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ABSTRACT

This work investigates the cross-industry relationship between robot adoption and the risk of contracting COVID-19 in the workplace in Italy. Using a novel dataset on the risk of workplace contagion, we show that industries employing more robots tend to exhibit lower risks, thereby providing some empirical support for the widely held, but so far untested, hypothesis that robots can help mitigate the risk of contagion among workers by reducing the need for physical interactions. While we acknowledge the relevance of robots in the fight against COVID-19 and their possible role in enhancing the resilience of economic systems against future pandemics, we also thoroughly discuss a series of potential trade-offs between workplace safety and employment conditions that could arise (especially in the short run) due to a substantial increase in the rate of robot adoption.

1. Introduction

With a worldwide death toll of millions, COVID-19 represents the most severe pandemic in contemporary history. Besides having a direct disruptive impact on the health and well-being of households and individuals, the pandemic has exposed the vulnerability of modern economies to outbreaks of highly infectious diseases. Indeed, in an effort to slow down the transmission of the infection and preserve public health, most governments have imposed full-fledged lockdown measures, severe restrictions on non-essential economic activities, and limitations on national and international mobility. Additionally, to minimize the chances of exposure to the SARS-CoV-2 virus, individual citizens and firms have voluntarily changed their usual routines by avoiding going out, restructuring business models and organizations, and limiting physical interactions with other people (Katafuchi et al., 2021; Kurita and Managi, 2020). As a result, according to the estimates of the International Monetary Fund, the global economy shrank by 4.4% in 2020—the worst downturn since the Great Depression—and unemployment rose sharply, with the crisis being particularly severe for specific sectors (e.g., the travel and hospitality industries, see Nakamura and Managi, 2020; Skare et al., 2021) and small businesses (Bloom et al., 2021; Gourinchas et al., 2020).

As pointed out by the literature, new technologies can play a key role in the fight against the COVID-19 pandemic. The adoption of technologies capable of strengthening the effectiveness of the healthcare system and increasing workers’ safety represents not only one of the instruments to mitigate the effects of the current pandemic but also an important element of a longer-term strategy aimed at shaping a “pandemic proof” economy. Indeed, enhancing the overall resilience of the economy to future pandemic events represents a critical policy goal (Blanchard and Pisani-Ferry, 2021; Morens and Fauci, 2020) to be pursued by each country as part of a collective global effort to prevent history from repeating itself. In the likely case of new outbreaks of old and new transmissible diseases, this resilience-enhancing strategy would reduce the need for extraordinary measures such as lockdowns and restrictions on personal mobility and social interactions. While these...
measures were necessary to bring the contagion rates under control and avoid further economic disruption (Aum et al., 2021; Kochariczyk and Lipniacki, 2021), they have high social and economic costs (Gharehgozli et al., 2020; Louhichi et al., 2021; Mahmoud and Riley, 2021; Mandel and Veetil, 2020; Martin et al., 2020; Tisdell, 2020).

In the discussion on how new technologies can improve the safety of working environments and help protect workers from infection, robots feature as one of the most prominent solutions (Abdul-Basset et al., 2021; Brakman et al., 2021; Zeng et al., 2020). Robots, which can perform a variety of tasks that could previously be done only by humans, are immune to viruses and therefore, the reasoning goes, increasing their presence in the workplace might reduce the risk of infection by reducing the occasions of physical contact among workers. While reasonable, this risk-mitigating effect of robots has been taken for granted so far, and no empirical test on its validity has been performed yet. Indeed, to the best of our knowledge, the negative relation between robot adoption and the risk of workplace contagion has been often assumed, but never tested. This lack of hard evidence represents a gap in the literature, as well as a limitation in the current debate about the most appropriate solutions to increase the infectious disease resilience of the economy and the society. This work aims to address this gap and limitation.

In this paper, therefore, we empirically analyze whether a higher degree of robotization is associated with a lower risk of workplace contagion, thus providing robust empirical evidence on a hypothesis that is widely accepted without empirical support. To this end, we are the first to exploit a novel industry-level measure against the risk of workplace contagion in Italy developed by the National Institute for Insurance against Accidents at Work (INAIL, a public agency) in the wake of the COVID-19 pandemic. Importantly, this measure specifically aims to evaluate the risk of contracting COVID-19. Since the measure is based on the detailed information gathered by the Inapp ICP survey (the Italian equivalent of the United States’ O*Net survey) on the activities and the working environment in about 800 occupations, it is tailored to the characteristics and peculiarities of the Italian labor market. As disclosed by one of the task forces appointed by the Italian government to manage the COVID-19 pandemic, the INAIL document has informed several decisions of Italian policy-makers regarding, for instance, industry-specific safety protocols and the temporary suspension of certain economic activities.

Overall, we find evidence that is consistent with the intuition that a more extensive use of robots in the workplace reduces the risk of contagion. More specifically, taking Italy as case study, we find that the number of robots per worker employed in each industry is negatively and significantly associated with the risk of contracting COVID-19 in the workplace. The results hold after controlling for several confounding factors, such as industry-level measures of capital intensity and proxies for the adoption of digital technologies. The results are robust to alternative model specifications (i.e., linear regression and ordered logit) and the exclusion of specific sectors, such as the automotive industry, which alone accounts for a non-negligible share of the robots adopted in the country, and healthcare. Notably, we mitigate omitted variable concerns related to the possible presence of industry-specific unobserved factors by instrumenting the sectoral robot density in Italy with the equivalent measure for Japan and South Korea, two advanced countries that are pioneers of robot adoption.

The negative relationship between robotization and risk of workplace contagion has important policy implications, but it simultaneously poses a conundrum. On one hand, policies aimed at incentivizing robotization could help in the fight against COVID-19 and, in the medium term, may help shape an economic system that is more resilient against future pandemics (as long as the diseases are characterized by similar modalities of transmission). For example, without speculating on the future trajectories of robot technology, we show that just by reaching the technological frontier in all the sectors in which Italy lags behind, the country could considerably decrease the average risk of workplace contagion. Moreover, as shown by several studies, the adoption of robots might improve workers’ productivity and economic growth (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). On the other hand, workers are always exposed to multiple risks, including that of losing their jobs (Nam, 2019), and robotization may interact with these risks. Hence, considering that, up to a certain degree, robots and human workers are substitutes in production (Dengler and Matthes, 2018; Frey and Osborne, 2017), any efforts aimed at increasing workplace safety by incentivizing the adoption of robots might end up having an unintentional negative effect on employment. Therefore, even though the evidence on this topic is mixed (e.g., see Acemoglu and Restrepo, 2020; Aghion et al., 2019; Caselli et al., 2021; Chiaccio et al., 2018) and a consensus is still lacking, the idea of expanding the use of robots raises serious social concerns, which are thoroughly discussed in this paper.

