that are not shared by other workers, and who were believed to be more at risk of serious health complications. We explore how their changes to the intensive, extensive, and organizational margins of their labor market outcomes were related to the job and individual characteristics, including measures of cognitive and non-cognitive abilities.

Our findings reveal the existence of an unexplained effect against women regarding the probability of suffering a job interruption (extensive margin) and an increase in worked hours (intensive margin). In the first case, this is mostly related to job characteristics, as self-employed women were substantially more likely to suffer a job interruption. This is coherent with the shecession hypothesis, proposed by Alon et al. (2022), on the older workers subpopulation. In the second case, the penalty is largely driven by family characteristics. This in turn may have to do with the increased workload at home, and less with the upbringing of children (Del Boca et al. 2020).

On the other hand, the difference in working from home is almost entirely explained by differences in observed characteristics. These are in turn a combination of differences in job characteristics between both genders, which made female workers more likely to work from home, as well as differences in educational achievement and cognitive ability.

Consistently with the findings by Heckman et al. (2006) and subsequent works in the human capital literature, our results reinforce the importance of controlling for cognitive ability in the determination of labor market outcomes. Relative to this stream of literature, we are the first to distinguish between the role of fluid and crystallized intelligence at a supranational level. In particular, differences between men and women in crystallized intelligence made male workers more likely to undergo a job interruption and less likely to work remotely than their female counterparts, whereas differences in fluid intelligence made them more likely to work remotely. In addition, we also find that some personality traits were responsible for some of the differences in labor market outcomes. Specifically, the agreeableness indicator was associated with a higher probability of experiencing a job interruption for men, as well as working more hours, the neuroticism indicator was also related to a higher probability of male workers undergoing a job interruption, and finally, women with higher values in the extraversion indicator were more likely to work remotely.

Appendix A: Additional results

See Tables 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22 and 23.

Table 12 Attrition

	Overall	Female	Male
Age	0.0002	−0.0340	0.0340
	(0.0439)	(0.0556)	(0.0739)
Age^2	−0.0000	0.0003	−0.0003
	(0.0004)	(0.0005)	(0.0006)
Low educ	0.0046	0.0027	0.0064
	(0.0078)	(0.0100)	(0.0127)
Couple	0.0181**	0.0293***	0.0007
	(0.0084)	(0.0106)	(0.0149)
Children	0.0037	0.0035	0.0047
	(0.0030)	(0.0037)	(0.0044)
Extraversion	−0.0080**	−0.0084*	−0.0071
	(0.0040)	(0.0051)	(0.0064)
Agreeableness	−0.0019	−0.0002	−0.0037
	(0.0045)	(0.0057)	(0.0070)
Conscientiousness	−0.0006	0.0058	−0.0094
	(0.0047)	(0.0060)	(0.0070)
Neuroticism	0.0041	0.0076*	−0.0011
	(0.0037)	(0.0046)	(0.0061)
Openness	−0.0069*	−0.0053	−0.0091
	(0.0038)	(0.0048)	(0.0060)
Low numeracy	0.0062	0.0031	0.0108
	(0.0072)	(0.0094)	(0.0118)
Recall	−0.0041***	−0.0046***	−0.0032
	(0.0012)	(0.0016)	(0.0020)
Fluency	−0.0013**	−0.0013**	−0.0012
	(0.0005)	(0.0007)	(0.0008)
Intercept	0.3083	1.2239	−0.5543
	(1.3203)	(1.6693)	(2.2296)

Probability of missing observations in the COVID questionnaire; estimates from a linear probability model; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 13 Attrition p-value

Age	0.459
Age^2	0.426
Low educ	0.818
Couple	0.115
Children	0.828
Extraversion	0.867
Agreeableness	0.694
Conscientiousness	0.098
Neuroticism	0.251
Openness	0.622
Bad numeracy	0.606
Recall	0.596
Fluency	0.930

p-value for the null hypothesis of equality between genders; coefficients from Table 12

Table 14 Geographical distribution of the observations

Country	Sample size
Germany	742
Sweden	169
Netherlands	110
Spain	190
Italy	575
France	488
Denmark	504
Greece	851
Switzerland	408
Belgium	545
Czech Republic	413
Poland	670
Luxembourg	289
Hungary	139
Slovenia	592
Estonia	704
Croatia	422
Lithuania	456
Bulgaria	229
Cyprus	77
Finland	358
Latvia	256
Malta	244
Romania	493
Slovakia	468

Number of observations by country

Table 15 Nonlinear estimates of probability of experiencing a job interruption

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Age	−0.0104	−0.0107	−0.0103	0.0095	0.0112	0.0096
	(0.0098)	(0.0096)	(0.0093)	(0.0077)	(0.0079)	(0.0076)
Age^2	0.0010	0.0010	0.0009	−0.0007	−0.0009	−0.0007
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
Low educ	0.0490**	0.0469**	0.0472**	0.0250	0.0320**	0.0273*
	(0.0193)	(0.0193)	(0.0187)	(0.0162)	(0.0160)	(0.0154)
Couple	−0.0100	−0.0098	−0.0099	0.0022	0.0045	0.0029
	(0.0249)	(0.0238)	(0.0225)	(0.0171)	(0.0168)	(0.0159)
Children	−0.0001	−0.0008	−0.0001	−0.0053	−0.0046	−0.0041
	(0.0069)	(0.0067)	(0.0065)	(0.0063)	(0.0062)	(0.0058)
Bad health	−0.0054	−0.0026	−0.0029	0.0271	0.0247	0.0237
	(0.0256)	(0.0251)	(0.0242)	(0.0212)	(0.0202)	(0.0189)
Extraversion	−0.0024	−0.0030	−0.0025	0.0068	0.0051	0.0065
	(0.0097)	(0.0095)	(0.0091)	(0.0085)	(0.0083)	(0.0079)
Agreeableness	0.0314***	0.0319***	0.0292***	0.0067	0.0070	0.0049
	(0.0112)	(0.0110)	(0.0105)	(0.0096)	(0.0094)	(0.0087)
Conscientiousness	0.0033	0.0029	0.0023	0.0042	0.0050	0.0038
	(0.0112)	(0.0112)	(0.0107)	(0.0100)	(0.0100)	(0.0096)
Neuroticism	0.0221**	0.0216**	0.0197**	−0.0022	−0.0026	−0.0018
	(0.0098)	(0.0094)	(0.0090)	(0.0080)	(0.0078)	(0.0073)
Openness	0.0061	0.0070	0.0064	0.0125	0.0113	0.0120
	(0.0092)	(0.0091)	(0.0087)	(0.0079)	(0.0078)	(0.0074)

