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OCCUPATIONAL EXPOSURE TO CONTAGION AND THE SPREAD OF COVID-19 IN EUROPE•

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Abstract

Social contacts are a key transmission channel of infectious diseases spread by the respiratory or close-contact route, such as COVID-19. There is no evidence, however, on the question of whether the nature and the organisation of work affect the spread of COVID-19 in different countries. I have developed a methodology to measure country-specific levels of occupational exposure to contagion driven by social contacts. I combined six indicators based on Occupation Information Network (O*NET) and the European Working Condition Survey (EWCS) data. I then applied them to 28 European countries, and found substantial cross-country differences in levels of exposure to contagion in comparable occupations. The resulting country-level measures of levels of exposure to contagion (excluding health professions) predict the growth in COVID-19 cases, and the number of deaths from COVID-19 in the early stage of pandemic (up to eight weeks after the 100th case). The relationship between levels of occupational exposure to contagion and the spread of COVID-19 is particularly strong for workers aged 45-64. I found that 20-25% of the cross-country variance in numbers of COVID-19 cases and deaths can be attributed to cross-country differences in levels of occupational exposure to contagion in European countries. My findings are robust to controlling for the stringency of containment policies, such as lockdowns and school closures. They are also driven by country-specific patterns of social contacts at work, rather than by occupational structures. Thus, I conclude that measuring workplace interactions may help to predict the next waves of the COVID-19 pandemic.

Keywords: COVID-19, contagion, exposure to disease, occupations, organisation of work.

JEL: J01, I10, J44

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1. Introduction and motivation

During February and March 2020, the COVID-19 pandemic spread rapidly across Europe and around the world. By 28 April 2020, more than three million people had been infected, and 213,000 people had died.[1] Between 21 February (Italy) and 18 March (Latvia), all European countries recorded at least 100 cases of COVID-19.[2]

Non-pharmaceutical interventions, such as social distancing and regulatory limits on economic activity and the mobility of people, have been introduced as necessary responses to the pandemic until a vaccine or a cure is developed (Kissler et al., 2020; Leung et al., 2020). Measuring levels of social contact is critical for understanding the spread of infectious diseases transmitted by the respiratory or close-contact route, such as COVID-19. Moreover, it is important to recognise that workplace interactions constitute the majority of social contacts among people of working ages (Kucharski et al., 2020; Mossong et al., 2008). For instance, there is evidence that the spread of influenza is greater when employment levels are higher (Markowitz et al., 2019) and during economic booms (Adda, 2016). It has also been shown that in China, social interactions between residents in Wuhan and other cities played a more important role in the transmission of SARS-CoV-2 between cities than geographical distance (Qiu et al., 2020). However, the intensity of social contacts may differ across occupations, sectors, and countries. An important question that arises in this context is whether labour markets structures and the organisation of work in various countries could have contributed to the transmission of COVID-19 in Europe.

In this paper, I study the occupational exposure to contagion at work, and assess the contribution of this exposure to the spread of COVID-19 in European countries. The patterns of social contacts at work may be particularly relevant for the spread of COVID-19 because of its potential for asymptomatic and presymptomatic transmission, and because of the high basic reproduction number of SARS-CoV-2 (Li et al., 2020). As the median incubation period of SARS-CoV-2 is estimated at approximately five days (Lauer et al., 2020), with the 95% confidence interval at between two and 14 days (Linton et al., 2020), the spread of COVID-19 in the first couple of weeks of the epidemic was most probably largely determined by infections that occurred before 100th case in each country. Only a handful of European countries introduced some form of workplace closures so early (Petherick et al., 2020). Figuring out the role of labour markets in these infections is important for understanding the progress of the COVID-19 pandemic, as well as for preparing for its next waves.

My first contribution in this paper is to develop a methodology to measure country-specific levels of occupational exposure to contagion spread by social contacts. I combine occupational indicators based on Occupation Information Network (O*NET) and European Working Condition Survey (EWCS) data. I use two O*NET variables that measure levels of occupational (1) exposure to disease or infections and (2) physical proximity at work; and four EWCS variables that measure the incidence of (3) dealing with clients, pupils, or patients; (4) working in public spaces; (5) working at the clients' premises; and (6) not being able to work from home. Importantly, the EWCS data allow me to capture the cross-country differences, including within comparable occupations. To my knowledge, my index of occupational exposure to contagion is the first to allow for within-occupation differences between countries. Indices developed by Markowitz et al. (2019) or Béland et al. (2020) used only O*NET data which are available just for the US, and were used to study only the US labour market.

[1] All data on COVID-19 cases and deaths used in this paper come from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) database.

[2] Due to the data availability, I focus on the EU member states, Iceland, Norway, Switzerland, and the United Kingdom.

I find substantial differences in levels of exposure to contagion of workers in comparable occupations in different countries. Specifically, the results show that workers in Southern European countries, France, Switzerland, Sweden, and the UK face the highest levels of exposure to contagion; while workers in Central Eastern European countries face the lowest levels of exposure. I also observe noticeable differences between occupations, with health professionals and personal service workers facing the highest levels of exposure to contagion; and agricultural workers, plant and machine operators, as well as information and communications technology, business, and administration professionals facing the lowest levels of exposure.

My second contribution in this study is to quantify the role of occupational exposure to contagion in the spread of COVID-19 in Europe. To do so, I estimate a range of cross-country regressions that relate the growth in COVID-19 cases and the number of deaths from COVID-19 to levels of occupational exposure to contagion, and to the share of highly exposed workers in particular countries. When calculating the country-level indicators of exposure, I exclude health professions. This ensures that my indicators are not affected by confounders that may also affect the spread of the epidemic, such as the age structure of the population or public choices regarding the health care system. Using employment data from 2015-2018, my indicators reflect the secular features of particular labour markets, and are plausibly exogenous to the spread of COVID-19, as well as to the containment policies introduced in various countries.

I find that higher levels of occupational exposure to contagion were associated with faster growth in COVID-19 cases and larger numbers of deaths. My results are robust to controlling for the stringency of containment policies, such as lockdowns and school closures, and for population density. The relationship between countries' levels of occupational exposure to contagion and the growth in COVID-19 cases is shown to be particularly strong in the first two weeks after the 100th case in each country, and to wane over time. However, the relationship with the number of deaths is found to be the strongest over four weeks after the 100th case. Both of these relationships are quantitatively important: I attribute about 20-25% of the cross-country variance in the growth of cases or in the number of deaths from COVID-19 to cross-country differences in levels of occupational exposure to contagion. The contribution of differences in the containment policies implemented in various countries is of a comparable size. Importantly, the effects associated with occupational exposure are driven by country-specific patterns of social contacts at work rather than by occupational structures. My results are consistent with the clinical and epidemiological evidence on COVID-19. As the median time delay from infection to onset of the illness is about five days, and the median time delay to death is additional 13-17 days (Linton et al., 2020), the growth in cases and in the number of deaths in the early stage of the epidemic are likely to be determined by infections that happened when the number of positive tests was still very low, and mobility was unrestricted. My findings show that cross-country differences in the patterns of social contacts at work could have contributed to differences in the severity of the COVID-19 epidemic across European countries.

In the second section, I outline my methodology for measuring country-specific levels of occupational exposure to contagion. I also present the econometric methodology I use. In the third section, I discuss cross-country differences in levels of exposure to contagion, and characterise the workers who are most exposed to contagion. In the fourth section, I examine the relationship between levels of occupational exposure to contagion and the spread of COVID-19 in European countries. The fifth section concludes.

2. Methodology and data

2.1 Measurement of the occupational exposure to contagious diseases

The concept of my index of occupational exposure to contagious diseases is similar to a job-exposure matrix (JEM) often used in occupational medicine to assess exposure to potentially hazardous agents in large populations (Nieuwenhuijsen, 2009). In order to create it, I combine Occupation Information Network (O*NET) and European Working Condition Survey (EWCS) data. The O*NET database provides detailed and periodically updated descriptions of the specific work activities and job demands associated with each occupation in the US. It provides information for finely disaggregated occupations, and can be used to measure nuanced differences between occupations. However, the O*NET data are available only for the US, and are based on expert assessments or small survey samples. Thus, applying these data to other countries requires the assumption that occupations in different countries are identical.[3] The EWCS data include broader definitions of occupations (two-digit ISCO-08 codes),[4] but are collected in a large number of European countries. Hence, they allow for the measurement of cross-country differences in the nature of work in comparable occupations. Indeed, the EWCS is a primary data source for studying what Europeans do at work (Fernández-Macías et al., 2016). I use the most recent releases of these dataset: O*NET 2018 and EWCS 2015.[5]

I have selected six variables that measure social contacts, the mixing patterns of people in the workplace, and the occupational hazards related to contact with disease, which are critical factors for the spread of infectious diseases transmitted by the respiratory or close-contact route. These variables are occupational (1) exposure to disease or infections (O*NET); (2) physical proximity at work (O*NET); (3) dealing with clients, pupils, or patients (at least around half of the time, EWCS); (4) working in public spaces (at least several times a month, EWCS); (5) working at the clients' premises (at least several times a month, EWCS); and (6) not working from home (working from home no more than a few times a year; EWCS).

The O*NET variables are defined according to importance scales (one to five) at the occupation level. The EWCS variables are defined as binary variables at the worker level, so I calculate their averages at the country-occupation level. To ensure their comparability, I apply the minmax normalisation to each indicator x_{ic}:

$$x_{ic}^{n} = (x - x_{min})/(x_{max} - x_{min}), \quad (1)$$

where x_{min} and x_{max} are the minimum and maximum values of indicator x_{ic} across all occupations i and countries c, and $x_{ic}^{n} \in \langle 0, 1 \rangle$ is the normalised indicator.

Combining indicators based on O*NET and EWCS data provides complementary information about various facets of work. While the two indicators based on O*NET are strongly correlated (0.72 in the pooled sample), the correlations between the O*NET indicators and particular indicators based on the EWCS data are moderate or small (maximum of 0.47). The correlations between particular EWCS indicators are small (maximum of 0.41).

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[3] Such an assumption is often made, for instance when the O*NET data are used to study the task content of jobs and occupational demands related to technology (Goos et al., 2014, Hardy et al., 2018).

[4] I have used 2-digit ISCO disaggregation if the number of observations in an occupation is higher than 15, and 1-digit disaggregation otherwise.

[5] The EWCS is conducted every five years. The next wave is supposed to be conducted in 2020.

Finally, I calculate the average of these normalised indicators to obtain the index of exposure to contagion, $ETC_{ic} \in \langle 0, 1 \rangle$, in occupation i and country c. I assign equal weight to each indicator. A higher value of the index indicates greater exposure to contagion in the workplace.