The remainder of the paper is organized as follows. We present the data used for the analysis in Section 2, where we provide an accurate description of the INAIL measure of the risk of workplace contagion. Section 3 illustrates the empirical strategy. Sections 4 and 5 present the empirical results, the robustness checks, and some extensions of the analysis. In section 6, we provide a thorough discussion of the results of the analysis and of their implications in terms of policy, particularly about the potential trade-off between workplace safety and employment rates. Moreover, we discuss the main limitations of the study and venues for future research. Section 7 concludes.

2. Data

The analysis conducted in this paper makes use of several data sources. First, it takes advantage of the work done by INAIL (2020), which estimates the integrated risk of COVID-19 workplace contagion at the level of two-digit NACE revision 2 industries (divisions). The risk of workplace contagion is classified based on three components: i) exposure, defined as the probability of coming in contact with the virus on a scale of 0 to 4; ii) proximity, which is related to the intrinsic job characteristics that may not permit sufficient social distancing, also defined on a scale of 0 to 4; and iii) aggregation, obtained by multiplying the product of the first two components by a factor ranging from 1 to 1.5, which describes whether some forms of contact with people other than colleagues is required. The resulting values, calculated at the job level based on 2019 data from the Italian labor force survey, are then aggregated at the level of two-digit industries and mapped into four integrated risk categories: low (assigned value 1), medium-low (value 2), medium-high (value 3), and high (value 4). Table 1 provides some examples of the level of risk of contagion for different industries in the manufacturing and service sectors.

Data on robots were purchased from the International Federation of Robotics (IFR), which defines an industrial robot as “an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.” The IFR dataset contains the stocks of industrial robots purchased in Italy and other countries (for our

| Industry | Risk level |
|----------|------------|
| Manufacture of motor vehicles, trailers and semi-trailers (29) | low (1) |
| Repair and installation of machinery and equipment (33) | medium-low (2) |
| Sewerage (37) | medium-high (3) |
| Land transport and transport via pipelines (49) | medium-low (2) |
| Air transport (51) | high (4) |
| Warehouse and support activities for transportation (52) | low (1) |
| Human health activities (86) | high (4) |
| Residential care activities (87) | medium-high (3) |

Notes: The values in parentheses in the first column correspond to the Nace rev. 2 industry codes, while the values in the parentheses in the second column correspond the numerical values attached to different levels of integrated risk codified by INAIL (2020).

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purposes, Japan and South Korea) by industry (up to three digits for specific industries) and by year for the period 1993 to 2018; the latter is the year used in our analysis. The IFR data are based on the ISIC revision 4 classification, and therefore can be easily matched with NACE revision 2 data from INAIL and EU KLEMS. In particular, we use employment data from EU KLEMS to construct a sectoral measure of robot use per 1000 workers that we adopt (in logs) as the main regressor of interest.2

Finally, our analysis includes a set of controls for possible confounding variables that make it possible to take into account other industry-specific characteristics. In particular, we are interested in controlling for other factors related to the automation of the production process to ensure that we capture only how robotization, rather than other technology-related factors, affect the risk of workplace contagion. Accordingly, we use data from ISTAT based on the survey on information and communication technology (ICT) in enterprises. This survey covers the universe of active enterprises with 10 or more employees and offers different variables related to the use and purchases of ICT by firms for different years at an aggregate industry level (up to two digits). Additionally, we include a control for capital intensity measured as the log of the capital-labor ratio at the two-digit sector level in 2017 and taken from EU KLEMS. Our dataset comprises variables that come from raw data at different levels of sectoral aggregation. To match the level of aggregation across all the variables in our analysis, we assign to all three-digit industries the values attached to the corresponding two-digit sectors. The reason for this approach is that using the three-digit level of aggregation provides more precise inference as our main explanatory variable of interest; that is, robots per 1000 workers is available at that level of aggregation for certain sectors. The first-stage results also benefit from more precise inference as both the potentially endogenous variable (robots per 1000 workers in Italy) and the instruments (robots per 1000 workers in Japan and South Korea) are available at the three-digit level of aggregation for certain sectors. Additionally, we do not need to worry about the fact that observations within a two-digit sector have the same values because we cluster the standard errors at the aggregate industry level used in the IFR dataset to match the level of aggregation of our main explanatory variable. Finally, we also provide a robustness check in which we aggregate all data at the two-digit industry level and show that the qualitative results do not change.

Table 2 provides descriptions and sources for the variables used in our empirical analysis. Table 3 shows some summary statistics for the two main variables used in our analysis, that is, the risk of COVID-19 workplace contagion and the number of robots per 1000 workers. The majority of three-digit industries are categorized as having low risk of virus contagion for their workers while, on average, there are about 7 robots per 1000 workers in Italy, even though this variable shows considerable variability across industries.

3. Empirical model

We conduct our analysis by estimating the following model, which is suitable to test the null hypothesis that the number of robots per 1000 workers across economic sectors is related to the risk of workplace contagion:

\[ \text{risk}_i = \alpha + \beta \log_{1000} \text{robots}_i + \gamma x_i + \epsilon_i, \]  

where \( \text{risk}_i \) is the risk of COVID-19 contagion in industry \( i \) in Italy as estimated by INAIL, \( \log_{1000} \text{robots}_i \) is the log of the number of robots per 1000 workers in industry \( i \) in Italy in 2018, \( x_i \) is a vector of additional controls at the industry level, and \( \epsilon_i \) is a random error. The vector \( x \) includes several variables useful to control for other ways through which firms can increase the automation of the production process. This is important as we would like to reduce the possibility of technology-related omitted factors that, by correlating with the adoption of robots and with the risk of contagion, may confound the estimates of coefficient \( \beta \). More specifically, the vector of additional controls includes the percentage of firms that bought cloud computing services in 2018; the percentage of firms in 2019 that used Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; the percentage of firms in 2019 that used Customer Relationship Management software to collect, file, and share data; the percentage of firms in 2019 that used Customer Relationship Management software for marketing analysis; the percentage of firms that purchased goods and services in the area Internet of Things between 2015 and 2017; and the percentage of workers in 2019 who were provided portable devices allowing internet connection for business purposes. This last variable was also used by Barrot et al. (2020) as a proxy for employees working from home. We posit that this set of controls is effective in capturing those technology-related features of companies operating in different economic sectors that may also be associated with robotization. In doing so, we believe that the empirical analysis captures specifically the role of robots, rather than other forms of automation and ICT investment. Moreover, we include the capital-labor ratio at the industry level to ensure that the degree of robotization does not work as a proxy for capital intensity.