Table 15 continued

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Low numeracy	0.0154	0.0146	0.0151	−0.0136	−0.0129	−0.0131
	(0.0178)	(0.0174)	(0.0166)	(0.0150)	(0.0148)	(0.0140)
Recall	−0.0023	−0.0025	−0.0021	0.0023	0.0029	0.0026
	(0.0031)	(0.0030)	(0.0029)	(0.0026)	(0.0026)	(0.0024)
Fluency	0.0000	−0.0000	−0.0001	−0.0027**	−0.0028***	−0.0027***
	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0010)
Public sector	−0.0838***	−0.0968***	−0.0978***	−0.0526***	−0.0618***	−0.0615***
	(0.0227)	(0.0241)	(0.0242)	(0.0178)	(0.0178)	(0.0172)
Self-employed	0.0049	0.0018	0.0017	0.2029***	0.1347***	0.1192***
	(0.0242)	(0.0225)	(0.0210)	(0.0278)	(0.0231)	(0.0202)
Part-time	0.0143	0.0162	0.0123	0.0209	0.0167	0.0135
	(0.0334)	(0.0320)	(0.0303)	(0.0222)	(0.0201)	(0.0184)
Potentially remote	−0.0262	−0.0268	−0.0244	−0.0310*	−0.0309*	−0.0267*
	(0.0205)	(0.0201)	(0.0194)	(0.0186)	(0.0170)	(0.0159)
Use PC	0.0165	0.0168	0.0141	−0.0979***	−0.0856***	−0.0788***
	(0.0204)	(0.0196)	(0.0186)	(0.0182)	(0.0167)	(0.0157)
Central	−0.0398	−0.0292	−0.0240	−0.0307	−0.0192	−0.0165
	(0.0290)	(0.0258)	(0.0236)	(0.0278)	(0.0246)	(0.0222)
North	−0.1865***	−0.1835***	−0.1757***	−0.0972***	−0.0827***	−0.0757***
	(0.0337)	(0.0338)	(0.0329)	(0.0317)	(0.0306)	(0.0291)
East	−0.1486***	−0.1313***	−0.1242***	−0.1243***	−0.1058***	−0.1005***
	(0.0271)	(0.0248)	(0.0231)	(0.0262)	(0.0237)	(0.0217)

Average partial effect of each variable for different estimators by gender; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 16 Nonlinear estimates of more hours worked

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Age	0.0261***	0.0296***	0.0302***	−0.0001	0.0011	0.0003
	(0.0092)	(0.0101)	(0.0100)	(0.0083)	(0.0082)	(0.0080)
Age^2	−0.0024***	−0.0027***	−0.0027***	−0.0004	−0.0005	−0.0004
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Low educ	−0.0052	−0.0028	−0.0026	−0.0492***	−0.0465***	−0.0449***
	(0.0183)	(0.0174)	(0.0161)	(0.0175)	(0.0174)	(0.0168)
Couple	−0.0844***	−0.0716***	−0.0650***	0.0104	0.0121	0.0119
	(0.0237)	(0.0203)	(0.0184)	(0.0185)	(0.0185)	(0.0179)
Children	0.0130**	0.0111*	0.0108*	0.0120*	0.0124*	0.0108*
	(0.0066)	(0.0061)	(0.0057)	(0.0068)	(0.0065)	(0.0062)
Bad health	−0.0099	−0.0129	−0.0106	−0.0429*	−0.0521**	−0.0494*
	(0.0254)	(0.0259)	(0.0250)	(0.0233)	(0.0253)	(0.0256)
Extraversion	0.0111	0.0095	0.0092	0.0083	0.0084	0.0074
	(0.0091)	(0.0086)	(0.0081)	(0.0090)	(0.0089)	(0.0086)
Agreeableness	0.0089	0.0082	0.0082	−0.0166	−0.0169*	−0.0164*
	(0.0107)	(0.0103)	(0.0098)	(0.0104)	(0.0101)	(0.0099)
Conscientiousness	−0.0130	−0.0145	−0.0125	0.0033	0.0037	0.0032
	(0.0106)	(0.0100)	(0.0094)	(0.0107)	(0.0105)	(0.0103)
Neuroticism	−0.0003	−0.0011	−0.0008	−0.0125	−0.0120	−0.0127
	(0.0094)	(0.0090)	(0.0086)	(0.0087)	(0.0086)	(0.0084)
Openness	−0.0070	−0.0067	−0.0064	0.0058	0.0057	0.0055
	(0.0087)	(0.0081)	(0.0075)	(0.0084)	(0.0082)	(0.0079)