Table 1. The pairwise correlation matrix between particular indicators and the index of occupational exposure to contagion

	Exposure to disease or infections (O*NET)	Physical proximity (O*NET)	Dealing with clients, pupils, or patients (EWCS)	Working in public spaces (EWCS)	Working at clients' premises (EWCS)	Working not from home (EWCS)	Exposure to contagion (index)
Exposure to disease or infections	1						
Physical proximity	0.72	1					
Dealing with clients, pupils, or patients	0.37	0.47	1				
Working in public spaces	0.03	0.05	0.25	1			
Working at clients' premises	0.00	-0.05	-0.03	0.42	1		
Working not from home	0.14	0.40	-0.08	-0.13	-0.12	1	
Exposure to contagion (index)	0.73	0.83	0.63	0.41	0.31	0.35	1

*Source: Own calculations on O*NET, EWCS, and EU-LFS data.*

Next, I merge the index of occupational exposure to contagion with the worker-level EU-LFS data that provide the most accurate estimates of occupational structures in the European countries.[6]

In order to study the relationship between countries' occupational exposure to contagion and the spread of COVID-19, I define two country-level variables: (1) the country-level average exposure to contagion, ETC_c; and (2) the share of workers who are highly exposed to infectious diseases, $HETC_c$, defined as workers in occupations and countries in which the value of ETC_{ic} is above the European median (calculated with standardised weights that give every country the same total weight).

Importantly, I exclude health professionals (ISCO 22) and associate health professionals (ISCO 32) when calculating the country-level measures of exposure to contagion. The employment shares of health professions are probably endogenous to the factors that may affect the spread of infectious diseases, such as the share of older people in the population, or public choices regarding public health. By excluding health professions from the calculation of country-level measures, I am able to construct variables that are plausibly exogenous to the state of public health and to demographic factors that may affect the spread of COVID-19.

[6] I use the 2018 EU-LFS data, which are the most recent data available at the time of writing.

2.2 Data on COVID-19 cases, policy responses, and other country-level variables

In order to measure the spread of COVID-19, I use data provided by Johns Hopkins CSSE.[7] For each country c, I define the date on which 100 confirmed cases were recorded for the first time. I calculate the average daily growth rate of cases, g_c^t, in period t: over the next $\{1,2,4,5\ to\ 8\}$ weeks after the 100th case. I also calculate the number of deaths due to COVID-19 recorded in these periods, d_c^t. As I study the early stage of the pandemic, I focus on the number of cases and deaths rather than their population rates.

In order to quantify the containment policy responses to the pandemic, I use data from the Oxford COVID-19 Government Response Tracker (OxCGRT, Hale et al., 2020).[8] I use the stringency index proposed by Petherick et al. (2020). Following Abaluck et al. (2020), I control for the average policy stringency over a week, p_c^w, and over a month, p_c^m, following the 100th case in a given country.

I also use two country-level measures of potential social contacts. First, I use population density data provided by Eurostat. Second, I use the mean of the number of reported social contacts calculated on the basis of the POLYMOD survey conducted in eight European countries (Mossong et al., 2008) which are commonly used to calibrate compartmental, epidemiological models.

My final sample for cross-country regressions includes 28 countries for which reliable data on the occupational exposure to contagion, COVID-19 cases and deaths, and OxCGRT policy indicators are available.

2.3 Econometric methodology

In order to characterise the differences in the exposure to contagion across occupations and countries, I regress the exposure to contagion of worker i in occupation j and country c, ETC_{jic}, against occupation fixed effects, γ_o, and country fixed effects, λ_c:

$$ETC_{jic} = \beta_0 + \gamma_o + \lambda_c + \varepsilon_{ijc} \tag{1}$$

In order to analyse the differences between various socio-economic groups in the exposure to contagion and the probability of working in a highly exposed occupation, I estimate linear OLS (2) and logistic (3) regressions:

$$ETC_{jic} = \beta_0 + \beta_1 X_j + \lambda_c + \varepsilon_{ijc} \tag{2}$$

$$\Pr(HETC_{jic} = 1) = F(\beta_0 + \beta_1 X_j + \lambda_c + \varepsilon_{ijc}) \tag{3}$$

where $F(Z) = \frac{e^Z}{1+e^Z}$, and X_j is a vector of personal and workplace characteristics (sex, age, education, contract type, and firm size).

Finally, in order to study the relationship between the spread of COVID-19 and the occupational exposure to contagion, I estimate a range of OLS regressions:

[7] https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series, accessed on 16 July 2020.

[8] https://raw.githubusercontent.com/OxCGRT/covid-policy-tracker/master/data/OxCGRT_latest.csv, accessed on 16 July 2020.

$$y_c^t = \beta_0 + contagion_c + policy_c + population\ density_c + \epsilon_c \quad (4)$$

where, $y_c^t \in \{g_c^t, d_c^t\}$ are the measures of COVID-19 spread (the growth rate of cases and the number of deaths) over the period t, $contagion \in \{ETC_c, HETC_c\}$ represents measures of occupational exposure to contagion, $policy_c$ is a measure of containment policies in country c. I also control for population density to isolate the effect of occupational exposure to contagion from the effect of general exposure to social contacts.

Having estimated the models, I assess the role of the occupational exposure to contagion and containment policies in explaining the cross-country differences in the spread of COVID-19 in Europe. I use the estimated coefficients to decompose the variance of each dependent variable, g_c^t, into the contributions of particular explanatory variables. I use the covariance-based decomposition proposed by Morduch and Sicular (2002). Formally, the contribution of a variable, x, to the cross-country variance of g_c^t is defined as follows:

$$\sigma_{xg_c^t} = \frac{cov(\beta_x x_c\ , g_c^t\ )}{var(g_c^t)} \quad (5)$$

3. Occupational exposure to contagion in European countries – descriptive results

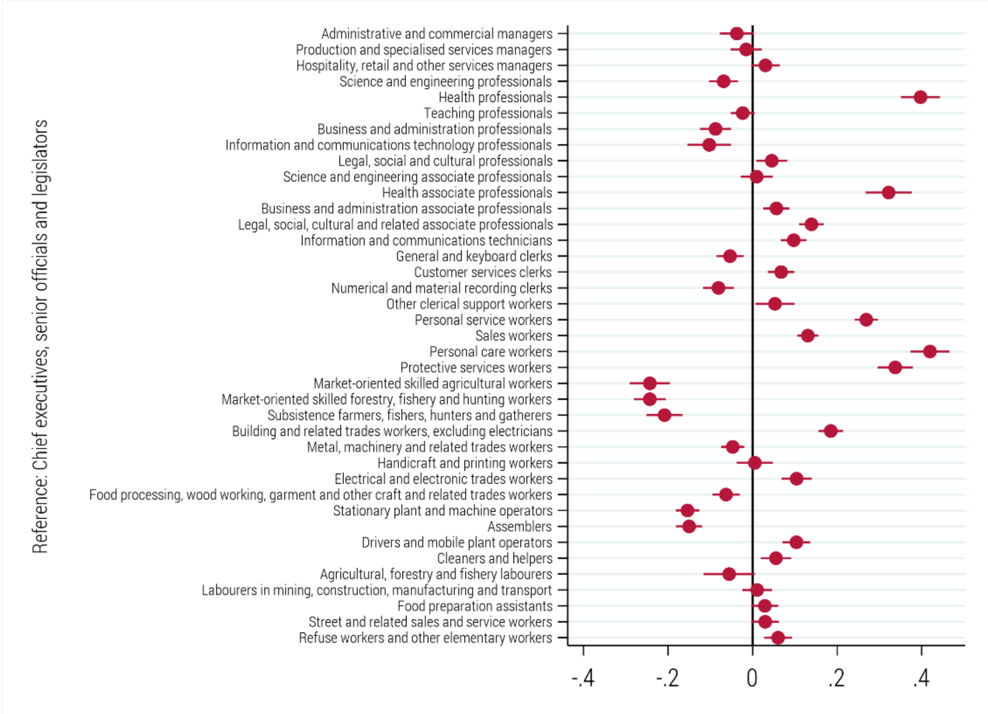
3.1 The differences between occupations and countries in the exposure to contagion

I find substantial differences between various occupations and countries in the exposure to contagion. To quantify these differences, I regress the exposure against occupation and country fixed effects (model 1).

Health professionals, associate health professionals, and personal care workers are found to be the most exposed occupations (Figure 1). Health professions are characterised by having high levels of exposure to infection, large numbers of social contacts, and close physical proximity at work, as shown by the estimates pertaining to particular indicators (Figures A1-A6 in Appendix A). However, personal service workers, protective service workers, sales workers, and building and related trade workers also face rather high levels of exposure to contagion. These are middle- or low-skilled occupations that frequently require workers to have contact with clients and to work at the customers' premises or in public spaces, while only rarely allowing employees to work from home (Figures A1-A6).

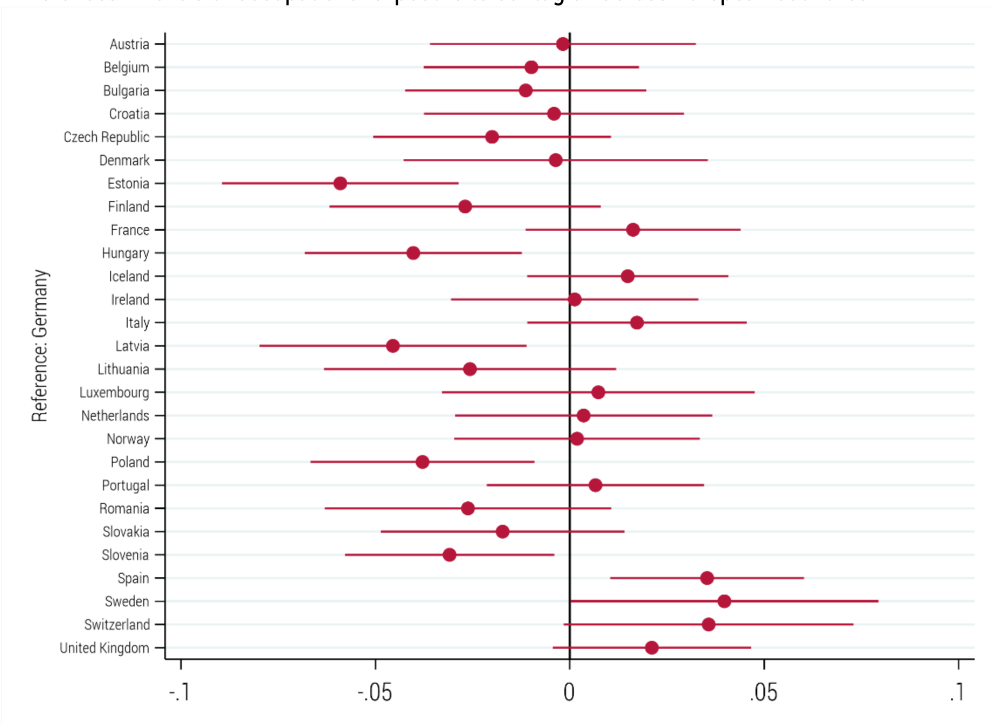
Three groups of occupations stand out as being the least exposed to infectious diseases. The first group is made up of farmers and agricultural workers, who can easily avoid physical proximity and social contact with clients, and who are often working at a home (or on a farm). The second group consists of plant and machine operator, and assemblers, who rarely have contact with clients, or who work in public spaces or at the clients' premises. However, these two groups work in above-average physical proximity to other workers, and do not work from home. The third group is made up of information and communication technology, business, and administration professionals; i.e., workers in high-skilled occupations that do not involve many social contacts or close physical proximity, do not require employees to work in public spaces, and can often be performed at home (Figures A1-A6).