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2 For Italy, we use employment data for 2017 because it is the last available year in EU KLEMS. As EU KLEMS data are more aggregated for some industries than the INAIL data, we check the robustness of our results by constructing robot use per 1000 workers based on employment data at the three-digit level from the 2011 census of industries and services (CIS) by ISTAT (Italy’s National Institute of Statistics) as well as from ISTAT’s 2017 ASIA UL that provides information for private non-agricultural sectors. All the results do not change qualitatively. For Japan and South Korea, we collect employment data at the industry level from EU KLEMS and World KLEMS. For these countries, the latest employment data available are of 2015 and 2012, respectively.
Table 4

|                      | Baseline (1) | Add controls (2) | Baseline (3) | Add controls (4) |
|----------------------|--------------|------------------|--------------|------------------|
| Robots per 1000      | OLS          | OLS              | 2SLS         | 2SLS             |
| workers, ln          | –0.000       | –0.000           | –0.000       | –0.000           |
| ICT adoption controls| ✓            | ✓                | ✓            | ✓                |
| Capital intensity    | ✓            | ✓                | ✓            | ✓                |
| Observations         | 259          | 257              | 259          | 257              |
| R-squared            | 0.138         | 0.275            | 0.138        | 0.273            |
| Kleibergen-Paap F   | 92.86        | 26.74            | 92.86        | 26.74            |
| Hansen J             | 1.678        | 3.299            | 1.678        | 3.299            |
| Pseudo R-squared     | 0.153        | 0.296            | 0.172        | 0.358            |

Notes: The dependent variable is the industry-level risk of Covid-19 contagion in the workplace, as estimated by INAIL (2020). The ICT adoption controls include: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Capital intensity is measured using the logged capital-labour ratio. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2018 using the same variable for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. ★★★ indicates coefficients significantly different from zero at the 1% level.

Our measure of robotization of an industry is taken from 2018 as it is the latest robotization data available to us at the time of the analysis. However, the fact that the robotization variable predates the risk of COVID-19 contagion (calculated using 2019 data on the labor force) does not fully exclude the possibility of endogeneity. In particular, in this case, there could be omitted variables that simultaneously affect the degree of robotization of an industry and its level of COVID-19 contagion risk. Such factors could be related either to the specific technologies used in that industry in Italy, such as other modes of automation absent in our additional controls, or to other industry-specific features, such as the strength of trade unions, which might be related with decisions to adopt robots and worker density in the workplace (Bellocc et al., 2020). They could also be related to the distribution of firm size that can affect the incentives to invest in robots and compliance with regulations, in turn impacting the risk of workplace contagion.

To tackle this potential issue of endogeneity, we run additional regressions based on the 2-Stage-Least-Square (2SLS) estimator. Particularly, we instrument the log of the number of robots per 1000 workers in Italy with the same variable for Japan and South Korea. The purpose of using these instruments is to capture the exogenous technological differences across industries that lead to different uses of robots in the production process. We chose Japan and South Korea because they have among the highest robot adoption rates, provide reliable and readily available data on employment by industry, and are not part of the European Union and so less likely to be influenced by factors shaping robot adoption in Italy as well. We will show that these instruments are informative and, given that we have more instruments than endogenous variables, we will also provide some evidence that the instruments are valid.

4. Results

This section presents the results of the analysis of the cross-industry relationship between robotization and the risk of COVID-19 contagion that, according to common wisdom, is expected to be negative and significantly different from zero.

The first two columns of Table 4 report the estimation results of Eq. (1) based on the OLS estimator (without and with additional controls, respectively). In both cases, the data reject the null hypothesis of an insignificant correlation between robot adoption and risk of workplace contagion. The introduction of various controls to capture possible technology-related omitted determinants appears appropriate as the estimated coefficient is twice as large (in absolute terms) with respect to the case without any controls.

The relevance of these controls suggests that it is important to address potential endogeneity issues, also associated with omitted variables that do not correlate with technology. Admittedly, industries in Italy differ because of sector-specific technologies, organizational solutions, business models, trade unions, and other firm-level characteristics (e.g., average firm size) that could influence both robot adoption and worker density (hence, their exposure to workplace contagion). To prevent these unobserved factors from introducing a bias in the estimated impact of robot adoption on the risk of workplace contagion, we need to run regressions based on a 2-Stage-Least-Square (2SLS) estimator. To do so, as anticipated, we employ two external instruments that, on one hand, can capture the exogenous component of cross-industry variation in robot adoption and, on the other hand, cannot directly affect contagion risk.

In particular, we instrument the log of the number of robots per 1000 workers in Italy with the same variable for Japan and South Korea. Thus, in columns 3 and 4 of Table 8, we report the estimates based on the 2SLS estimator with these two instruments. As done before, we report the estimates with and without additional controls for other technological

Table 5

|                      | Baseline (1) | Add controls (2) | Baseline (3) | Add controls (4) |
|----------------------|--------------|------------------|--------------|------------------|
| Robots per 1000      | Ologit       | Ologit           | Ologit-IV    | Ologit-IV        |
| workers, ln          | –0.01        | –1.011           | –0.01        | –1.011           |
| ICT adoption controls| ✓            | ✓                | ✓            | ✓                |
| Capital intensity    | ✓            | ✓                | ✓            | ✓                |
| Observations         | 259          | 257              | 259          | 257              |
| R-squared            | 0.138        | 0.275            | 0.138        | 0.273            |
| Kleibergen-Paap F   | 92.86        | 26.74            | 92.86        | 26.74            |
| Hansen J             | 1.678        | 3.299            | 1.678        | 3.299            |
| Pseudo R-squared     | 0.153        | 0.296            | 0.172        | 0.358            |

Notes: The dependent variable is the industry-level risk of Covid-19 contagion in the workplace, as estimated by INAIL (2020). The OLS adoption controls include: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Capital intensity is measured using the logged capital-labour ratio. The IV specifications instrument the log of the number of robots per 1000 workers in Italy in 2018 using the same variable for Japan and South Korea. Two-step bootstrapped standard errors are shown in parentheses (500 repetitions). ★★★, ★★ and ★ indicate coefficients significantly different from zero at the 1, 5 and 10% level.

We are inclined to exclude the relevance of reverse causality issues in this framework because before the pandemic, firms did not adopt robots with the goal of reducing the exposure to transmittable diseases and risk of contagion. Clearly, this problem will become relevant in studies on the relationship between robotization and contagion risk in the period after COVID-19.
factors. The OLS results are qualitatively confirmed and the 2SLS estimates are quantitatively similar to those obtained with the OLS estimator. This suggests that cross-industry differences in aspects associated with technological readiness are already well captured by our controls, whereas the effects of other potentially omitted factors are negligible.