Table 16 continued

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Low numeracy	−0.0296*	−0.0274*	−0.0272*	0.0164	0.0163	0.0145
	(0.0171)	(0.0164)	(0.0156)	(0.0161)	(0.0158)	(0.0152)
Recall	0.0021	0.0022	0.0021	0.0005	0.0000	0.0002
	(0.0029)	(0.0028)	(0.0026)	(0.0028)	(0.0027)	(0.0027)
Fluency	0.0005	0.0004	0.0005	0.0004	0.0004	0.0005
	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Public sector	−0.0182	−0.0155	−0.0149	0.0396**	0.0375**	0.0364**
	(0.0214)	(0.0204)	(0.0193)	(0.0191)	(0.0187)	(0.0179)
Self-employed	0.0190	0.0195	0.0175	−0.0137	−0.0212	−0.0163
	(0.0230)	(0.0211)	(0.0197)	(0.0317)	(0.0335)	(0.0332)
Part-time	−0.0097	−0.0050	−0.0040	−0.0423*	−0.0418	−0.0429
	(0.0325)	(0.0306)	(0.0291)	(0.0250)	(0.0260)	(0.0262)
Potentially remote	0.0370*	0.0352*	0.0315*	0.0155	0.0199	0.0200
	(0.0195)	(0.0181)	(0.0168)	(0.0204)	(0.0210)	(0.0209)
Use PC	0.0143	0.0201	0.0173	0.0190	0.0270	0.0245
	(0.0199)	(0.0201)	(0.0195)	(0.0204)	(0.0215)	(0.0214)
Central	0.0205	0.0144	0.0117	0.0978***	0.0960***	0.0925***
	(0.0290)	(0.0273)	(0.0259)	(0.0309)	(0.0318)	(0.0319)
North	0.0588*	0.0423	0.0378	0.0380	0.0414	0.0395
	(0.0324)	(0.0300)	(0.0281)	(0.0345)	(0.0348)	(0.0350)
East	−0.0290	−0.0341	−0.0366	−0.0034	−0.0012	0.0016
	(0.0274)	(0.0273)	(0.0263)	(0.0293)	(0.0312)	(0.0318)

Average partial effect of each variable for different estimators by gender; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 17 Nonlinear estimates of fewer hours worked

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Age	−0.0080	−0.0088	−0.0085	0.0106	0.0119	0.0112
	(0.0117)	(0.0121)	(0.0120)	(0.0096)	(0.0099)	(0.0098)
Age^2	0.0008	0.0009	0.0009	−0.0009	−0.0010	−0.0009
	(0.0011)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)
Low educ	0.0132	0.0088	0.0129	0.0256	0.0278	0.0260
	(0.0232)	(0.0233)	(0.0229)	(0.0201)	(0.0204)	(0.0201)
Couple	0.0278	0.0292	0.0292	−0.0098	−0.0092	−0.0101
	(0.0301)	(0.0307)	(0.0303)	(0.0213)	(0.0214)	(0.0210)
Children	−0.0031	−0.0034	−0.0028	−0.0027	−0.0025	−0.0025
	(0.0084)	(0.0085)	(0.0084)	(0.0079)	(0.0081)	(0.0080)
Bad health	−0.0051	−0.0067	−0.0044	−0.0372	−0.0371	−0.0364
	(0.0323)	(0.0331)	(0.0327)	(0.0268)	(0.0276)	(0.0276)
Extraversion	−0.0030	−0.0028	−0.0027	0.0026	0.0015	0.0024
	(0.0116)	(0.0117)	(0.0115)	(0.0104)	(0.0106)	(0.0105)
Agreeableness	0.0085	0.0091	0.0084	−0.0032	−0.0038	−0.0040
	(0.0135)	(0.0136)	(0.0133)	(0.0120)	(0.0121)	(0.0119)
Conscientiousness	−0.0042	−0.0062	−0.0048	−0.0073	−0.0088	−0.0079
	(0.0135)	(0.0137)	(0.0134)	(0.0123)	(0.0124)	(0.0122)
Neuroticism	0.0243**	0.0254**	0.0244**	0.0066	0.0051	0.0060
	(0.0120)	(0.0120)	(0.0118)	(0.0101)	(0.0102)	(0.0100)
Openness	0.0307***	0.0322***	0.0316***	0.0220**	0.0229**	0.0230**
	(0.0110)	(0.0114)	(0.0111)	(0.0097)	(0.0101)	(0.0100)
Low numeracy	0.0099	0.0099	0.0100	−0.0186	−0.0192	−0.0186
	(0.0217)	(0.0220)	(0.0216)	(0.0186)	(0.0188)	(0.0185)

Table 17 continued

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Recall	−0.0035	−0.0037	−0.0036	0.0034	0.0033	0.0034
	(0.0037)	(0.0038)	(0.0037)	(0.0032)	(0.0033)	(0.0033)
Fluency	−0.0001	−0.0000	−0.0000	−0.0006	−0.0006	−0.0006
	(0.0016)	(0.0016)	(0.0015)	(0.0013)	(0.0013)	(0.0013)
Public sector	−0.0680**	−0.0682**	−0.0710**	−0.0492**	−0.0502**	−0.0493**
	(0.0272)	(0.0282)	(0.0282)	(0.0221)	(0.0221)	(0.0220)
Self-employed	0.0994***	0.0869***	0.0829***	0.1976***	0.1604***	0.1506***
	(0.0292)	(0.0278)	(0.0262)	(0.0368)	(0.0336)	(0.0311)
Part-time	−0.0049	−0.0086	−0.0071	0.0287	0.0246	0.0243
	(0.0411)	(0.0412)	(0.0398)	(0.0288)	(0.0279)	(0.0266)
Potentially remote	0.0378	0.0341	0.0357	0.0390*	0.0347	0.0354
	(0.0247)	(0.0247)	(0.0241)	(0.0235)	(0.0232)	(0.0229)
Use PC	0.0355	0.0333	0.0353	−0.0432*	−0.0417*	−0.0403*
	(0.0253)	(0.0258)	(0.0254)	(0.0235)	(0.0231)	(0.0225)
Central	−0.0403	−0.0301	−0.0294	−0.0493	−0.0434	−0.0420
	(0.0368)	(0.0343)	(0.0323)	(0.0357)	(0.0336)	(0.0320)
North	−0.1635***	−0.1547***	−0.1504***	−0.1620***	−0.1737***	−0.1726***
	(0.0412)	(0.0408)	(0.0396)	(0.0398)	(0.0405)	(0.0403)
East	−0.1533***	−0.1410***	−0.1390***	−0.0914***	−0.0822**	−0.0798***
	(0.0348)	(0.0334)	(0.0317)	(0.0337)	(0.0321)	(0.0306)