Figure 1. Differences in levels of exposure to contagion across two-digit ISCO occupations in Europe.



Note: The coefficients are estimated in a worker-level model on the index of exposure to contagion against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
*Source: Own estimation on the basis of EU-LFS, EWCS and O*NET data.*

Figure 2. Differences in levels of occupational exposure to contagion across European countries.



Note: The coefficients are estimated in a worker-level model on the index of exposure to contagion against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
*Source: Own estimation on the basis of EU-LFS, EWCS and O*NET data.*

Importantly, I find noticeable cross-country differences in levels of exposure to contagion among workers in the same occupations. Workers in Southern European countries, France, Switzerland, Sweden, and the UK face the highest levels of exposure, while workers in Central Eastern European countries face the lowest levels of exposure (Figure 2). These differences are driven by cross-country differences in the facets of work that I measure using the EWCS data. Workers in Southern European countries, France, and the UK exhibit high levels of social contact with clients, students, or patients; and they rarely work from home (Figure A7). Workers in Nordic countries also frequently work in public spaces or at the clients' premises (Figure A8), but they also work from home relatively often (Figure A10). On the other hand, compared to workers in Western European countries, workers in Central and Eastern European countries deal with clients, pupils, or students and work at the clients' premises much less frequently, (Figures A7, A9), although they also work from home less often (Figure A10).

3.2 The socio-economic characteristics of workers exposed to contagion

Here, I estimate a linear OLS model and the logit model to characterise the correlates of occupational exposure to contagion, and of the probability of working in a highly exposed occupation, respectively. The results are presented in Table 2.

Female workers face higher levels of exposure to contagion than male workers, and are also by 7 pp. more likely to work in the highly exposed occupations.[9] Moreover, the levels of occupational exposure to contagion are the highest for younger workers, especially those aged 15-34; and are the lowest for older workers, especially those aged over 65. Higher levels of exposure to contagion are also related to lower levels of educational attainment. However, in terms of the likelihood of working in highly exposed occupations, it is only the tertiary educated workers who stand out as having a significant, by 13 pp. lower risk than less educated workers. Compared to single workers, workers who are married or in a relationship are by 10 pp. less likely to work in highly exposed occupations. Workers with temporary contracts exhibit higher levels of exposure than workers with permanent contracts, but the effect is small, and they are not more likely to work in highly exposed occupations. The presented evidence shows that the workers who are more exposed to contagion are those with weaker labour market positions: i.e., these workers are disproportionately likely to be less educated, young, female, and employed with a temporary contract.

[9] Note that I do not control for occupational nor sectoral fixed effects, as I am interested in describing how the patterns of occupational and sectoral gender segmentation (Jarman et al., 2012) translate into differences in levels of occupational exposure to contagion.

Table 2. The individual and workplace correlates of occupational exposure to contagion

	Occupational exposure to contagion	Probability of working in a highly exposed occupation (marginal effects)
Female	0.047***	0.069***
	(0.007)	(0.019)
Married / in relationship	0.000	-0.010**
	(0.001)	(0.004)
Age 15-24	0.023***	0.091***
	(0.004)	(0.013)
Age 25-34	0.008***	0.026***
	(0.001)	(0.005)
Age 45-54	-0.001	-0.011***
	(0.001)	(0.004)
Age 55-65	0.001	-0.021***
	(0.002)	(0.007)
Age 65-74	-0.014	-0.052***
	(0.011)	(0.020)
Education: Primary or less	-0.028**	0.011
	(0.012)	(0.040)
Education: Lower secondary	-0.019***	-0.007
	(0.007)	(0.019)
Education: College or higher	-0.032***	-0.134***
	(0.009)	(0.023)
Temporary contract	0.017***	0.014
	(0.005)	(0.012)
Country fixed effects	Yes	Yes
R2 / pseudo R2	0.082	0.048
Observations	1 582 646	1 582 646

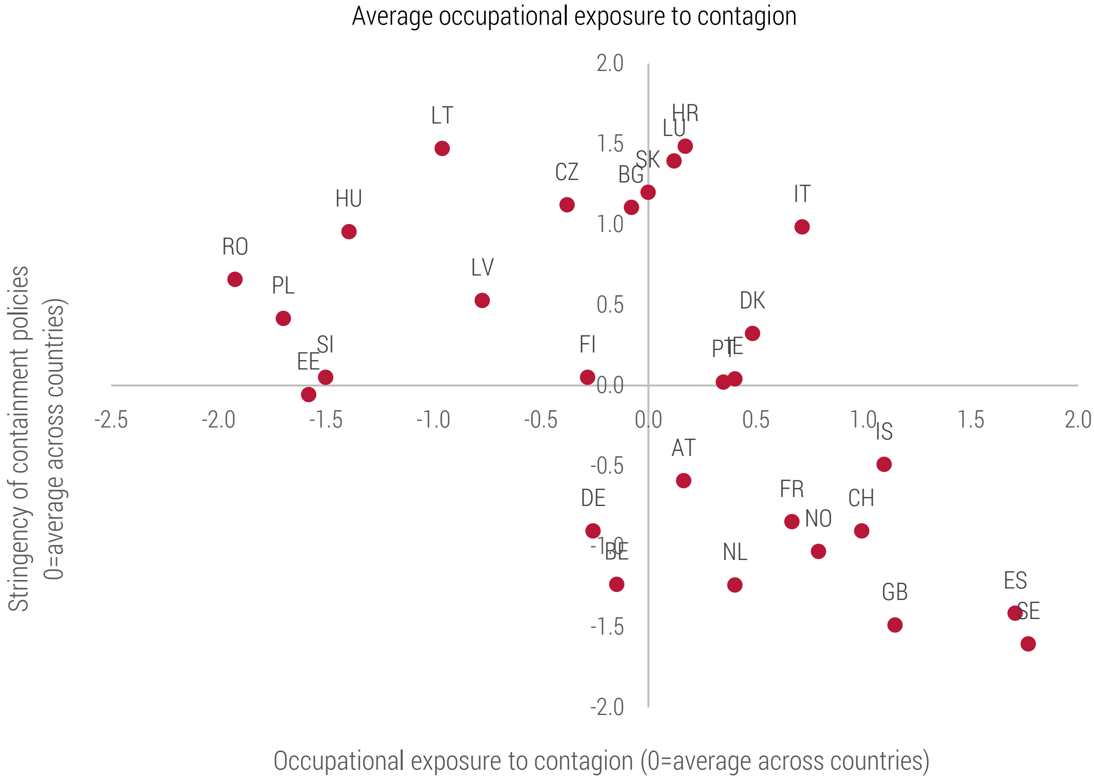
Note: The coefficients estimated in pooled regressions are estimated in a worker-level model with standardised weights, which gives each country equal importance. Reference groups: male, ages 34-45, upper secondary education, firm size up to 10 workers, Germany. Results for firm size are available upon request. Standard errors clustered at country x occupation level.
*Source: Own estimation on the basis of EU-LFS, EWCS and O*NET data.*

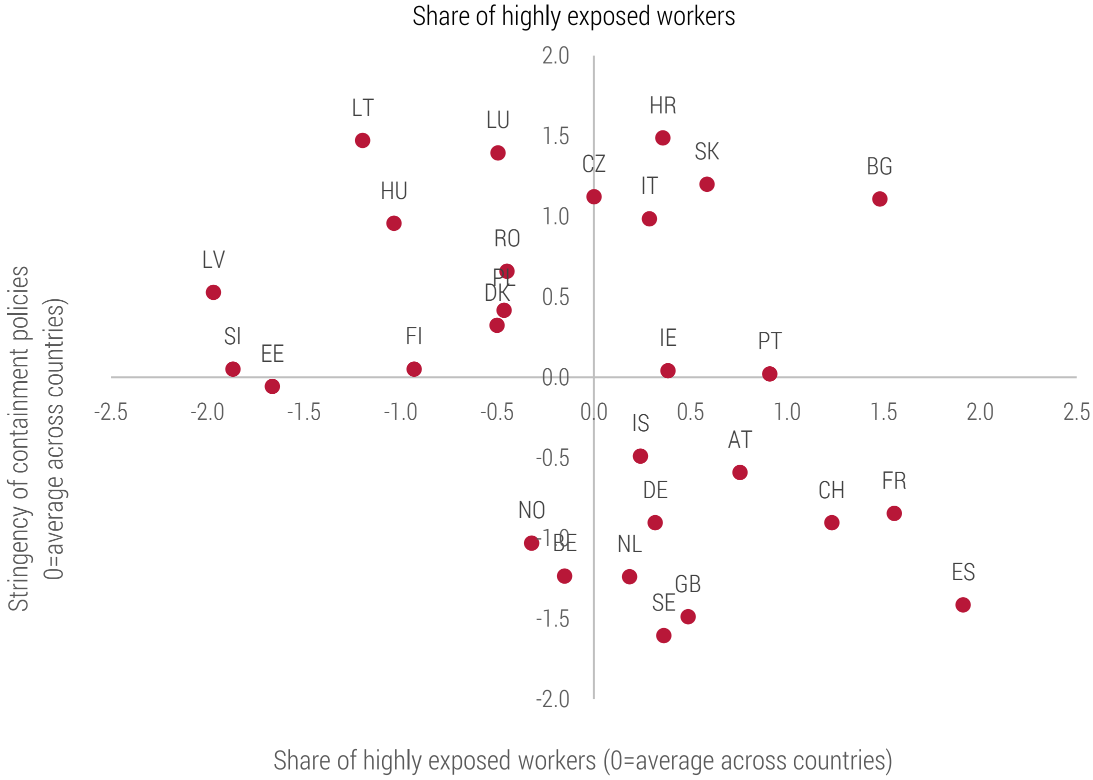
3.3 Cross country differences in the occupational exposure to contagion and containment policy

I exclude the health professions (ISCO 22 and ISCO 32) from the remainder of my analysis, in particular from the calculation of country-level indicators and from the econometric analysis. This allows me to measure the differences in the levels of exposure to contagion in jobs that generally are not tailored to dealing with contagion.

The cross-country differences found in the average level of exposure to contagion, as well as in the share of workers in highly exposed jobs, are consistent with the within-occupation differences discussed above. The Southern European countries, the Nordic countries, and the United Kingdom exhibit the highest average exposure levels, while the Central and Eastern European countries exhibit the lowest average exposure levels (Figure 3). The Southern European countries also stand out as having the largest shares of workers who are highly exposed to contagion. Interestingly, in the Nordic countries, these shares are moderate in size, which suggests that the high average exposure level in those countries is related to the relatively high exposure levels across all occupations, rather than to the presence of occupations that are very highly exposed. The opposite is shown to be the case for some Central and Eastern European countries and some Balkan countries, as well as for Switzerland and Austria.