It can be noticed that the R-squared ranges from 0.138 to 0.257, which we consider as satisfactory given the lack of any fixed effects in the estimations. More importantly, since we have more instruments than endogenous variables, we can show that our instrumental variables are both informative and valid. The Kleibergen-Paap F statistics are relatively high (and higher than the corresponding Stock-Yogo critical values), suggesting that the instruments used in the 2SLS specifications are informative. They also appear to be valid as the Hansen J statistics are quantitatively similar to those obtained with the OLS estimation.

Before illustrating a number of auxiliary regressions performed as robustness checks and extensions of the analysis, we would like to comment on the interpretation and quantitative implications of the estimates in Table 4. In all cases, they provide evidence that the industries employing more robots per 1000 workers tend to be characterized by lower risk of COVID-19 contagion. These findings support the hypothesis that the greater the adoption of robots, the lower the need for workers to operate in physical proximity and the lower the risk of contagion. These results, in turn, corroborate the widely held, but so far unfounded, view that robot adoption can help prevent the diffusion of transmissible diseases in the workplace.

The effect of robotization appears to be quantitatively relevant. The coefficient changes only marginally across the four specifications, ranging from -0.072 to -0.149. If one considers that the risk of contagion is measured with a discrete variable with a fairly left-skewed distribution, this result is particularly worth noting. Based on the specification in which we use the 2SLS estimator with the controls (i.e., column 4), the size of the estimated coefficient implies that an increase in the use of robots equal to the difference in robot usage between the industries at 25th percentile and 75th percentile is associated with a lower risk of contagion by more than one standard deviation. This implies a non-negligible impact of robotization on the risk of workplace contagion.

It is worth clarifying that, with this quantitative exercise, we do not implicitly claim that all sectors could and should adopt the same level of robots per worker: this might be neither technically possible, nor socially desirable. The quantitative example above serves exclusively to show the importance of the average effect of robotization on the risk of contagion implied by the estimates. A more realistic projection of robot adoption and the associated reduction in the risk of contagion will be illustrated in Section 5, where we will consider the hypothetical case in which Italy manages to increase its use of robots so as to reach the world technological frontier. Notably, this projection does not represent a normative recommendation either. Rather, it should be considered as an attempt to predict, in the statistical sense, the impact of robotization on the risk of contagion stemming from a traditional process of technological catching-up. As we shall explain in section 6, the creation of alternative scenarios and forecasts is not the aim of this study; rather, it focuses on the identification of the contribution that robotization may have on the containment of transmissible diseases in the workplace, and on the trade-off associated with it.

4.1. Robustness checks and extensions

As our dependent variable takes integer values having an ordinal scale, we re-estimate our model using the ordered logit estimator. The ordered logit estimator can also include an IV strategy to take into account our endogenous variable. However, as the ordered logit model is nonlinear, it is preferable to include, in the second stage, the error term

4 Appendix A shows the results of the first stage regressions.

Table 6

| Robots per 1000 workers, ln | OLS Baseline (1) | OLS Add controls (2) | 2SLS Baseline (3) | 2SLS Add controls (4) |
|-----------------------------|------------------|----------------------|-------------------|-----------------------|
| ICT adoption controls       | ✓                | ✓                    | ✓                 | ✓                     |
| Capital intensity           | ✓                | ✓                    | ✓                 | ✓                     |
| Observations                | 251              | 249                  | 251               | 249                   |
| Hansen J                    | 1.990            | 2.856                | 1.990             | 2.856                 |

Table 7

| Robots per 1000 workers, ln | OLS Baseline (1) | OLS Add controls (2) | 2SLS Baseline (3) | 2SLS Add controls (4) |
|-----------------------------|------------------|----------------------|-------------------|-----------------------|
| ICT adoption controls       | ✓                | ✓                    | ✓                 | ✓                     |
| Capital intensity           | ✓                | ✓                    | ✓                 | ✓                     |
| Observations                | 250              | 248                  | 250               | 248                   |
| Hansen J                    | 1.357            | 3.249                | 1.357             | 3.249                 |

Notes: The dependent variable is the industry-level risk of Covid-19 contagion in the workplace, as estimated by INAIL (2020). The ICT adoption controls include: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Capital intensity is measured using the logged capital-labour ratio. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2018 using the same variable for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. ★★★ indicates coefficients significantly different from zero at the 1% level.
from the first stage alongside the original endogenous variable rather than the predicted values of the endogenous variable (Caselli and Schiavo, 2020; Papke and Wooldridge, 2008). Given the two-step structure of the procedure, the standard errors in the second stage are computed by bootstrapping (i.e., resampling the cross-sectional units based on 500 repetitions).

The estimates are reported in Table 5, again with and without controls, and with and without instrumental variables. Notice that the sign of the coefficient of interest is negative and the estimated parameter is significantly different from zero. As the ordered logit differs from the OLS and 2SLS, so does the interpretation of the estimated parameter. A unit increase in robots per worker is expected to lead to a 1 point reduction in the log odds of being at a higher risk of contagion, all other variables held constant. These findings represent supporting evidence of a negative relationship between robots per 1000 workers and risk of COVID-19 contagion.

We would like to proceed with our robustness checks by showing that our results remain valid if we exclude some sensitive industries. First, we show that the results are robust to the exclusion of the automotive industry, which is known to make relatively extensive use of robots in production. The results, in Table 6, are consistent with the main findings. Second, we show that our conclusions are robust to the exclusion of industries strictly related to the provision of health services and social assistance (industries 86-88 according to NACE revision 2), in which the risk of contagion is obviously relatively higher and robot adoption intrinsically limited by the need of human contact. As can be seen in Table 7, our main conclusions are qualitatively unaffected, but the estimated coefficients for the variable of interest are smaller when all controls are included. This can be explained with the fact that these sectors are characterized by very high risk of contagion and their exclusion from the regression reduces the overall variability in the dependent variable that we aim to explain. Still, the results remain valid even when dropping these industries.

As an additional robustness check, we re-run the OLS and 2SLS regressions at a lower level of aggregation, that is at the two-digit level, because the variable capturing the risk of contagion is measured at this level. We show that the results remain valid and statistically significant. The estimated coefficients, reported in Table 8, do not differ substantially from those reported before.