Average partial effect of each variable for different estimators by gender; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 18 Nonlinear estimates of working remotely

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Age	0.0222*	0.0309**	0.0302**	0.0042	0.0043	0.0055
	(0.0115)	(0.0151)	(0.0148)	(0.0106)	(0.0124)	(0.0128)
Age^2	−0.0020*	−0.0027*	−0.0026*	−0.0009	−0.0010	−0.0011
	(0.0011)	(0.0014)	(0.0014)	(0.0011)	(0.0013)	(0.0013)
Low educ	−0.2133***	−0.2040***	−0.1892***	−0.1972***	−0.2094***	−0.2113***
	(0.0227)	(0.0259)	(0.0248)	(0.0222)	(0.0251)	(0.0255)
Couple	0.0122	0.0164	0.0169	0.0211	0.0301	0.0322
	(0.0295)	(0.0358)	(0.0341)	(0.0235)	(0.0274)	(0.0279)
Children	0.0040	0.0064	0.0053	−0.0213**	−0.0254**	−0.0269**
	(0.0082)	(0.0102)	(0.0098)	(0.0087)	(0.0104)	(0.0107)
Bad health	−0.0459	−0.0567	−0.0516	−0.0427	−0.0501	−0.0481
	(0.0315)	(0.0412)	(0.0396)	(0.0296)	(0.0358)	(0.0367)
Extraversion	−0.0168	−0.0172	−0.0178	0.0167	0.0190	0.0190
	(0.0114)	(0.0135)	(0.0129)	(0.0115)	(0.0133)	(0.0135)
Agreeableness	0.0179	0.0188	0.0179	0.0207	0.0276*	0.0287*
	(0.0133)	(0.0161)	(0.0154)	(0.0132)	(0.0157)	(0.0160)
Conscientiousness	−0.0127	−0.0080	−0.0074	−0.0098	−0.0098	−0.0105
	(0.0132)	(0.0161)	(0.0153)	(0.0135)	(0.0157)	(0.0159)
Neuroticism	0.0006	0.0031	0.0011	0.0105	0.0130	0.0124
	(0.0118)	(0.0144)	(0.0138)	(0.0111)	(0.0129)	(0.0132)
Openness	0.0140	0.0157	0.0150	0.0181*	0.0216*	0.0222*
	(0.0109)	(0.0129)	(0.0122)	(0.0107)	(0.0124)	(0.0127)
Low numeracy	−0.0502**	−0.0587**	−0.0554**	−0.0670***	−0.0811***	−0.0812***
	(0.0213)	(0.0258)	(0.0246)	(0.0204)	(0.0234)	(0.0238)

Table 18 continued

Variable	Male			Female		
	OLS	Probit	Logit	OLS	Probit	Logit
Recall	0.0058	0.0078*	0.0075*	0.0077**	0.0092**	0.0096**
	(0.0037)	(0.0044)	(0.0042)	(0.0036)	(0.0042)	(0.0042)
Fluency	0.0000	0.0011	0.0011	0.0034**	0.0040**	0.0040**
	(0.0015)	(0.0018)	(0.0018)	(0.0015)	(0.0017)	(0.0017)
Public sector	0.0563**	0.0710**	0.0670**	0.0556**	0.0631**	0.0626**
	(0.0267)	(0.0314)	(0.0297)	(0.0243)	(0.0280)	(0.0285)
Self-employed	0.0084	0.0201	0.0129	0.0956**	0.1159**	0.1153**
	(0.0287)	(0.0335)	(0.0320)	(0.0403)	(0.0457)	(0.0474)
Part-time	0.0806**	0.0983**	0.0947**	−0.0154	−0.0167	−0.0187
	(0.0404)	(0.0474)	(0.0451)	(0.0318)	(0.0377)	(0.0389)
Potentially remote	0.1228***	0.1184***	0.1098***	0.0563**	0.0660**	0.0708**
	(0.0243)	(0.0280)	(0.0265)	(0.0259)	(0.0307)	(0.0318)
Use PC	0.2050***	0.2984***	0.3126***	0.2110***	0.2860***	0.2992***
	(0.0248)	(0.0326)	(0.0326)	(0.0259)	(0.0326)	(0.0347)
Central	0.0553	0.0258	0.0224	−0.0834**	−0.1007**	−0.1034**
	(0.0361)	(0.0409)	(0.0389)	(0.0393)	(0.0450)	(0.0466)
North	−0.0090	−0.0312	−0.0309	−0.1543***	−0.1809***	−0.1873***
	(0.0404)	(0.0464)	(0.0437)	(0.0439)	(0.0498)	(0.0515)
East	−0.1214***	−0.1684***	−0.1682***	−0.1325***	−0.1574***	−0.1603***
	(0.0342)	(0.0405)	(0.0393)	(0.0372)	(0.0428)	(0.0447)

Average partial effect of each variable for different estimators by gender; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 19 Additional nonlinear decompositions