Figure 3. Cross country differences in the occupational exposure to contagion and containment policy.





Note: Excluding health professionals (ISCO 22) and health associate professionals (ISCO 32). Stringency of containment policy calculated as an average over 7 days after the 100th case in each country.
*Source: Own calculations on the basis of EU-LFS, EWCS, O*NET, and John Hopkins CSEE data.*

There are also noticeable cross-country differences in the stringency of containment policies introduced in the early stage of the epidemic. The Central and Eastern European countries implemented relatively more strict policies, while the Western continental countries, the United Kingdom, Spain and Sweden implemented rather lax containment policies (Figure 3).

4. Econometric results and discussion

4.1 The growth of COVID-19 cases

Next, I present the results of estimated cross-country models (4) that relate the spread of COVID-19 to occupational exposure to contagion, while controlling for the stringency of containment policies and population density.

I find a positive, significant relationship between the level of occupational exposure to contagion and the growth in COVID-19 cases in European countries (Table 3). This relationship is robust to controlling for the stringency of containment policies and population density. The effects pertaining to the share of workers in highly exposed jobs, $HETC_c$, are stronger than the effects pertaining to the average exposure, ETC_c. Moreover, the former are significant for all time horizons, while the latter are significant only for the growth in cases over seven days. My findings suggest that the incidence of workers who have particularly high numbers of social contacts due to meetings with clients, pupils, or patients, or due to working in public spaces or at the clients' premises, may be more relevant for the spread of SARS-CoV-2 than the average levels of such activities in a particular labour market.

Table 3. The effects of occupational exposure to contagion on COVID-19 case growth (in pp)

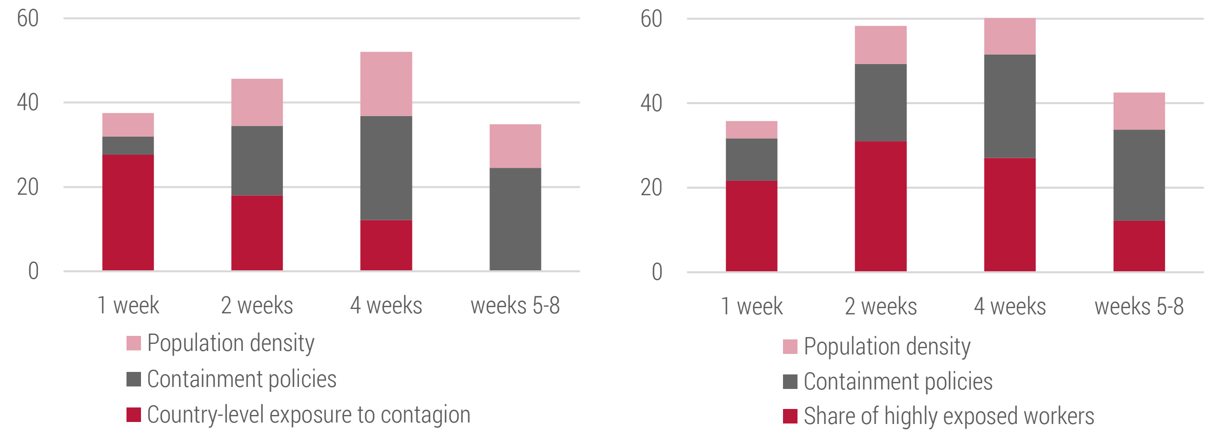
	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
	Country-level occupational exposure to contagion							
ETC	0.052***	0.045***	0.041***	0.026*	0.029***	0.014	0.004	0.000
	(0.011)	(0.016)	(0.012)	(0.014)	(0.009)	(0.011)	(0.003)	(0.003)
R2	0.321	0.375	0.282	0.456	0.246	0.521	0.087	0.349
	Share of workers highly exposed to contagion							
HETC	0.048***	0.038**	0.049***	0.037**	0.036***	0.026***	0.006***	0.004**
	(0.014)	(0.017)	(0.012)	(0.013)	(0.009)	(0.009)	(0.002)	(0.002)
R2	0.272	0.358	0.405	0.583	0.382	0.647	0.180	0.425
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case (results of regressions using the average of containment policy averaged of over 7 days consistent with these presented and are available upon request).
**** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

As the time horizon expanded and countries tightened their containment measures, the contribution of labour market interactions waned while the role of containment policies increased.[10] This is shown by the regression-based decompositions of cross-country variance in the growth in cases (Figure 4). In the first seven days after the 100th case in each country, 28% of variance in the growth in cases can be attributed to the cross-country differences in the average levels of occupational exposure to contagion, while only 4% can be attributed to the differences in containment policies. As the time horizon expands, the contribution of occupational exposure declines (12% over the first four weeks, and no contribution in the following four weeks of the epidemic in each country). In the model in which I include the share of highly exposed workers, the highest contribution is recorded over the first two weeks after the 100th case in each country (31%). It declines to 27% in the first four weeks, and 12% in the following four weeks. In both specifications, the contribution of containment policy increases as the time horizon expands, to 20-25% over the first four weeks and the following four weeks. The contribution of differences in population density is about 10% across all time horizons considered.

In the first two weeks after the 100th case, the growth in the number of COVID-19 positive tests was largely determined by the infections that occurred before the 100th case. Thus, my findings suggest that international differences in patterns of labour market interactions could have contributed to the differences in the numbers of such infections across European countries.

Figure 4. Regression-based decomposition of the cross-country variance of the average daily growth of COVID-19 cases, by period after the 100th case in each country (in % of variance).



Note: The variance decompositions are based on the models presented in Table 3, calculated in line with equation (5).
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Next, I examine whether the effects differ between subpopulations. To do so, I focus on the share of workers in highly exposed occupations, $HETC_c$, which I have just found to be a more relevant measure of exposure. The results for the group-specific average occupational exposure, ETC_c, are comparable to those presented in Tables 3-4, and are available upon request.

I find important differences between age groups. The relationship between the share of highly exposed workers and the spread of COVID-19 is noticeably stronger for older workers than for prime-aged and young workers (Table 4). It is most pronounced for workers aged 45-54, followed by for workers aged 55-64. The cross-country differences in the share of highly exposed workers in these two age groups contribute more to the variance in COVID-19 growth

[10] For clarity of presentation, I do not show the estimated coefficients pertaining to policy variables. They are available upon request.

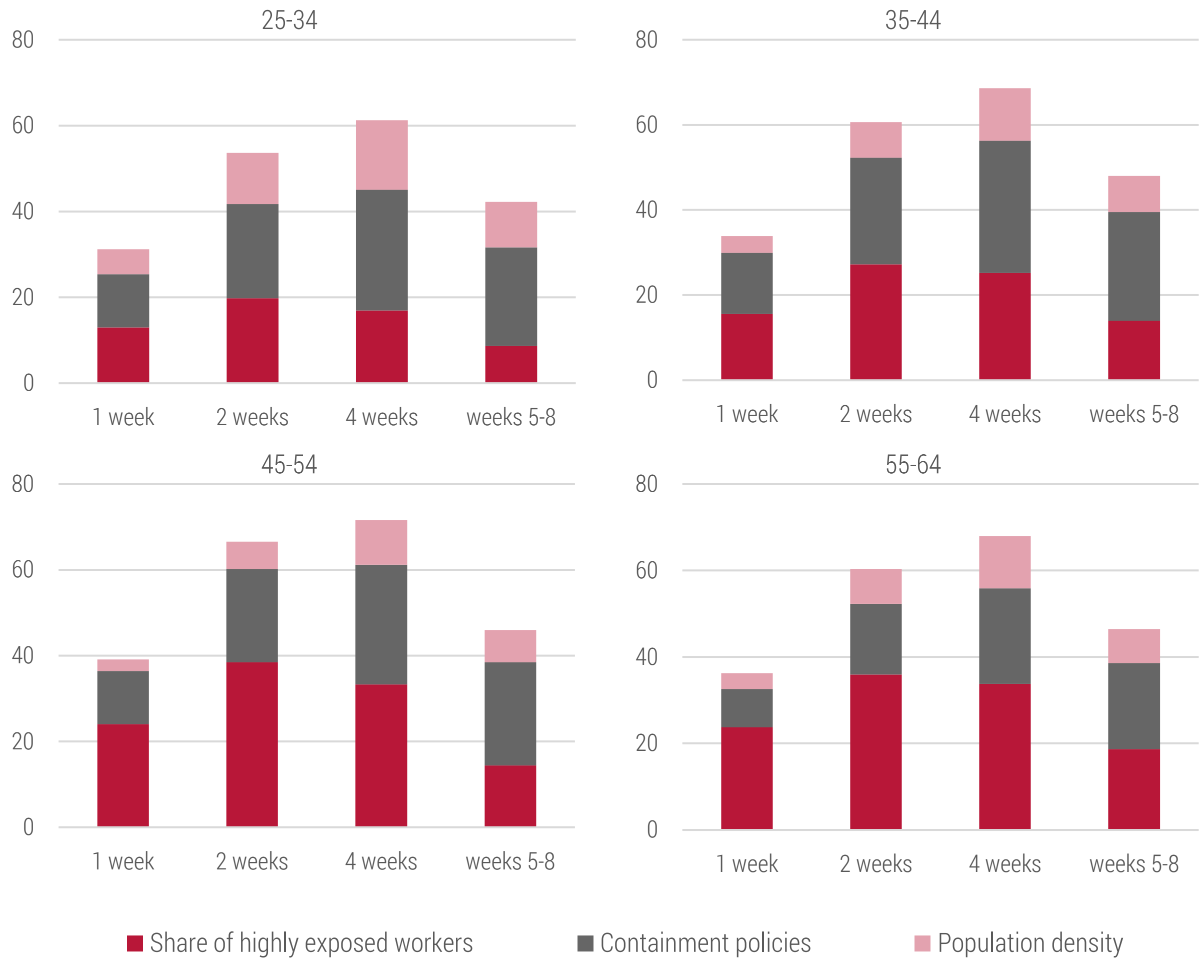
rates than the cross-country differences in containment policies (Figure 8). For workers aged 35-44, the relationship with the growth in COVID-19 cases is also significant, but is weaker than the effects for older workers. On the other hand, the coefficients pertaining to the share of highly exposed workers among young workers (15-24) are insignificant (Table 4), and their resulting contributions to the variance in the growth in COVID-19 cases are noticeably smaller than the contributions of older groups and the overall contribution (Figure 5).