Besides these robustness checks, we would like to explore more deeply the mechanisms at work in the attempt of improving the interpretation of our empirical results. The first extension we consider refers to the mediating effects of the technological characteristics of the different industries. We borrow a revised Pavitt taxonomy for manufacturing and business services developed by Bogliacino and Pianta (2010) to see whether the negative relationship between the risk of contagion and robot adoption is stronger in sectors characterized by use of technological advancements to substitute workers. In particular, we isolate the Supplier Dominated industries (SD) that include traditional sectors (such as food, textile, retail services). In these industries, internal innovative activities are less relevant, small firms are prevalent, and technological change is mainly introduced through the inputs and machinery provided by suppliers from other industries with a view to reducing production costs. We build two binary variables, one for the supplier dominated industries and one for the other industries in the revised Pavitt taxonomy, that in turn exclude some sectors such as health and education. The results of the OLS and 2SLS estimations, in which the variable robots per 1000 workers is interacted with the dummy variables from the Pavitt taxonomy, are reported in Table 9. The negative and significant relationship between robotization and the risk of workplace contagion is confirmed for the group of supplier dominated industries. By construction, this group encompasses all the industries that follow strategies of cost competitiveness and try to reduce labor costs through investments in machinery, hence all the industries where
robot adoption and worker density tend to be negatively correlated. This is in line with the mechanism we have in mind, and these estimates support our working hypothesis that robotization is associated with greater physical distancing between workers and a lower risk of workplace contagion.

This result, notably, bears on the trade-off between workplace safety and employment that will be discussed in Section 6. As the SD industries are naturally prone to substitute labor with machinery to decrease production costs, the fact that robotization is effective in reducing the risk of contagion may provide additional incentives to reduce the number of workers in the future. This is likely to make the trade-off between workplace safety and employment rates particularly difficult in industries where the risk of labor substitution is already higher for other economic reasons.

Our last extension regards the interaction of robotization with the other solution introduced to reduce workers’ proximity and associated risks of COVID-19 contagion, i.e., remote work. Should the mechanism underpinning our working hypothesis be correct, we would expect that the risk-mitigating effect of robotization is stronger in industries where workers cannot be kept at distance from each other via remote working. Thus, we classify industries by the possibility for workers to work remotely. In particular, we use the remote work index from Barbieri et al. (2020) and classify an industry as a high remote-work industry if it exhibits an index above the country’s average and as a low remote-work industry otherwise.

The results of the OLS and 2SLS estimates, reported in Table 10, suggest that the negative impact of robotization on the risk of contagion is indeed stronger in industries where remote work is less prevalent. This is further evidence for the relevance of robotization as a means of creating social distancing in the workplace, especially where it is needed the most due to the absence of the possibility of remote work. This, in turn, strengthens the idea that companies and policy-makers may favor the adoption of robotic solutions to reduce the exposure to transmissible diseases in the workplace and increase economic resilience.

It is worth noting that all our findings are based on variables calculated on data that reflect the business models and work practices established before the pandemic. Further, the INAIL measure of the risk of contagion is based on data that reflect the business models and work practices established before the pandemic. Further, the INAIL measure of the risk of contagion before the spread of COVID-19. This is perfectly in line with our attempt of establishing the INAIL data available for all the variables. More importantly, however, using recent data would weaken the empirical estimation of the risk-

| Table 10 | Robotisation and risk of Covid-19 contagion in the workplace, by remote work. |
|----------|--------------------------------------------------------------------------------------------------|
|          | Baseline Add controls | Baseline Add controls |                  |                  |
|          | OLS (1) GLS (2) 2SLS (3) 2SLS (4) |                  |                  |                  |
| Robots per 1000 workers, ln × | 0.300** 0.388** | 0 | 0 | 0 |
| Remote work – 0 workers, ln × | 0.107 (0.167) | 0.100 (0.163) | 0.070** | 0.070** |
| Remote work dummy | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ |
| ICT adoption controls | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ |
| Capital intensity | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ | ✓ ✓ ✓ ✓ |
| Observations | 259 257 259 257 | 259 257 259 257 | 0.216 0.312 0.215 0.311 |
| R-squared | 0.126 0.852 0.126 0.852 |

Notes: The dependent variable is the industry-level risk of Covid-19 contagion in the workplace, as estimated by INAIL (2020). The remote work dummy is based on the remote work index in Barbieri et al. (2020), and takes value 1 if the sector exhibits a level above the country average. The ICT adoption controls include: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Capital intensity is measured using the logged capital-labour ratio. The 2SLS specifications instrument the log of the number of robots per 1000 workers in Italy in 2018 using the same variable for Japan and South Korea. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.
mitigation effects of robotization. If the conviction that robots may mitigate the risk of contagion has already created additional incentives for firms to increase the use of robots, this generates a serious reverse causality problem that is absent in analyses (like ours) using pre-COVID-19 data. Moreover, as both the epidemic and the conviction that robotization may help reduce the risk of contagion are global phenomena, the foreign stocks of robots might stop being good instruments because in the future all countries will increase robot adoption due to similar contagion-related concerns. Hence, the use of data from 2020 onwards may both lead to greater endogeneity issues due to reverse causality problems, and also invalidate the instrumental variables adopted in works based on data from the pre-COVID-19 period.

5. A simple projection

To understand the potential for further robotization in Italy that is associated with a process of technological catching-up, we calculate what can be considered as the technological frontier in robotization at the industry level. Then, we compare the level of robotization in Italy with that at the technological frontier to determine to what extent Italy could increase its use of robots by reaching the frontier. In particular, we calculate the number of robots per 1000 workers for each aggregate industry and for every major country (e.g., Germany, France, Japan, South Korea, United Kingdom, and United States) as well as for the smaller European countries that exhibit large-scale robot adoption in certain industries (Austria, Belgium, Czech Republic, Denmark, Netherlands, Spain, Slovakia and Sweden). Then, we take the industry-by-industry ratio between the number of robots per 1000 workers in the country at the frontier and in Italy.

The results of this exercise are summarized in Table 11. Focusing on the comparison with respect to the large economies, the industries in which Italy is at the frontier (or close to it) are food and beverages, wood, furniture and paper, pharmaceuticals, chemical products, basic metals and metal products, utilities, and construction. On the other hand, in textiles, electronic and electrical equipment, industrial equipment, automotive and other non-manufacturing industries, Italy lags behind, especially when compared to Germany, Denmark and South Korea. These are the countries that are most frequently at the frontier in terms of robot adoption. It is possible to observe that Italy could increase the use of robots per 1000 workers by a factor of approximately 2.3 to 3.9, depending on which countries it is compared to.