	Job interruption		More hours worked		Fewer hours worked		Worked remotely	
	Endowments	Components	Endowments	Components	Endowments	Components	Endowments	Components
Baseline	0.0474***	−0.0453***	0.0118	−0.0426**	0.0124	−0.0159	−0.0587***	−0.0170
	(0.0128)	(0.0166)	(0.0127)	(0.0168)	(0.0152)	(0.0201)	(0.0175)	(0.0211)
Probit	0.0483***	−0.0463***	−0.0190**	−0.0119	0.0183**	−0.0218	−0.0686***	−0.0071
	(0.0127)	(0.0157)	(0.0077)	(0.0124)	(0.0089)	(0.0175)	(0.0146)	(0.0164)
Logit	0.0461***	−0.0440***	−0.0183**	−0.0125	0.0161*	−0.0196	−0.0689***	−0.0068
	(0.0131)	(0.0158)	(0.0081)	(0.0129)	(0.0092)	(0.0177)	(0.0148)	(0.0164)
Sectors								
Linear	0.0262**	−0.0242	0.0095	−0.0403**	0.0059	−0.0093	−0.0580***	−0.0177
	(0.0123)	(0.0160)	(0.0117)	(0.0161)	(0.0143)	(0.0192)	(0.0166)	(0.0202)
Probit	0.0210**	−0.0189	−0.0141*	−0.0167	0.0107	−0.0142	−0.0449***	−0.0308*
	(0.0100)	(0.0119)	(0.0084)	(0.0153)	(0.0086)	(0.0179)	(0.0124)	(0.0176)
Logit	0.0193**	−0.0173	−0.0141	−0.0167	0.0089	−0.0124	−0.0451***	−0.0306*
	(0.0097)	(0.0116)	(0.0088)	(0.0154)	(0.0085)	(0.0180)	(0.0122)	(0.0178)

"Baseline" denotes the baseline specification, "Probit" and "Logit" denote the nonlinear specifications with the baseline covariates; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 20 Decomposition for the probability of experiencing a job interruption

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual demographics	−0.0042	−0.0083	−0.0060	−0.0033	−0.0195	−0.0236	−0.0171	−0.0136
	(0.0075)	(0.0073)	(0.0075)	(0.0075)	(0.0254)	(0.0243)	(0.0251)	(0.0254)
Family demographics	0.0002	−0.0008	0.0009	0.0007	0.0004	−0.0008	−0.0056	−0.0064
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0288)	(0.0273)	(0.0284)	(0.0288)
Health	−0.0003	−0.0002	−0.0004	−0.0006	−0.0042	−0.0019	−0.0053	−0.0118
	(0.0004)	(0.0003)	(0.0004)	(0.0036)	(0.0043)	(0.0041)	(0.0042)	(0.0109)
Non cognitive ability	−0.0009		−0.0012	−0.0006	0.0887		0.0949	0.0881
	(0.0027)		(0.0027)	(0.0027)	(0.1032)		(0.1016)	(0.1038)
Cognitive ability	0.0073*		0.0080**	0.0081**	0.0244		0.0160	0.0256
	(0.0040)		(0.0039)	(0.0040)	(0.0553)		(0.0546)	(0.0553)
Type of job	0.0322***	0.0358***	0.0398***	0.0316***	−0.0472***	−0.0459***	−0.0664***	−0.0468***
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0168)	(0.0163)	(0.0159)	(0.0168)
Job characteristics	0.0091	0.0090	0.0025	0.0094	0.0828***	0.0684***	0.0233	0.0817***
	(0.0063)	(0.0062)	(0.0075)	(0.0063)	(0.0216)	(0.0200)	(0.0276)	(0.0216)

Table 20 continued

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Geographic	0.0040*	0.0058**	0.0047**	0.0041*	−0.0268	−0.0351	−0.0228	−0.0177
	(0.0023)	(0.0023)	(0.0020)	(0.0022)	(0.0305)	(0.0259)	(0.0319)	(0.0308)
Intercept					−0.1439	0.0035	−0.0721	−0.1451
					(0.1287)	(0.0550)	(0.1275)	(0.1293)
Total	0.0474***	0.0412***	0.0262**	0.0494***	−0.0453***	−0.0355**	−0.0242	−0.0460***
	(0.0128)	(0.0118)	(0.0123)	(0.0133)	(0.0166)	(0.0155)	(0.0160)	(0.0170)

Baseline denotes the baseline specification, No ability denotes the specification excluding and including the cognitive and non-cognitive ability variables, Sectors denotes the specification using sectorial dummies, Obj. health denotes the specification with objective health measures; individual demographics contains the quadratic polynomial of age and low education, family demographics contains couple and children, health contains bad health, type of job contains public sector, self-employed and part-time, job characteristics contains potentially remote and use PC, geographic contains Central, North and East, cognitive ability contains low numeracy, recall and fluency, non-cognitive ability contains extraversion, agreeableness, conscientiousness, neuroticism and optimism; in specification (3), the variable potentially remote is dropped due to multicollinearity, and the sectorial dummies are included in type of job; in specification (4) the variable bad health is substituted by the following objective health measures: having a problem that limits the amount of paid work, having difficulties for doing everyday activities, having been limited in activities due to a health problem in the previous six months, having too little energy in the previous month, and having been depressed in the previous month; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 21 Decomposition for the probability of more hours worked