Table 4. The effects of age-specific occupational exposure to contagion on COVID-19 case growth in Europe

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
Share of workers highly exposed to contagion among workers aged 15-24								
HETC, 15-24	0.037** (0.017)	0.024 (0.021)	0.025* (0.013)	0.005 (0.014)	0.017 (0.010)	-0.001 (0.011)	0.003 (0.003)	-0.001 (0.003)
R2	0.160	0.255	0.106	0.377	0.086	0.478	0.050	0.354
Share of workers highly exposed to contagion among workers aged 25-24								
HETC, 25-34	0.036* (0.020)	0.031 (0.019)	0.037** (0.017)	0.031** (0.014)	0.027** (0.013)	0.022** (0.010)	0.005** (0.002)	0.004** (0.002)
R2	0.150	0.312	0.231	0.536	0.206	0.612	0.101	0.422
Share of workers highly exposed to contagion among workers aged 35-44								
HETC, 35-44	0.039* (0.019)	0.034* (0.017)	0.043** (0.016)	0.037*** (0.013)	0.032** (0.012)	0.027*** (0.009)	0.006** (0.002)	0.005** (0.002)
R2	0.178	0.338	0.312	0.606	0.298	0.686	0.146	0.480
Share of workers highly exposed to contagion among workers aged 45-54								
HETC, 45-54	0.049*** (0.013)	0.041*** (0.014)	0.052*** (0.010)	0.043*** (0.010)	0.039*** (0.008)	0.030*** (0.006)	0.006*** (0.002)	0.005** (0.002)
R2	0.286	0.391	0.466	0.666	0.429	0.716	0.177	0.460
Share of workers highly exposed to contagion among workers aged 55-64								
HETC, 55-64	0.050*** (0.011)	0.040** (0.016)	0.052*** (0.009)	0.040*** (0.012)	0.040*** (0.007)	0.029*** (0.008)	0.008*** (0.002)	0.005** (0.002)
R2	0.298	0.362	0.468	0.604	0.472	0.679	0.269	0.464
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case (results of regressions using the average of containment policy averaged of over 7 days consistent with these presented and are available upon request).
**** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Figure 5. Regression-based decomposition of the cross-country variance in the average daily growth of COVID-19 cases, using age-specific shares of workers highly exposed to contagion, by period after the 100th case in each country (in % of variance).



Note: The variance decompositions are based on the models presented in Table 4, calculated in line with equation (5). To save space, I do not show the results for the 15-24 age group, for whom the contribution of exposure variable to the variance is close to zero; these results are available upon request.
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

On an individual level, older people are less likely to be working in the highly exposed occupations (Table 2). The strong relationship between the level of occupational exposure to contagion among older workers and the spread of COVID-19 is related to the observation that in countries with higher shares of highly exposed workers, these workers tend to be older. The correlation between the share of highly exposed workers and the average ages of these workers in a country is positive (0.18), while the correlation between this share and the average age of all workers in a country is zero (-0.01). My findings are consistent with evidence that people aged 50-59 are particularly likely to get sick and transmit the virus, and that people aged 60 or older are the most likely to be severely ill when infected with SARS-CoV-2 (Goldstein et al., 2020).

Importantly, I find that the effect of occupational exposure to contagion on the spread of COVID-19 is driven by cross-country differences in the nature of work within particular occupations, rather than by differences in occupational structures. This observation is confirmed by the regression results based on the assumption that occupations are identical across countries (Table B1 Appendix B). If I use occupational averages of my indicators (calculated across countries) instead of country-specific values of exposure to contagion, I find no significant effect of levels of exposure on COVID-19 spread. Hence, these are the country-specific patterns of social contacts at work that matter most, and that drive the results described above.

As a robustness check, I change the definition of highly exposed workers to workers who belong to the top 40% of the joint distribution of levels of occupational exposure to contagion across all countries (using standardised weights), instead of the top 50%. After re-estimating the models, I obtained comparable coefficients and the same conclusions. The results are presented in Tables B2-B3 in Appendix B.

Finally, although I control for the stringency of containment policies, many other factors cannot be controlled for in a cross-country study like this one. Therefore, I test whether potential key confounders can explain the identified relationship between the levels of occupational exposure to contagion and the spread of COVID-19 in Europe. I focus on social contacts, measured by the number of average daily social contacts reported by Mossong et al. (2008). I re-estimate model (4) using this variable instead of levels of occupational exposure to contagion. The data on the average number of social contacts reported by Mossong et al. (2008) are available for eight countries only.[11] Considering this small sample size, these results should be treated as indicative. Nevertheless, they indicate that there was no significant relationship between the average number of social contacts and the growth in COVID-19 cases up to the first four weeks of epidemic in each country. At the same time, a significant relationship is found between the share of highly exposed workers and the growth in COVID-19 cases in the same country sample (Table B4 in Appendix B). At a later stage of the pandemic (weeks five to eight), both the average number of social contacts and the share of workers in highly exposed occupations are modestly and positively related to the growth in the number of cases. In general, the occupational exposure to contagion turns out to be a better predictor of the spread of COVID-19 than the average number of social contacts.[12]

4.2 The number of deaths from COVID-19

In this subsection, I repeat the analysis by focusing on the number of deaths from COVID-19 rather than on the number of cases. While the number of cases is a more intuitive measure of the epidemic spread, testing rates and the rules that define the classification of cases may vary between countries, and measurement error may affect the data on cases. Therefore, deaths may be measured more precisely than case numbers.

Findings on the importance of levels of occupational exposure to contagion are confirmed. Across European countries, higher levels of occupational exposure to contagion were significantly and positively related to the number of deaths from COVID-19, even after controlling for the stringency of containment policies (Table 5). The effects are again shown to be the strongest for workers aged 45-54 and 55-64, and to be insignificant for workers aged 15-24 and 25-34.

[11] These are: Belgium, Finland, Germany, Italy, Luxembourg, Netherlands, Poland, United Kingdom.

[12] The data reported by Mossong et al. (2008) were collected in 2006-2007, but are likely to be a good proxy of the current patterns of social contacts. Klepac et al. (2020) used recently collected data for the UK to show that the patterns of social contacts have remained remarkably stable over time, except for teenagers, among whom the number of social contacts has declined.

Table 5. The effects of occupational exposure to contagion on the number of deaths from COVID-19, by period

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
Country-level occupational exposure to contagion								
ETC	2.52	3.61	36.13*	40.02	798.75*	722.65	3024.78**	2229.36*
	(1.72)	(2.12)	(19.62)	(24.79)	(423.01)	(444.81)	(1179.56)	(1230.86)
R2	0.097	0.197	0.161	0.207	0.207	0.234	0.201	0.289
Share of workers highly exposed to contagion								
HETC	2.66*	2.85	36.88*	34.54*	813.23*	695.45	3022.20**	2363.33*
	(1.50)	(1.73)	(18.06)	(19.64)	(428.50)	(415.46)	(1148.06)	(1194.03)
R2	0.108	0.163	0.168	0.195	0.214	0.251	0.201	0.325
Share of workers highly exposed to contagion among workers aged 15-24								
HETC, 15-24	0.91	1.41	15.79	12.33	354.36	117.78	1259.44	-186.72
	(1.16)	(1.16)	(12.48)	(13.14)	(263.07)	(222.08)	(881.88)	(965.68)
R2	0.013	0.076	0.031	0.079	0.041	0.116	0.035	0.211
Share of workers highly exposed to contagion among workers aged 25-24								
HETC, 25-34	2.17	2.4	32.47*	32.21	678.76	619.74	2226.23*	2028.68*
	(1.60)	(1.73)	(18.90)	(19.59)	(414.87)	(378.93)	(1148.59)	(1112.21)
R2	0.072	0.139	0.130	0.188	0.149	0.232	0.109	0.300
Share of workers highly exposed to contagion among workers aged 35-44								
HETC, 35-44	2.91*	2.76	37.26*	34.62*	785.13*	722.36*	2811.85**	2691.63**
	(1.57)	(1.72)	(19.16)	(19.47)	(431.05)	(410.66)	(1233.41)	(1226.87)
R2	0.129	0.168	0.171	0.210	0.200	0.278	0.174	0.366
Share of workers highly exposed to contagion among workers aged 45-54								
HETC, 45-54	3.25**	3.17*	41.21**	37.83*	896.35*	801.30*	3334.78***	2929.16**
	(1.48)	(1.74)	(18.38)	(19.95)	(441.99)	(443.09)	(1116.65)	(1147.50)
R2	0.162	0.195	0.210	0.228	0.260	0.305	0.244	0.388
Share of workers highly exposed to contagion among workers aged 55-64								
HETC, 55-64	2.65*	2.93	36.65*	34.52*	842.89*	724.4	3423.41***	2685.09**
	(1.50)	(1.73)	(18.07)	(19.56)	(438.82)	(438.62)	(1211.17)	(1247.06)
R2	0.107	0.163	0.166	0.188	0.230	0.255	0.257	0.351
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case (results of regressions using the average of containment policy averaged of over 7 days consistent with these presented and are available upon request).

***** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Figure 6. Regression-based decomposition of the cross-country variance in the number of deaths from COVID-19, by period after the 100th case in each country (in % of variance).

Note: The variance decompositions are based on the models presented in Table 5, calculated in line with equation (5). To save space, I do not show results for the 15-24 age group, for whom the contribution to the variance is close to zero; these results are available upon request.
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Importantly, the contribution of levels of occupational exposure to contagion to the cross-country variance in the number of deaths was increasing with time (Figure 6). The contribution of containment policies was also increasing with time but at all time horizons it was noticeably smaller than the contribution of occupational exposure. Overall, my models explain a larger share of the variance in the number of deaths recorded in the weeks 5-8 after the 100th case than in the number of deaths recorded in the first four weeks after the 100th case. My results are consistent with the clinical and epidemiological evidence on COVID-19: the median time delay from the onset of the illness to death is estimated at 13-17 days (Linton et al., 2020), and there is a lag of approximately three weeks between the start of social distancing and the peak of critical care demand (Kissler et al., 2020). Hence, the number of deaths in the first few weeks of the epidemic was largely driven by infections that occurred when the number of confirmed cases was still relatively low. My findings show that the cross-country differences in the patterns of social contacts at work could have contributed substantially to the differences in the severity of the COVID-19 epidemic across European countries.

5. Summary and conclusions

In this paper, I have developed a methodology to measure levels of occupational exposure to contagion, in particular to contagion by infectious diseases transmitted by the respiratory or close-contact route, such as COVID-19. I have combined six indicators based on the Occupation Information Network (O*NET) and the European Working Condition Survey (EWCS) data that measure occupational (1) exposure to disease or infections; (2) physical proximity at work; as well as the incidence of (3) dealing with clients, pupils, or patients; (4) working in public spaces; (5) working at the clients' premises; and (6) not being able to work from home. The use of EWCS data allowed me to quantify the cross-country differences between workers in comparable occupations. I have shown that there are clear differences: workers in Southern European countries, in the Nordic countries, and in France and the UK are the most exposed to contagion at work; while workers in Central Eastern European countries are the least exposed to contagion at work. Health professionals are the most exposed occupations, followed by workers in sales and personal and protective services. Conversely, farmers, plant and machine operators, as well as technology and business professionals are the least exposed occupations. Moreover, the workers who are most exposed to contagion tend to be those with weaker labour market positions: i.e., they are disproportionately female, young, and less educated.