Given this potential for further robotization associated with technological catching-up, it is possible to calculate the impact of such additional adoption of robots on the risk of contagion based on the estimated parameter in Table 4. If Italy were to reach the technological frontier in each industry in terms of robot adoption, it could mitigate the risk of workplace contagion by approximately half of one standard deviation. This is a significant effect and it could even become the object of ad hoc policy incentives if the authorities give priority to the minimization of the risk of contagion in order not to suspend, again, the economic activities at risk. We shall discuss the implications of this possibility in the next Section.

6. Discussion of the results and limitations

As anticipated, our findings and our simple projection should be interpreted with care before drawing out policy recommendations and normative conclusions. Assuming that our results are correct and that there is potential room in Italy for boosting robot adoption to reduce the risk of workplace contagion, it is worth recalling that this could also have, particularly in the short term, negative effects on the employment rate. Several recent studies (such as Acemoglu and Restrepo, 2019; 2020; Chiacchio et al., 2018; Dauth et al., 2017; de Vries et al., 2020; Grezet and Michaels, 2017; 2018) have shown that robotization may have a positive impact on productivity, but also negative effects on the employment conditions and opportunities for various groups of workers. In fact, the aggregate positive effect on productivity and competitiveness from robot adoption may fail to translate into a widespread improvement in income, employment opportunities and welfare.

While there is no disagreement on the fact that automation contributes to reshaping income distribution and altering employment opportunities for the most exposed workers, there is no consensus on the importance and characteristics of such effects. Some studies find evidence that automation has particularly adverse effects on routine and manual occupations (de Vries et al., 2020) and it risks reducing (ceteris paribus) the number of “human hands” at work on conveyor belts along the production process. Workers in other occupations, instead, may even gain. Blanas et al. (2020) find that, in Europe, robots reduced the demand for low- and medium-skill workers, young people, and women, but raised the demand for high-skill workers, older workers, and men. Grigoli et al. (2020) show that automation has negative effects on the participation rates of prime-age men and women, and that workers employed in routinizable occupations are more likely to drop out of the labor force, unless involved in active labor market programs. Jung and Lim (2020) find that, despite a positive impact on hourly compensation, the expansion of the use of industrial robots leads to a productivity-enhancing effect exceeding the wage-increasing effect, and this might be conducive (conditional on unchanged aggregate demand) on subdued employment growth for low-skilled workers. Vannutelli et al. (2021) show that routine-biased technical change in Italy has induced both job and wage polarization. On the other hand, Dengler and Matthes (2018) point out that only certain tasks in an occupation can be substituted by automation and warn that neglecting this aspect (as done, for instance, in the seminal work by Frey and Osborne, 2017) can lead to an overestimation of automation probabilities and effects. Moreover, a number of firm-level studies find that robotization is not pursued by the companies with the objective of cutting labor costs and shedding workers, but rather with a view to improving quality, innovating products, and increasing control over the production process. Caselli et al. (2021) find that the employment shares of Italian workers performing tasks associated with robot installation and maintenance increased remarkably more in regions where robotization was more intensively adopted, with a limited negative impact on other professions.

These controversial conclusions suggest that it is important to handle robotization with care and with full awareness that, in the short term, it may mitigate the risk of workplace contagion, but also hinder the reabsorption of the labor force expelled during the COVID-19 pandemic (Fairlie et al., 2020). This warning to use caution in employing robotization as a solution to reduce workers’ exposure to transmissible diseases is not a platitude. On April 10, 2020, for instance, a column in the New York Times argued that “broad unease about losing jobs to machines could dissipate as people focus on the benefits of minimizing close human contact.” Other influential observers, such as Martin Ford, stressed the crucial contribution that robotization may make in limiting the circulation of transmissible diseases in several work environments and maintained that this might in fact even reduce workers’ skepticism towards robots and advanced technologies. While our empirical analysis offers supportive evidence for the idea that robotization may help reduce the risk of contagion, we beg to differ from an excessively positive view of quickly implementing higher levels of robotization in society. A trade-off between workplace health safety and employment rate, in fact, may emerge both at the aggregate level, with the authorities torn between providing incentives to reduce the exposure to viruses

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through robots and preventing the substitution of labor with capital, and at the firm level, with trade unions and workers’ representatives involved in the exploration of alternative solutions to improve health safety while preserving jobs. Given the heterogeneity in the regional composition of economic activities and occupations Acemoglu and Restrepo (2020); Caselli et al. (2021); Chernoff and Warman (2020); Dauth et al. (2017); Leigh and Kraft (2018), this may also have differentiated consequences at the regional level.

While taking no action to prepare for future pandemics will not be a viable option, it is necessary to acknowledge that all measures have employment-related and redistributive effects. If robotization entails the risks discussed above, the emergency solutions adopted to halt the spread of the epidemic (such as the suspension of non-essential activities) also led to an increase in labor market inequalities and hurt the most exposed workers (Beland et al., 2020; Fairlie et al., 2020). Even remote working, as shown by Bonacini et al. (2021), raises the risk of exacerbating pre-existing inequalities in the labor market, at least if not adequately regulated.7

Besides its impact on employment opportunities, it is worth noting that robotization is bound to challenge existing business models, management practices, and workers’ activities in a company that heavily depends on robots. To be effective, automation requires profound changes in the organizational structure and substantial modifications in the tasks performed by the workers involved in the different phases of production. A global survey by Boston Consulting Group in 2019 found that the share of non-routine tasks will increase in all jobs after the introduction of advanced robots, particularly as technical capabilities and soft skills will become more important to address the errors that automated systems cannot handle. This reshaping of tasks and activities within the firm, in turn, will affect the distribution of control and power across the employee force, the top management, and the shareholders, with further repercussions on industrial relations and income distribution (Caliendo et al., 2015; Qian, 1994).

Finally, it is worth mentioning that the unpredictability of individual-specific consequences of robotization may increase job insecurity and lower the welfare of even those workers that do not compete, so to speak, with technological innovation (see, for instance, Nam, 2019 and Lingmont and Alexiou, 2020). Again, job insecurity concerns should not prevent action; rather, their existence has to be kept in mind while designing solutions to tackle the pandemic-related challenges. Lingmont and Alexiou (2020), for instance, find that employees with higher expectations of being retrained and re-employed have lower perceptions of job insecurity: this implies that a greater use of robots could and should be accompanied by firm-level and country-level efforts to improve employability and training. Brougham and Haar (2020) show that job insecurity (also known as STAR - Smart Technology, Artificial Intelligence, Robotics, and Algorithms - awareness) is stronger where organizational commitment and career satisfaction are lower, and turnover intentions higher. Similarly, Lingmont and Alexiou (2020) find that an authoritarian organizational culture enhances the effects of STAR awareness on perceived job insecurity among employees. Hence, from the perspectives of entrepreneurs, top managers, and trade unions representatives, these findings suggest weighing the pros and cons of increasing robotization in a company, and accompanying it both with enablers of fruitful deployment, such as organizational competencies, and solutions to mediate any unintended consequences.