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual demographics	0.0117	0.0103	0.0098	0.0114	0.0699***	0.0598**	0.0641**	0.0686***
	(0.0072)	(0.0071)	(0.0072)	(0.0073)	(0.0251)	(0.0237)	(0.0252)	(0.0252)
Family demographics	0.0016	0.0007	0.0016	0.0015	−0.0791***	−0.0691**	−0.0788***	−0.0793***
	(0.0021)	(0.0020)	(0.0021)	(0.0021)	(0.0289)	(0.0272)	(0.0289)	(0.0290)
Health	0.0008	0.0006	0.0008	−0.0014	0.0038	0.0044	0.0042	0.0006
	(0.0006)	(0.0005)	(0.0006)	(0.0036)	(0.0040)	(0.0039)	(0.0040)	(0.0107)
Non cognitive ability	0.0044		0.0046*	0.0048*	0.0196		0.0202	0.0072
	(0.0028)		(0.0028)	(0.0028)	(0.1042)		(0.1042)	(0.1049)
Cognitive ability	−0.0043		−0.0042	−0.0043	0.0007		0.0090	0.0001
	(0.0039)		(0.0039)	(0.0039)	(0.0563)		(0.0565)	(0.0564)
Type of job	0.0031	0.0033	−0.0006	0.0039	−0.0180	−0.0151	−0.0079	−0.0206
	(0.0056)	(0.0055)	(0.0054)	(0.0056)	(0.0171)	(0.0164)	(0.0164)	(0.0171)
Job characteristics	−0.0063	−0.0100	−0.0050	−0.0063	0.0047	0.0009	−0.0042	0.0014
	(0.0069)	(0.0068)	(0.0073)	(0.0070)	(0.0234)	(0.0216)	(0.0295)	(0.0234)
Geographic	0.0008	−0.0006	0.0015	0.0010	−0.0285	−0.0302	−0.0240	−0.0318
	(0.0020)	(0.0018)	(0.0015)	(0.0020)	(0.0330)	(0.0284)	(0.0351)	(0.0334)

Table 21 continued

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept					−0.0157	0.0108	−0.0373	0.0124
					(0.1308)	(0.0568)	(0.1316)	(0.1317)
Total	0.0118	0.0043	0.0095	0.0105	−0.0426**	−0.0383**	−0.0403**	−0.0414**
	(0.0127)	(0.0116)	(0.0117)	(0.0131)	(0.0168)	(0.0156)	(0.0161)	(0.0171)

Baseline denotes the baseline specification, No ability denotes the specification excluding and including the cognitive and non-cognitive ability variables, Sectors denotes the specification using sectorial dummies, Obj. health denotes the specification with objective health measures; individual demographics contains the quadratic polynomial of age and low education, family demographics contains couple and children, health contains bad health, type of job contains public sector, self-employed and part-time, job characteristics contains potentially remote and use PC, geographic contains Central, North and East, cognitive ability contains low numeracy, recall and fluency, non-cognitive ability contains extraversion, agreeableness, conscientiousness, neuroticism and optimism; in specification (3), the variable potentially remote is dropped due to multicollinearity, and the sectorial dummies are included in type of job; in specification (4) the variable bad health is substituted by the following objective health measures: having a problem that limits the amount of paid work, having difficulties for doing everyday activities, having been limited in activities due to a health problem in the previous six months, having too little energy in the previous month, and having been depressed in the previous month; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 22 Decomposition for the probability of fewer hours worked

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual demographics	−0.0071	−0.0085	−0.0103	−0.0085	−0.0327	−0.0291	−0.0444	−0.0367
	(0.0086)	(0.0086)	(0.0086)	(0.0087)	(0.0305)	(0.0290)	(0.0304)	(0.0305)
Family demographics	−0.0012	−0.0006	−0.0010	−0.0007	0.0313	0.0302	0.0280	0.0303
	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0352)	(0.0333)	(0.0350)	(0.0352)
Health	0.0007	0.0003	0.0007	−0.0050	0.0037	0.0019	0.0034	0.0148
	(0.0007)	(0.0004)	(0.0006)	(0.0043)	(0.0048)	(0.0047)	(0.0048)	(0.0131)
Non cognitive ability	−0.0041		−0.0044	−0.0043	0.1078		0.0996	0.1199
	(0.0034)		(0.0034)	(0.0034)	(0.1265)		(0.1256)	(0.1272)
Cognitive ability	0.0064		0.0073	0.0059	−0.0564		−0.0770	−0.0588
	(0.0048)		(0.0048)	(0.0048)	(0.0687)		(0.0684)	(0.0687)
Type of job	0.0319***	0.0327***	0.0337***	0.0322***	−0.0286	−0.0241	−0.0390**	−0.0286
	(0.0075)	(0.0074)	(0.0073)	(0.0075)	(0.0208)	(0.0201)	(0.0198)	(0.0208)
Job characteristics	−0.0159*	−0.0197**	−0.0097	−0.0169**	0.0578**	0.0431	0.0270	0.0602**
	(0.0081)	(0.0079)	(0.0089)	(0.0081)	(0.0283)	(0.0262)	(0.0354)	(0.0283)
Geographic	0.0017	0.0025	0.0040	0.0017	−0.0243	−0.0186	−0.0229	−0.0268
	(0.0021)	(0.0020)	(0.0026)	(0.0022)	(0.0399)	(0.0344)	(0.0420)	(0.0403)

Table 22 continued

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept					−0.0745	−0.0082	−0.0041	−0.0811
					(0.1588)	(0.0692)	(0.1588)	(0.1597)
Total	0.0124	0.0068	0.0059	0.0043	−0.0159	−0.0048	−0.0093	−0.0068
	(0.0152)	(0.0140)	(0.0143)	(0.0158)	(0.0201)	(0.0188)	(0.0192)	(0.0206)

Baseline denotes the baseline specification, No ability denotes the specification excluding and including the cognitive and non-cognitive ability variables, Sectors denotes the specification using sectorial dummies, Obj. health denotes the specification with objective health measures; individual demographics contains the quadratic polynomial of age and low education, family demographics contains couple and children, health contains bad health, type of job contains public sector, self-employed and part-time, job characteristics contains potentially remote and use PC, geographic contains Central, North and East, cognitive ability contains low numeracy, recall and fluency, non-cognitive ability contains extraversion, agreeableness, conscientiousness, neuroticism and optimism; in specification (3), the variable potentially remote is dropped due to multicollinearity, and the sectorial dummies are included in type of job; in specification (4) the variable bad health is substituted by the following objective health measures: having a problem that limits the amount of paid work, having difficulties for doing everyday activities, having been limited in activities due to a health problem in the previous six months, having too little energy in the previous month, and having been depressed in the previous month; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