I have used my occupational indicators to quantify the levels country-level exposure to contagion. In doing so, I have excluded health professions. This ensured that the country-level measures are not related to public choices regarding health care systems, and are likely exogenous to the spread of COVID-19. After estimating a range of cross-country regressions, I found that countries with higher levels of occupational exposure to contagion recorded faster growth in numbers of COVID-19 cases, and in numbers of deaths. I found that these effects were the strongest for the measures of exposure to contagion among workers aged 45-64, which is consistent with evidence that older workers are more likely to be seriously infected by SARS-CoV-2. My findings are robust to controlling for the stringency of containment policies, such as lockdowns and school closures. The estimated effects are also quantitatively relevant. In the first 1-2 weeks after the 100th confirmed case, about 20-25% of the cross-country variance in the growth in cases was attributable to differences in countries' levels of occupational exposure to contagion. Over a longer time horizon, the contribution of exposure declined while the contribution of containment policies became dominant. In the case of deaths, however, the contribution of countries' levels of occupational exposure to contagion was the highest in the four-week time horizon. These patterns are consistent with clinical and epidemiological evidence showing that the COVID-19 incubation period can last a week or more, and that the median time from the onset of symptoms to death can be around two weeks. Thus, the early trajectory of the epidemic in particular countries was probably determined by infections that were passed when the number of cases was still low and social distancing had not yet been implemented. My findings suggest that differences in the nature of work in particular countries might have contributed to differences in the numbers of these infections. Indeed, my results are driven by country-specific patterns of social contacts at work, rather than by occupational structures.

My study has limitations. First, I measure the spread of COVID-19 with the number of positive tests and deaths, but countries may differ in the testing effort. Indeed, according to the Our World in Data (2020) data, there are differences in the number of tests per 1,000 people in European countries. However, the correlation between the testing effort and the growth in cases or the number of deaths in my country sample is negative. Hence, the cross-country differences in the number of cases and deaths are not driven by the differences in testing. Second, I focus on country level exposure while outbreaks may be driven by local transmission clusters. However, my findings are consistent with the evidence that settings such as bars & restaurants, elderly care units, and conferences contribute a substantial share of SARS-CoV-2 transmission clusters (Leclerc et al., 2020). The occupations that I have found as highly exposed – for instance personal and protective services workers, and sales workers – are usually employed in such establishments. Third, I control for the *de iure* differences in containment policies while compliance and social norms towards social norms may differ between countries. Fourth, my measures are based no the pre-lockdown data and do not provide precise measurements of occupational exposure during and post-lockdown. It is because the intensity of contacts and workplace interactions have most likely changed due to restrictions and endogenous, uncoordinated social distancing (Toxvaerd, 2020).

The levels of complexity of social networks differ between countries. Larger social networks can facilitate technology diffusion and increase productivity, but the prevalence of infectious pathogens can undermine these benefits by accelerating disease spread (Fogli and Veldkamp, 2019). Before the arrival of COVID-19, the European countries studied in this paper had been relatively free from infectious diseases outbreaks, barring a sporadic flu epidemic. The organisation of work could have been tailored to reap the benefits from these networks. My findings help to explain why some of the richer European countries, such as France, Italy, the UK, and Sweden, have recorded more serious outbreaks than the less developed countries in my sample, especially those in Central Eastern Europe. Finally, my findings also suggest that measuring workplace interactions and the incidence of work in public spaces, clients' premises, etc., may help to predict the next waves of the COVID-19 pandemic. The regularly conducted, large-scale labour force surveys can be adapted to collect such data during lockdowns and when the restrictions are lifted. This would allow to measure exposure at a more finely disaggregated level, for instance between men and women or workers at different age in the same occupation, and would help to apply economic methods to detect pandemic spread in economic networks (Murray, 2020).

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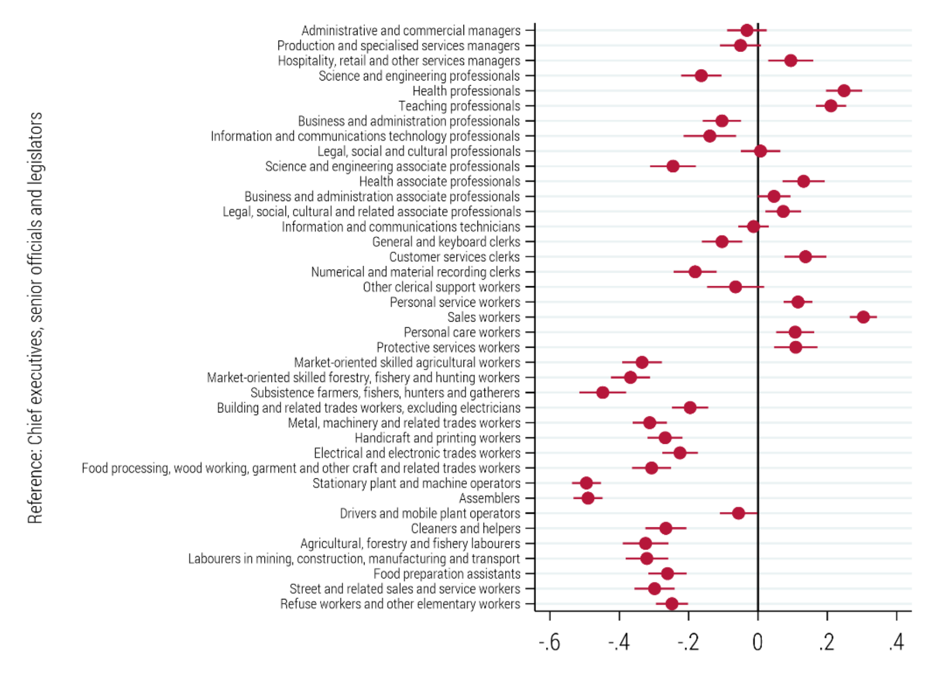
Appendices

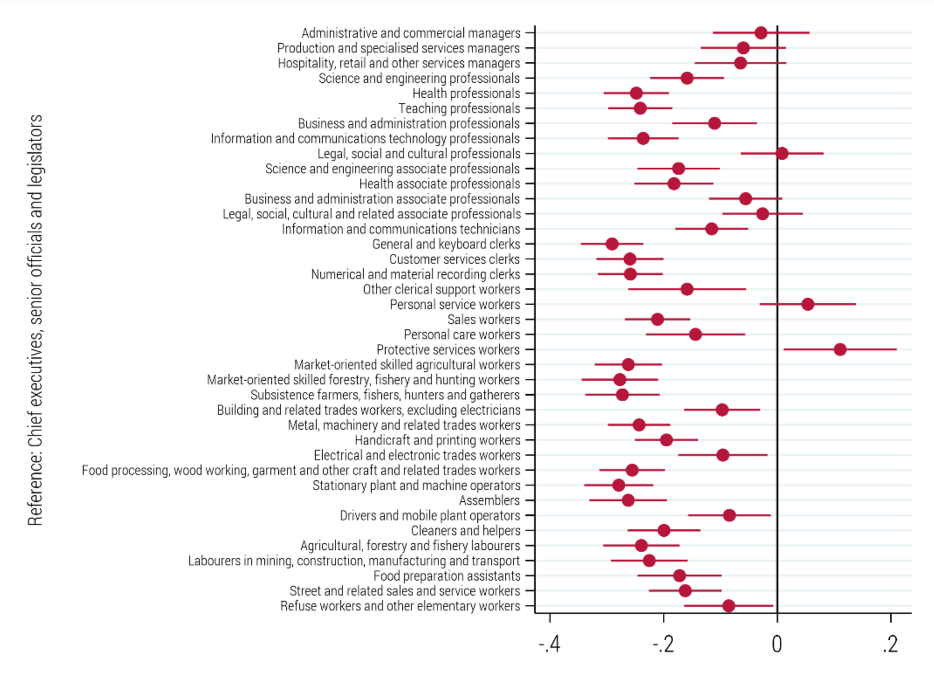
Appendix A. Cross-country and occupational differences in particular indicators

Figure A1. Differences in the incidence of dealing with clients, pupils, or patients across two-digit ISCO occupations in Europe.



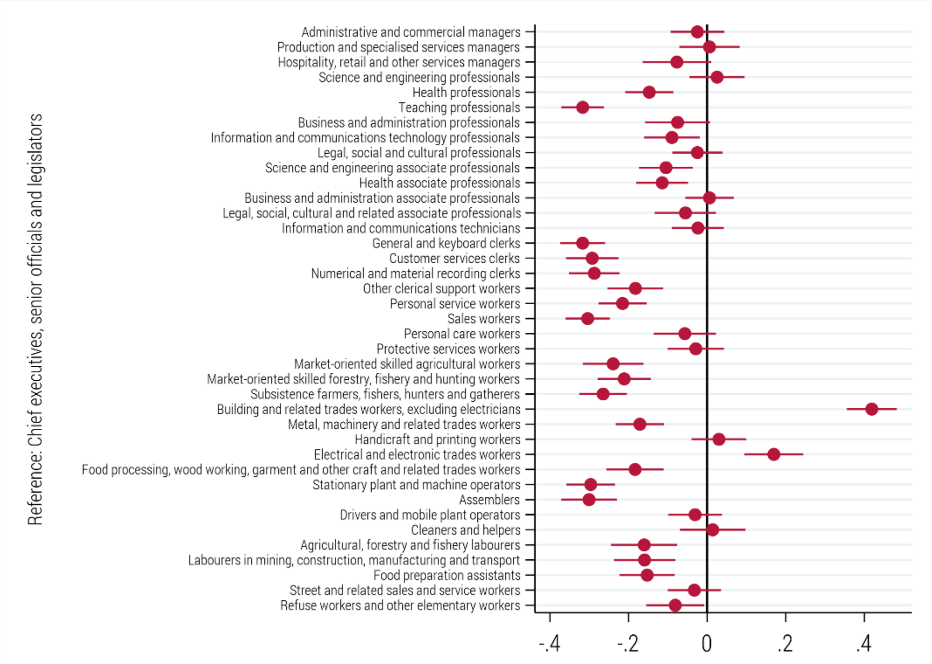
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A2. Differences in the frequency of working in public spaces across two-digit ISCO occupations in Europe.