All these considerations strengthen the case for introducing robots into the firms with the involvement of unions and workers’ representatives who can help shape the interaction between humans and robots. Although reducing workers’ exposure to transmissible diseases can be seen as a good reason to increase robotization both at the firm and at the aggregated level, its effects on employment rate and income risk bringing with them unintended and unpleasant re-distributional consequences that must be monitored and counterbalanced.

We argue that the urgency of considering the drawbacks of increasing automation to reduce the risk of contagion will be particularly acute in the post-pandemic period. This period will be characterized by subdued aggregate demand, a large portion of the population affected by the abrupt termination of short-term contracts, and a complex reconfiguration of international value chains. This is particularly important because, as pointed out by Mongey et al. (2020), the jobs characterized by the highest level of physical proximity and the lowest level of working place flexibility are those performed by workers with poor socioeconomic background. Hence, workers whose activities were suspended during the pandemic and who are susceptible to robot substitution would also face less favorable conditions in normal times:8 this makes them very exposed to a further worsening in working conditions and in standards of living. In line with this, Fairlie et al. (2020) find evidence that the overlap of automation potential and viral transmission risk can hit particularly hard some local labor market areas and specific (vulnerable) demographic groups.

In a few recent works, in particular Boeri et al. (2020) and Basso et al. (2020), workers employed in manufacturing activities are considered as facing lower risk of contagion than workers involved in other industries (such as health and education). Industrial robots, thus, could appear a less important tool to reduce the risk of contagion than the measures focusing on services, such as social distancing, work-from-home, and the like. While it might be the case that these measures are more important in certain service sectors (though not all, as in the case of logistics), it is worth noting that the reason why workers in the manufacturing sectors are considered to be at medium-low and low risk of contagion is that they already benefit from reduced physical proximity in the workplace due to past automation (Basso et al., 2020). Most manufacturing jobs cannot be performed remotely and do need people to be present in the same workplace, but their overall riskiness is reduced by the moderate physical proximity and the limited interactions with the public that derive from automation adopted in the past. Should infectious diseases increase in the future, as many observers warn about, the incentive to introduce robots and other technological advances that help maintain social distancing and prevent workplace contagion is likely to grow. One can think, for instance, of the employees in meat and livestock processing plants, who are among the workers hit the hardest by COVID-19 (Taylor et al., 2020): while most of the workers still operate in close proximity along the conveyor belt, there exist already plenty of robot applications reproducing (part of) their tasks that could be installed in the future.

In 2020, the combined impact of COVID-19 and the preventive restrictions gave a major shock to the economy and the society, similar in size to a large natural disaster with highly differentiated effects across regions and individuals. Preventing this scenario from happening again is of paramount importance and, because diffusion of other viruses is likely in the future, it is essential to adopt policies that are effective and respectful of the socioeconomic fabric of countries. If the world has truly entered a pandemic era, this policy concern is likely to rank higher in future agendas than it did in the past. In late March 2021, several global

7 Besides legally binding measures to impose social distancing and reduce mobility, a number of governments (such as Japan and Sweden) introduced non-legally binding policies based on individual self-restraint. These measures worked thanks to the role played by the strong psychological costs associated with stigma, as shown by Kurita and Managi, 2020 and Katafuchi et al., 2021. Another set of restrictions that impacted the diffusion of the virus was the national and international travel limitations, as every city or country has the potential to be both the epicenter and the destination of disease spread through international mobility of people (Nakamura and Managi, 2020; Chinazzi et al., 2020). While these measures have no relation with changes in the production process within businesses, they do impact international value chains (Barba Navaretti et al., 2020; Mandel and Vestil, 2020).

8 Lekfuangfu et al. (2020) notice that low-income households face a disproportionately larger risk of income loss from the suspension of economic activities.
leaders (including U.K. Prime Minister Boris Johnson, the French President Emmanuel Macron, the German Chancellor Angela Merkel, the World Health Organization’s Director General Tedros Adhanom Ghebreyesus) warned, in a joint article, that other pandemics will inevitably follow the COVID-19 one, and they called for an international pandemic treaty.9 This suggests that the efforts to deploy macro- and micro-economic measures to make the economies less exposed to epidemics and more resilient to their impact will grow. Our work seeks to contribute to the debate about the trade-offs associated with the available anti-contagion solutions. Ultimately, as argued in the Introduction, policy-makers will have to make hard choices about what policy responses might help the private sector to adapt to the increased risk of transmissible diseases. We have discussed the trade-off associated with greater robotization, but similar considerations apply also for other solutions to mitigate risks. The drastic stay-at-home orders and self-restrain policies adopted during the most acute phases of the pandemic, for instance, massively impacted output, household income, and consumption (Beland et al., 2020; Bonacini et al., 2021; Fairlie et al., 2020; Koren and Peto, 2020; Martin et al., 2020).

Even assuming that robot adoption could be promoted without a very negative impact on employment and welfare, it is not clear to what extent it would be possible to increase the adoption of robots in the various sectors. Robotization could have already reached its limits in certain industries, as it would be the case if sunk costs of adoption were too large to be sustained by small companies. This is a reasonable concern, but many companies have already started exploring new possibilities. For example, fast-food chains have tested the introduction of robots as cooks and servers, and warehouses have increased the use of robots to sort and pack. The Danish company Universal Robots, one of the leaders in the production of collaborative robots, described its products as affordable and effective solutions to the volatile, uncertain, complex, and ambiguous (VUCA) conditions that COVID-19 created,10 and recorded high rates of growth in sales in early 2021. Because of the problems in gauging the extent of robot adoption in the future, in Section 5 we did a simple thought experiment. We assumed that Italy increases its use of robots to reach the current world technological frontier in each sector, and calculated its impact on the industry-specific risk of contagion. This exercise represents a projection associated with an industry-specific development of robot adoption that is driven exclusively by the current gap between Italy and other countries. This does not represent a forecast, as sophisticated forecasts would need to account for many more features that this work does not address. To start, one aspect to model would be the actual boost that robot adoption might receive in Italy from the increased awareness of growing pandemic-related risks in the future. Moreover, a forecast would need to consider combinations of alternative cost-effective solutions (e.g., remote work, new business models, new organizational practices, temporary suspensions of non-essential activities, rapidly produced and distributed vaccines,...) that could be adopted by enterprises and authorities to reduce workplace contagion.11 Finally, should robot adoption receive a boost in all countries and sectors because of the greater awareness of the risk of contagion, the global technological frontier would move further out, whereas other innovations, such as additive manufacturing, could move the frontier in the opposite direction. As the evolution of the frontier goes beyond the scope of this paper, we restrained ourselves to provide a quantitative projection associated with a catching-up process, ceteris paribus: despite its simplicity, this could represent a benchmark against which to assess the actual trajectories of robot adoption that will be observed in the future in Italy.