Table 23 Decomposition for the probability of working remotely

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual demographics	−0.0172*	−0.0216**	−0.0193**	−0.0167*	0.0392	0.0255	0.0258	0.0403
	(0.0095)	(0.0095)	(0.0096)	(0.0095)	(0.0314)	(0.0298)	(0.0315)	(0.0314)
Family demographics	0.0024	0.0006	0.0020	0.0019	0.0450	0.0311	0.0411	0.0480
	(0.0026)	(0.0024)	(0.0026)	(0.0025)	(0.0363)	(0.0343)	(0.0363)	(0.0362)
Health	0.0007	0.0005	0.0009	0.0100**	−0.0004	0.0008	0.0006	0.0169
	(0.0007)	(0.0006)	(0.0008)	(0.0046)	(0.0050)	(0.0049)	(0.0051)	(0.0135)
Non cognitive ability	−0.0021		−0.0019	−0.0029	−0.1814		−0.2026	−0.2067
	(0.0036)		(0.0036)	(0.0036)	(0.1311)		(0.1311)	(0.1315)
Cognitive ability	−0.0040		−0.0047	−0.0040	−0.0958		−0.0991	−0.0973
	(0.0052)		(0.0052)	(0.0052)	(0.0709)		(0.0711)	(0.0708)
Type of job	−0.0078	−0.0034	−0.0246***	−0.0081	−0.0018	−0.0201	0.0189	−0.0019
	(0.0072)	(0.0071)	(0.0071)	(0.0072)	(0.0215)	(0.0208)	(0.0207)	(0.0215)
Job characteristics	−0.0360***	−0.0384***	−0.0388***	−0.0365***	0.0209	0.0056	−0.0165	0.0217
	(0.0095)	(0.0093)	(0.0100)	(0.0094)	(0.0294)	(0.0273)	(0.0371)	(0.0294)
Geographic	0.0053**	0.0042**	0.0032	0.0051**	0.0668	0.0539	0.0612	0.0610
	(0.0024)	(0.0020)	(0.0033)	(0.0024)	(0.0417)	(0.0359)	(0.0443)	(0.0420)

Table 23 continued

Variable	Endowments component				Coefficients component			
	Baseline	No ability	Sectors	Obj. health	Baseline	No ability	Sectors	Obj. health
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept					0.0906	−0.1181*	0.1655	0.0949
					(0.1645)	(0.0717)	(0.1656)	(0.1650)
Total	−0.0587***	−0.0580***	−0.0580***	−0.0512***	−0.0170	−0.0214	−0.0177	−0.0231
	(0.0175)	(0.0159)	(0.0166)	(0.0179)	(0.0211)	(0.0197)	(0.0202)	(0.0214)

Baseline denotes the baseline specification, No ability denotes the specification excluding and including the cognitive and non-cognitive ability variables, Sectors denotes the specification using sectorial dummies, Obj. health denotes the specification with objective health measures; individual demographics contains the quadratic polynomial of age and low education, family demographics contains couple and children, health contains bad health, type of job contains public sector, self-employed and part-time, job characteristics contains potentially remote and use PC, geographic contains Central, North and East, cognitive ability contains low numeracy, recall and fluency, non-cognitive ability contains extraversion, agreeableness, conscientiousness, neuroticism and optimism; in specification (3), the variable potentially remote is dropped due to multicollinearity, and the sectorial dummies are included in type of job; in specification (4) the variable bad health is substituted by the following objective health measures: having a problem that limits the amount of paid work, having difficulties for doing everyday activities, having been limited in activities due to a health problem in the previous six months, having too little energy in the previous month, and having been depressed in the previous month; *, ** and ***, respectively, denote statistical significance at the 90%, 95% and 99% confidence level; heteroskedasticity-robust standard errors reported in parentheses

References

Adams-Prassl A, Boneva T, Golin M, Rauh C (2020) Inequality in the impact of the coronavirus shock: evidence from real time surveys. J Public Econ 189:104245

Alderotti G, Rapallini C, Traverso S (2023) The big five personality traits and earnings: a meta-analysis. J Econ Psychol 94:102570

Alon T, Coskun S, Doepke M, Koll D, Tertilt M (2022) From mancession to shecession: women's employment in regular and pandemic recessions. NBER Macroecon Annu 36(1):83–151

Alon T, Doepke M, Olmstead-Rumsey J, Tertilt M (2020) This time it's different: the role of women's employment in a pandemic recession. Technical report, National Bureau of Economic Research

Aum S, Lee SYT, Shin Y (2021) Covid-19 doesn't need lockdowns to destroy jobs: the effect of local outbreaks in Korea. Labour Econ 70:101993

Barrero JM, Bloom N, Davis SJ (2021) Why working from home will stick. Technical report, National Bureau of Economic Research

Basso G, Boeri T, Caiumi A, Paccagnella M (2022) The new hazardous jobs and worker reallocation. Econ Policy 37(110):229–267

Bauer A, Weber E (2020) Covid-19: how much unemployment was caused by the shutdown in Germany? Appl Econ Lett, 1–6

Bauer TK, Sinning M (2008) An extension of the blinder-oaxaca decomposition to nonlinear models. AStA Adv Stat Anal 92(2):197–206

Bergmann M, Börsch-Supan A (2021) SHARE wave 8 methodology: collecting cross-national survey data in. Munich center for the economics of aging

Bertoni M, Cavapozzi D, Pasini G, Pavese C et al (2021) Remote working and mental health during the first wave of covid-19 pandemic. Technical report, Institute of Labor Economics (IZA)