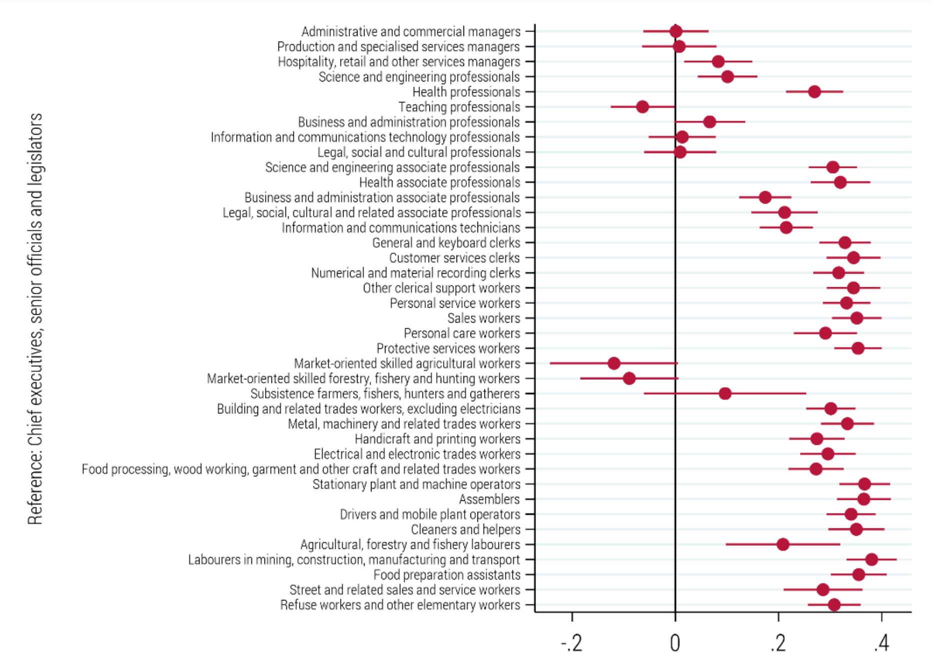
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A3. Differences in the frequency of working at the clients' premises across two-digit ISCO occupations in Europe.



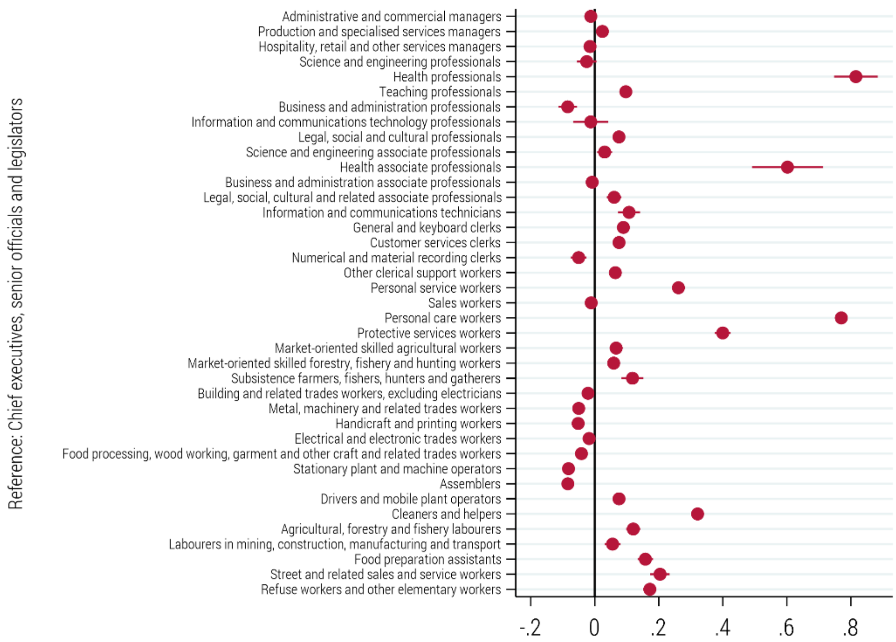
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A4. Differences in not being able to work from home across two-digit ISCO occupations in Europe.



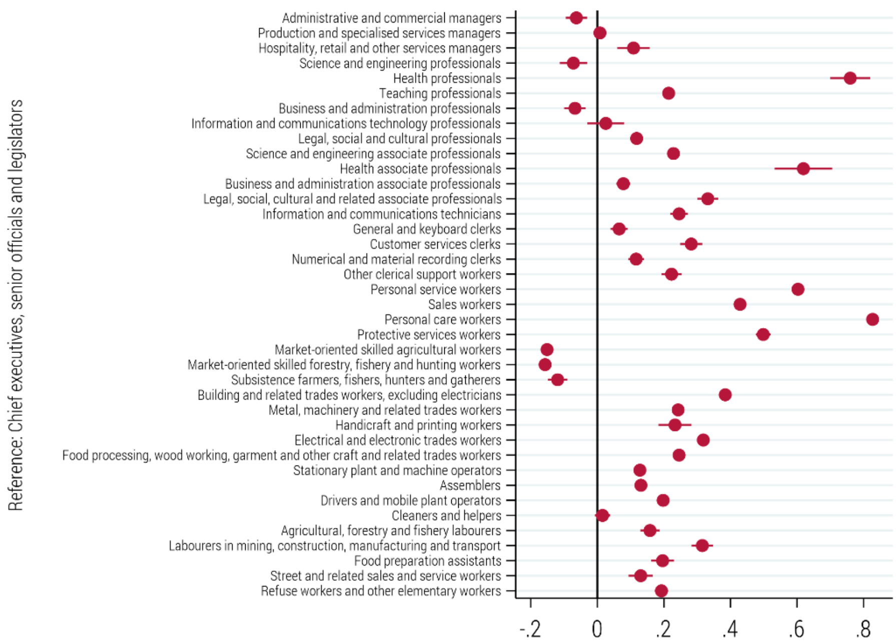
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A5. Differences in levels of exposure to infection or disease across two-digit ISCO occupations in Europe.



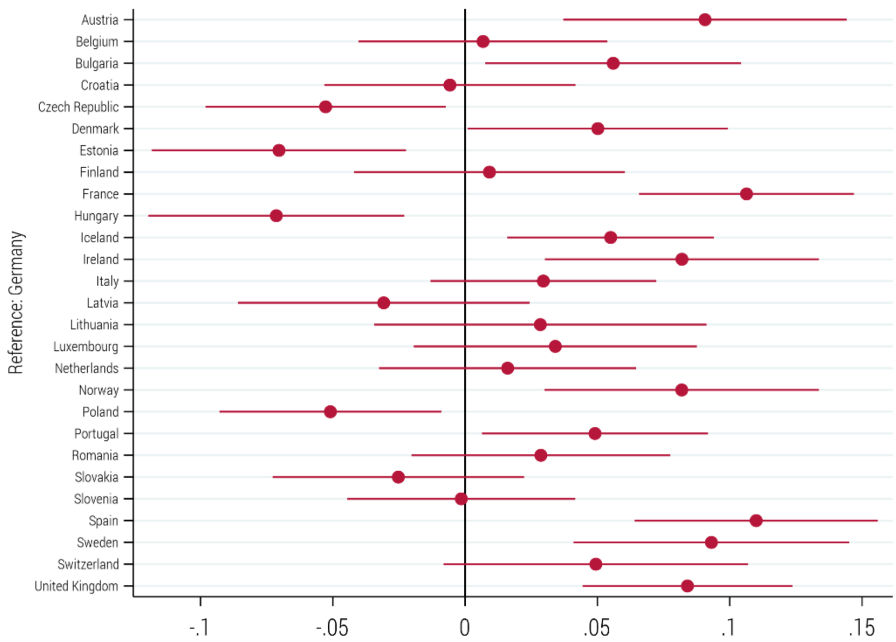
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A6. Differences in levels of physical proximity at work across two-digit ISCO occupations in Europe.



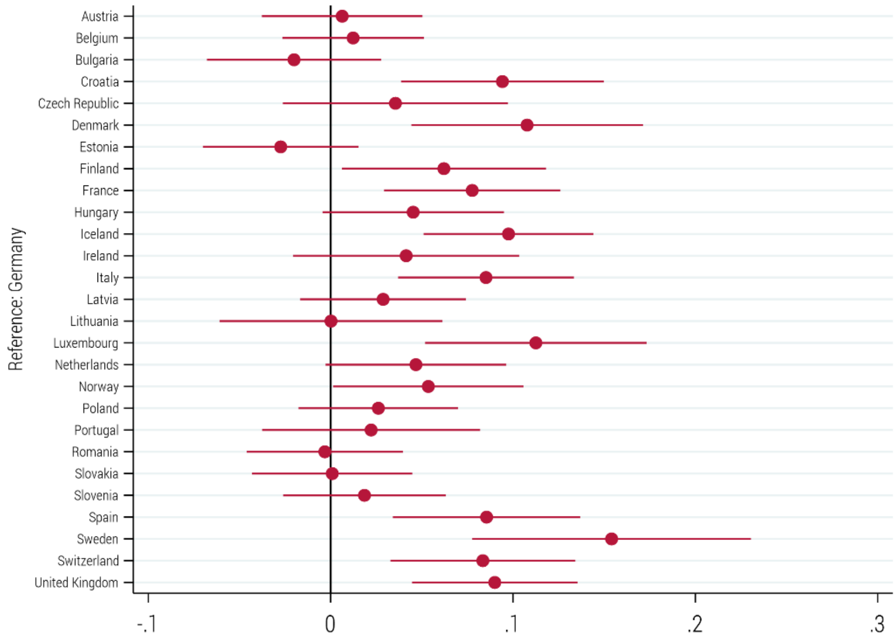
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A7. Differences in the incidence of dealing with clients, pupils, or patients across countries in Europe.



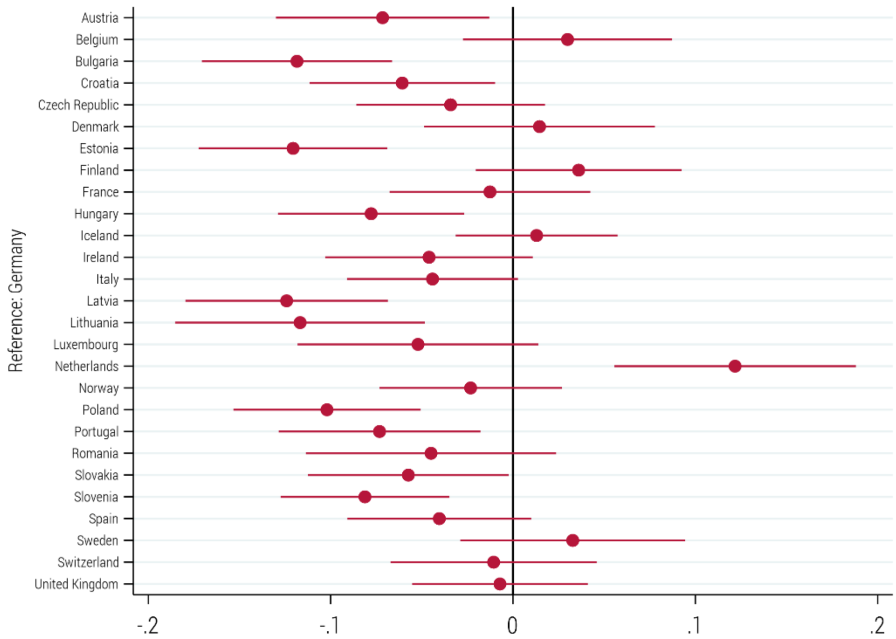
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A8. Differences in the frequency of working in public spaces across two-digit ISCO occupations in Europe.