Another limitation of this work is its focus on the analysis of the types of industrial robots covered by IFR. Clearly, there exist other non-industrial robots that could be used, particularly in critical services, e. g., healthcare robotics is an emerging area of application (Cresswell et al., 2018). While we do not study these robot applications, a number of interesting insights can be drawn from this literature. Focusing on the interaction between robots and social change, for instance, Soras et al. (2021) show that, in a context with a multiplicity of actors, social bonds and different ways of using the technology can lead to very different outcomes. Similarly, Saborowski and Kollak (2015) argue that care professionals tend to perceive themselves in a competitive situation with assistive technology, but that this perception changes if they are involved in the process of developing new assistive solutions. These observations derived from the experience with healthcare robotics strengthen our claim that the impact of robot adoption in the workplace is mediated by the culture and the organization. Indeed, the implementation of robots in an industrial enterprise cannot but challenge habits and practices, require non-trivial changes in the organizational structure,modify workers’ tasks, alter the distribution of control and power across employees, and impact job insecurity. A process of increased robot adoption, even when motivated by the genuine goal of mitigating the risk of workplace contagion, requires a number of accompanying actions to be balanced and socially sustainable.

As to the technical limitations of our analysis, we would like to point out two. The first one regards the level of aggregation of the analysis. Working with data on robot adoption at the firm level would have allowed us to explore various factors and mechanisms. As such data are not available, the analysis has to remain at a lower level of disaggregation. The second issue regards the cross-sectional nature of the data we use. The lack of a time dimension does not allow us to introduce industry fixed-effects and other time-varying controls. This is due to the nature of the variable for the risk of contagion in each industry that was calculated by INAIL only in 2020 to provide valuable information to the government during the first phase of the pandemic. Even so, it is worth noting that industry taxonomies (e.g., Pavitt) and classifications of occupations (e.g., routine intensive, manual, and the like) vary little over short periods of time and are typically used for cross-sectional analyses at a given point in time.

7. Conclusion

Following the rapid and dramatic spread of the COVID-19 epidemic and the measures adopted by the authorities to prevent its transmission, a fervent discussion started as to the ways to decrease the risk of workplace contagion while preserving employment levels. This paper contributes to this debate and studies the cross-industry relationship between a novel measure against the risk of COVID-19 contagion at work computed by INAIL on the basis of the characteristics of Italian occupations, on the one hand, and the adoption of robots, on the other hand. We find evidence that industries employing more robots per worker in production tend to exhibit a lower risk of contagion. Our results are robust to the inclusion of several controls for capital intensity and other forms of automation in production. They are also robust to the exclusion of particular sectors and solutions made to address potential issues of endogeneity.

These findings provide novel evidence supporting the hypothesis that greater robotization is associated with more physical distancing.

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9 As pointed out by Nakamura and Managi (2020), several infectious diseases are already in the spotlight and receiving public attention: Zika virus, yellow fever, the influenza virus, Ebola, SARS, just to mention a few.

10 https://www.universal-robots.com/blog/what-have-manufacturers-learned-after-a-year-of-covid-19/

11 In fact, one could push the modelling even further. For instance, robots and workers have been traditionally kept separated by safety systems preventing the former from hurting humans (Bicchi et al., 2008). Some observers have argued that such separation hinders human-robot collaboration (Robla-Gomez et al., 2017) and will have to be tackled via artificial intelligence and Industry 4.0 solutions so as to provide room for greater sharing of the workspace between humans and robots. Paradoxically, this development would compromise the risk-mitigation impact of robots, as it would cancel the robot-induced distance among workers. While this represents a purely speculative possibility, it is an example of the aspects that a fully-fledged forecast would need to consider.
between workers and a lower risk of workplace contagion. While this may strengthen the case for massive robotics investment to reduce the risk of workplace contagion while preserving economic activity, we offer a thorough discussion of the trade-off between changes in workplace safety and variations in employment levels and job insecurity driven by automation. We maintain that entrepreneurs, managers, and workers’ representatives may have to cooperate to combine greater robotization with organizational changes alongside strategies to develop workers’ skills and competencies. At the same time, by weighing the costs and benefits of greater automation against the costs and benefits of other contagion control solutions, policy-makers might find ways to dilute the heterogeneous impact that robotization may bring about on employment rates and conditions.

In the attempt to provide a simple procedure of robot adoption in Italy as the nation attempts to catch up with the global technological frontier in each sector, we show that, even though Italy shows some of the highest rates of robot adoption in several industries, further robotization until the global technological frontier is reached in all industries may remarkably reduce the risk of workplace contagion.

As many influential observers and global leaders have argued, the world has entered a pandemic era. Accordingly, it is most likely that individuals and policy-makers will intensify their efforts to make economies more resilient and lower the risk of workplace contagion. Robotization, as we empirically show, may play an important role in this, but caution and various accompanying measures to reduce unintended consequences on employment conditions are in order.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Appendix A. First-Stage Results

Table A.1

| Table A.1 First-stage results of robotisation. |
|---------------------------------------------|
| Baseline | Add controls |
| (1) | (2) |
| Robots per 1000 workers, In, Japan | 0.954*** | 0.859*** |
| | (0.132) | (0.147) |
| Robots per 1000 workers, In, South Korea | –0.088 | –0.113 |
| | (0.153) | (0.135) |
| ICT adoption controls | ✓ | ✓ |
| Capital intensity | ✓ | ✓ |
| Observations | 259 | 257 |
| Kleibergen-Paap F | 92.86 | 26.74 |

Notes: The dependent variable is the log of the number of robots per 1000 workers in Italy in 2018. The ICT adoption controls are: percentage of firms buying cloud computing services in 2018; percentage of firms in 2019 that use Enterprise Resource Planning software package to share information on sales/purchases with other internal functional areas; percentage of firms in 2019 that use Customer Relationship Management software to collect, file and share data; percentage of firms in 2019 that use Customer Relationship Management software for marketing analysis; percentage of firms that have purchased between 2015 and 2017 goods and services in the area Internet of Things; percentage of workers in 2019 that were provided portable devices allowing internet connection for business purposes. Capital intensity is measured using the logged capital-labour ratio. Standard errors clustered at the aggregate industry level used in the IFR dataset are shown in parentheses. *** indicate coefficients significantly different from zero at the 1% level.
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