Bertoni M, Celidoni M, Dal Bianco C, Weber G (2021) How did European retirees respond to the covid-19 pandemic? Econ Lett 203:109853

Blinder AS (1973) Wage discrimination: reduced form and structural estimates. J Hum Resour 8(4):436–455

Blinder AS, Krueger AB (2013) Alternative measures of offshorability: a survey approach. J Law Econ 31(S1):S97–S128

Borjas GJ, Van Ours JC (2010) Labor economics. McGraw-Hill, Irwin Boston

Brugiavini A, Buia R, Simonetti I (2022) Occupation and working outcomes during the coronavirus pandemic. Eur J Ageing 19:863–882

Brunello G, Schlotter M (2011) Non-cognitive skills and personality traits: labour market relevance and their development in education and training systems

Bui TTM, Button P, Picciotti EG (2020) Early evidence on the impact of coronavirus disease 2019 (covid-19) and the recession on older workers. Public Policy Aging Rep 30(4):154–159

Ceurstemont S (2020) Teleworking is here to stay - here's what it means for the future of work. Horizon - The EU Research and Innovation Magazine

Chesher A, Rosen AM (2012) Simultaneous equations models for discrete outcomes: coherence, completeness, and identification. Technical report, cemmap working paper

Chodorow-Reich G, Coglianese J (2021) Projecting unemployment durations: a factor-flows simulation approach with application to the covid-19 recession. J Public Econ 197:104398

De Luca G, Magnus JR, Peracchi F (2022) Asymptotic properties of the weighted-average least squares (wals) estimator. Technical Report 22/03, EIEF Working Paper

De Paula A (2013) Econometric analysis of games with multiple equilibria. Annu Rev Econ 5(1):107–131

Del Boca D, Oggero N, Profeta P, Rossi M (2020) Women's and men's work, housework and childcare, before and during covid-19. Rev Econ Household 18(4):1001–1017

Depalo D, Viviano E (2021) Fear of contagion and labour supply: evidence from Italy. Working papers, Bank of Italy

Dingel JI, Neiman B (2020) How many jobs can be done at home? J Public Econ 189:104235

European Commission (2020) European network of public employment services: short-time work schemes in the EU : April 2020 Study Report. Publications Office of the European Union

Faberman RJ, Mueller AI, Şahin A (2022) Has the willingness to work fallen during the covid pandemic? Labour Econ 79:102275

Fairlie RW (2005) An extension of the blinder-oaxaca decomposition technique to logit and probit models. J Econ Soc Meas 30(4):305–316

Fletcher JM (2013) The effects of personality traits on adult labor market outcomes: evidence from siblings. J Econ Behav Organ 89:122–135
Flinn C, Todd P, Zhang W (2020) Personality traits, job search and the gender wage gap
Fortin N, Lemieux T, Firpo S (2011) Decomposition methods in economics. In: Handbook of labor economics, volume 4, pp 1–102. Elsevier
Goda GS, Jackson E, Nicholas LH, Stith SS (2023) The impact of covid-19 on older workers' employment and social security spillovers. J Popul Econ 36(2):813–846
Goldin C (2014) A grand gender convergence: its last chapter. Am Econ Rev 104(4):1091–1119
Hale T, Webster S, Petherick A, Phillips T, Kira B (2020) Oxford covid-19 government response tracker (oxcgrt). last updated 8, 30
Heckman JJ, Stixrud J, Urzua S (2006) The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. J Law Econ 24(3):411–482
Hermo S, Päällysaho M, Seim D, Shapiro JM (2022) Labor market returns and the evolution of cognitive skills: theory and evidence. Q J Econ 137(4):2309–2361
Horrace WC, Oaxaca RL (2006) Results on the bias and inconsistency of ordinary least squares for the linear probability model. Econ Lett 90(3):321–327
Kalenkoski CM, Pabilonia SW (2022) Impacts of COVID-19 on the self-employed. Small Bus Econ 58(2):741–768
Kline P (2011) Oaxaca-blinder as a reweighting estimator. Am Econ Rev 101(3):532–37
Lamo A, Pérez JJ, Schuknecht L (2013) The cyclicality of consumption, wages and employment of the public sector in the euro area. Appl Econ 45(12):1551–1569
Lin D, Lutter R, Ruhm CJ (2018) Cognitive performance and labour market outcomes. Labour Econ 51:121–135
Lindqvist E, Vestman R (2011) The labor market returns to cognitive and noncognitive ability: evidence from the Swedish enlistment. Am Econ J Appl Econ 3(1):101–28
Mincer JA (1974) Schooling, experience, and earnings. NBER Books
Oaxaca R (1973) Male-female wage differentials in urban labor markets. Int Econ Rev 14(3):693–709
Pietschnig J, Voracek M (2015) One century of global iq gains: A formal meta-analysis of the flynn effect (1909–2013). Perspect Psychol Sci 10(3):282–306
Profeta P (2021) Gender equality and the covid-19 pandemic: labour market, family relationships and public policy. Inter Econ 56(5):270
Sanders C, Taber C (2012) Life-cycle wage growth and heterogeneous human capital. Annu Rev Econ 4(1):399–425
Scherpenzeel A, Axt K, Bergmann M, Douhou S, Oepen A, Sand G, Schuller K, Stuck S, Wagner M, Börsch-Supan A (2020) Collecting survey data among the 50+ population during the covid-19 outbreak: the survey of health, ageing and retirement in Europe (share). In Survey Research Methods 14:217–221
UN (2019) World population prospects 2019: Highlights
Yasenov VI (2020) Who can work from home?
Yun M-S (2004) Decomposing differences in the first moment. Econ Lett 82(2):275–280
Zhang Y (2020) The epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (Covid-19)-China, 2020. China CDC weekly 2(8):113