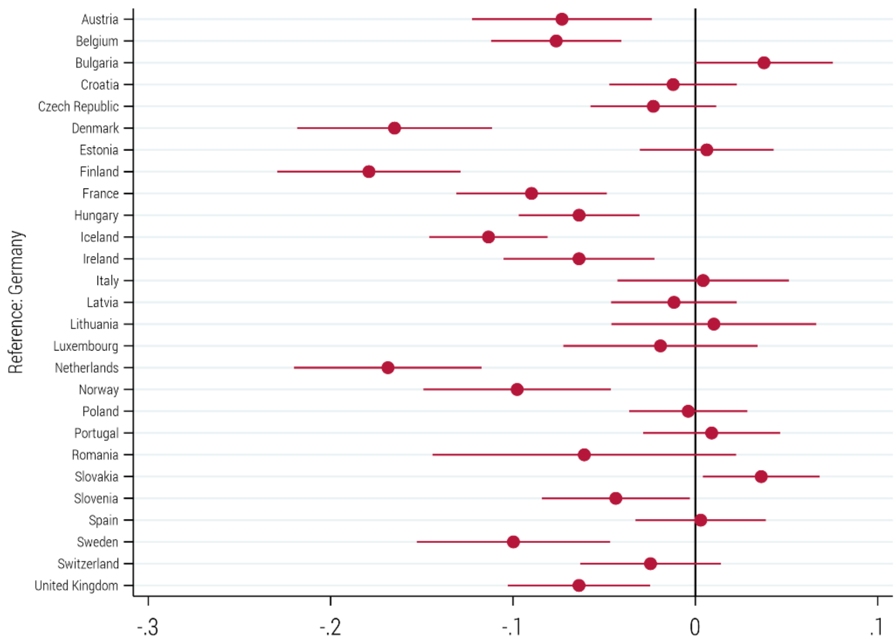
Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A9. Differences in the frequency of working at the clients' premises across two-digit ISCO occupations in Europe.



Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Figure A10. Differences in not being able to work from home across two-digit ISCO occupations in Europe.



Note: The coefficients are estimated in a worker-level model on normalised indicator, x_{ic}^{n}, against occupation fixed effects and country fixed effects, with standardised weights. Sample size 1,490,730. Reference groups: chief executives, senior officials, and legislators (ISCO 11), Germany. Standard errors clustered at the country x occupation level.
Source: Own estimation on the basis of EU-LFS and EWCS data.

Appendix B. Additional regression results on the relationship between occupational exposure to contagion and the spread of COVID-19

Table B1. The effects of occupational exposure to contagion on COVID-19 case growth under the assumption that occupations are identical across countries

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
ETC	0.030**	0.018	0.018	-0.001	0.013	-0.003	0.003	-0.002
	(0.012)	(0.017)	(0.011)	(0.013)	(0.009)	(0.010)	(0.003)	(0.003)
R2	0.106	0.233	0.053	0.374	0.051	0.480	0.030	0.359
HETC	0.024*	0.015	0.018	0.005	0.013	0.002	0.003	0
	(0.014)	(0.017)	(0.014)	(0.015)	(0.011)	(0.011)	(0.003)	(0.003)
R2	0.071	0.224	0.053	0.377	0.052	0.479	0.048	0.349
HETC, 15-24	0.015	0.007	0.015	0.007	0.014	0.007	0.004*	0.003
	(0.018)	(0.019)	(0.015)	(0.015)	(0.010)	(0.010)	(0.002)	(0.002)
R2	0.026	0.209	0.040	0.380	0.058	0.490	0.071	0.374
HETC, 25-34	0.033**	0.019	0.019	-0.001	0.014	-0.004	0.002	-0.003
	(0.012)	(0.016)	(0.011)	(0.011)	(0.009)	(0.008)	(0.003)	(0.002)
R2	0.127	0.238	0.064	0.374	0.055	0.482	0.017	0.387
HETC, 35-44	0.027**	0.013	0.013	-0.008	0.009	-0.01	0.001	-0.005***
	(0.011)	(0.014)	(0.009)	(0.010)	(0.008)	(0.007)	(0.003)	(0.002)
R2	0.087	0.220	0.028	0.381	0.021	0.499	0.004	0.422
HETC, 45-54	0.027**	0.017	0.014	-0.004	0.011	-0.005	0.002	-0.002
	(0.012)	(0.016)	(0.010)	(0.013)	(0.009)	(0.010)	(0.003)	(0.003)
R2	0.089	0.227	0.035	0.375	0.035	0.482	0.024	0.359
HETC, 55-64	0.030**	0.021	0.016	-0.002	0.012	-0.003	0.003	-0.001
	(0.012)	(0.018)	(0.011)	(0.015)	(0.009)	(0.011)	(0.003)	(0.003)
R2	0.106	0.239	0.044	0.374	0.045	0.479	0.040	0.350
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case.

**** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Table B2. The effects of the share of highly exposed workers on COVID-19 case growth, using alternative definition of highly exposed workers – top 40% workers in the distribution of occupational exposure to contagion (pooled sample, standardised weights)

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
HETC	0.055***	0.046***	0.049***	0.038***	0.036***	0.025***	0.005**	0.003*
	(0.010)	(0.011)	(0.010)	(0.010)	(0.008)	(0.007)	(0.002)	(0.002)
R2	0.355	0.433	0.414	0.598	0.369	0.645	0.12	0.388
HETC, 15-24	0.044***	0.032*	0.028**	0.007	0.020**	0.001	0.004	-0.001
	(0.013)	(0.018)	(0.011)	(0.013)	(0.009)	(0.010)	(0.003)	(0.003)
R2	0.229	0.295	0.133	0.381	0.112	0.478	0.063	0.351
HETC, 25-34	0.044***	0.040***	0.037***	0.032***	0.026***	0.022***	0.004*	0.004**
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.007)	(0.002)	(0.002)
R2	0.231	0.39	0.237	0.549	0.201	0.616	0.083	0.403
HETC, 35-44	0.047***	0.045***	0.045***	0.041***	0.032***	0.029***	0.004**	0.004***
	(0.009)	(0.010)	(0.011)	(0.009)	(0.008)	(0.006)	(0.002)	(0.001)
R2	0.267	0.438	0.339	0.656	0.296	0.71	0.087	0.432
HETC, 45-54	0.054***	0.047***	0.053***	0.045***	0.038***	0.030***	0.005**	0.004**
	(0.009)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.002)	(0.002)
R2	0.347	0.452	0.484	0.693	0.423	0.724	0.107	0.407
HETC, 55-64	0.057***	0.048***	0.056***	0.044***	0.042***	0.030***	0.007***	0.004**
	(0.010)	(0.011)	(0.008)	(0.009)	(0.006)	(0.007)	(0.002)	(0.002)
R2	0.389	0.433	0.529	0.644	0.501	0.692	0.193	0.410
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case.

**** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Table B3. The effects of the share of highly exposed workers on the number of deaths from COVID-19, using alternative definition of highly exposed workers – top 40% workers in the distribution of occupational exposure to contagion (pooled sample, standardised weights)

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
HETC	3.83*	3.96*	49.68**	47.69*	977.99*	879.90*	3117.52**	2462.46**
	(1.95)	(2.28)	(23.34)	(26.68)	(491.85)	(514.16)	(1228.09)	(1171.00)
R2	0.225	0.269	0.304	0.317	0.31	0.338	0.214	0.334
HETC, 15-24	1.6	1.87	21.14	16.11	412.76*	172.61	1667.49	214.57
	(1.24)	(1.55)	(12.60)	(17.98)	(229.43)	(301.01)	(1042.97)	(1047.75)
R2	0.039	0.095	0.055	0.089	0.055	0.12	0.061	0.211
HETC, 25-34	3.14	3.13	41.15*	39.46	760.43*	702.05	2366.96*	2096.81*
	(1.98)	(2.07)	(22.91)	(24.18)	(428.07)	(430.48)	(1197.92)	(1191.77)
R2	0.151	0.201	0.209	0.254	0.187	0.27	0.123	0.306
HETC, 35-44	4.18*	3.97*	50.70**	48.77*	949.49*	922.36*	2821.42**	2787.21**
	(2.06)	(2.19)	(24.63)	(25.59)	(496.17)	(501.88)	(1187.83)	(1205.83)
R2	0.267	0.288	0.317	0.349	0.292	0.38	0.175	0.374
HETC, 45-54	4.50**	4.47*	56.92**	54.70**	1132.96**	1063.36*	3466.73***	3093.11***
	(1.91)	(2.19)	(22.92)	(25.24)	(504.90)	(517.86)	(1155.16)	(1100.90)
R2	0.31	0.337	0.4	0.408	0.416	0.453	0.264	0.409
HETC, 55-64	3.98**	4.53*	53.30**	54.54*	1120.47**	1059.76*	3750.23***	3031.99**
	(1.80)	(2.29)	(20.92)	(26.48)	(477.51)	(542.46)	(1155.44)	(1086.40)
R2	0.242	0.312	0.35	0.367	0.406	0.413	0.309	0.387
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	28	28	28	28	28	28	28	28

Note: ETC – average exposure to contagion; HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case.

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, and OxCGRT data.*

Table B4. The effects of average number of social contacts on COVID-19 case growth

	1 week after the 100th case		2 weeks after the 100th case		4 weeks after the 100th case		Weeks 5-8 after the 100th case	
	Average no. of social contacts							
Social contacts	0.036	0.037	0.004	0.026	-0.009	0.019	-0.004	0.012*
	(0.033)	(0.062)	(0.027)	(0.050)	(0.025)	(0.041)	(0.006)	(0.005)
R2	0.241	0.241	0.005	0.132	0.03	0.264	0.072	0.631
	Share of workers highly exposed to contagion							
HETC	0.040	0.070***	0.050***	0.059***	0.047***	0.047***	0.010*	0.007*
	(0.029)	(0.015)	(0.010)	(0.007)	(0.007)	(0.007)	(0.005)	(0.003)
R2	0.295	0.813	0.815	0.902	0.845	0.845	0.449	0.621
Containment policy	N	Y	N	Y	N	Y	N	Y
Population density	N	Y	N	Y	N	Y	N	Y
No. of obs.	8	8	8	8	8	8	8	8

*Note: Average number of social contacts taken from Mossong et al. (2008). HETC – share of workers highly exposed to contagion. In the regressions pertaining to weeks 1, 2, and 4, I use the average strictness of containment policy over 7 days after the 100th case in each country. In the regressions pertaining to weeks 5 to 8, I use the average strictness of containment policy over 30 days after the 100th case (results of regressions using the average of containment policy averaged of over 7 days consistent with these presented and are available upon request). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*
*Source: Own estimation on the basis of EU-LFS, EWCS, O*NET, John Hopkins CSEE, OxCGRT and Mossong et al. (2008) data.*